# New Modelling Approaches to Analyse Unsafe Traffic Conditions in Real-Time

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# Abstract

Unsafe traffic conditions are associated with traffic crashes and traffic conflicts. Predicting unsafe traffic conditions is a fundamental component of a proactive traffic safety management system, enabling real-time monitoring of traffic conditions, identifying complex traffic dynamics, implementing pertinent interventions and formulating policy for traffic management. This thesis utilises video analytics through deep learning models to extract dynamic traffic variables from roadside surveillance cameras and drones over freeway segments and urban junctions. Both macroscopic traffic flow variables and microscopic traffic conditions are employed to build models for predicting near future crashes and traffic conflicts.

Short-term crash prediction models are complex to develop. This is because such models should handle both excessive zeros resulting from crash counts associated with highly disaggregated observational units and temporal auto-correlation inherent in time-series crash data. To address this challenge, this PhD thesis developed a new crash prediction model termed as Zero-Inflated integer-valued Logarithmic link Time-series (ZILT) model to predict hourly traffic crashes.

Predicting traffic crashes shorter than one hour period in advance is more difficult. Classical statistical models fail to predict half-hourly crashes. Therefore, a joint model consisting of the Time-series Generalised Regression Neural Network and the Weighted CNN (WCNN) model was built. This joint model obtains the predicted values of the covariates at the next time epoch through TRGNN and makes them as the input to the WCNN model to forecast the probability of a crash event in the same time dimension.

Proactive and predictive traffic safety management system can be established based on traffic conflict and crash prediction results to monitor real-time traffic conditions. The predicted conflicts and crashes, along with the identification of influential crash affecting variables, provide instant pre-crash information to assist road control centre to conduct timely pertinent

interventions to reduce hazardous conditions, prevent traffic crashes, and eventually promote roadway safety.

# Acknowledgement

Time flies by like a white horse, and it's just a snap of a finger. Standing at the moment when I am about to submit with my doctoral thesis, looking back on the past four years, there are too many moments worth remembering. Transferring from Loughborough University to Imperial College London, from the anxiety during the epidemic to the feeling of being in another world after the epidemic, from the curiosity when I first came to the UK to the reluctance to leave London now, from working at Tongji University when I first enrolled, to now preparing to find a development direction after graduating with a doctorate. The joys and sorrows, the happiness and torment, the taste of it, are difficult for outsiders to feel.

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*To my beloved family,*

*Cai & Wu*

*My dedicated supporters, who always inspired me to strive for greatness, never forsook and never lost faith in me. Thank you for your companionship and unconditional love, which has made me what I am today.*

## Statement of Originality

This PhD thesis is original and the result of Bowen Cai's own efforts. Bowen Cai is the sole author of the work. Material from other people's work are appropriately referenced. This thesis has not been submitted for another academic degree or professional qualification.

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# List of Abbreviations

AdaBoost: Adaptive Boosting

Adam: Adaptive Moments

ADT: Annual Daily Traffic

AI: Artificial Intelligence

ANN: Artificial Neural Network

ARIMA: Autoregressive integrated moving average

AUC: Area Under Curve

AV: Autonomous Vehicle

BN: Bayesian Networks

BOF: Bayesian Occupancy Filtering

CAI: Crash Index

CAR: Multivariate conditional Autoregressive Regression

CART: Classification And Regression Trees

CAV: Connected and Autonomous Vehicle

CCTV: closed-circuit television (CCTV) systems

CI: Crash Index

CNN: Convolutional Neural Network

CPI: Crash Potential Index

CV: Computer Vision

DMS: Driver Monitoring Systems

DNN :Deep Neural Network

DRAC: Deceleration Rate to Avoid a Crash

DRAC: Deceleration Rate to Avoid a Crash (DRAC)

DSS: Difference of Stopping distance and Safety distance

FP: False Positive

GAN: Generative Adversarial Network

GARCH: generalised Autoregressive Conditional Heteroscedasticity

GBM: Gradient Boosting Machine

GBRT: Gradient Boosting Regression Trees

GNN: Graph Neural Network

GNSS: Global Navigation Satellite System

GPS: Global Positioning System

GPU: Graphics Processing Unit

GT: Gap Time

H: Headway (H)

HM: Hurdle Model

HOG: Histogram of Oriented Gradient

ICAV: Intermediate Convnet Activations Visualization

IMU: Inertial Measurement Unit

INAR: Integer-valued Autoregressive

INGARCH: Integer Valued generalised Autoregressive Conditional Heteroscedasticity Models

INS: Inertial Navigation System

IoU: Intersection over Union

IPM: Inverse Perspective Mapping

IR: Infrared

ITS: Intelligent Transportation Systems

KF: Kalman Filter

KNN: K-Nearest neighbours

LCV: Lane Changing Vehicle

LDW: Lane Departure Warning

LF: Linear Function

LiDAR: Light Detection and Ranging

LIME: Local Interpretable Model-agnostic Explanations

LR: Logistic Regression

LSTM: Long Short-Term Memory

LSTM-CNN: Long Short-Term Memory Convolutional Neural Network

MAE: Mean Absolute Error

MLP: Multi Layer Perceptron

MSD: Minimum Stopping Distance

MSE: Mean Squared Error

MTTC: Modified time to collision

NB: Negative Binomial

NPV: Negative Predictive Value

PET: Post-Encroachment Time

PIT: Probability Integral Transform Plot

PICUD: Potential Index for Collision with Urgent Deceleration

PPV: Positive Predictive Value

PRT: Perception-Reaction Time

PSD: Proportion of Stopping Distance

PV: Preceding Vehicle

RF: Random Forest

RFE: Recursive Feature Elimination

RL: Reinforcement Learning

RMSE: Root Mean Squared Error

RMSProp: Root Mean Squared Propagation

RNN: Recurrent Neural Network

ROC: Receiver Operating Characteristic

ROI: Regions of Interest

RPN: Region Proposal Network

RWIS: Road Weather Information Systems

SD: Standard Deviation

SEM: Stacked Ensemble Model

SGD: Stochastic Gradient Descent

SMOTE: Synthetic Minority Oversampling Technique

SPF: Safety Performance Function

SSM: Surrogate Safety Measures

STGCN: Spatio-temporal Graph Convolutional Neural Network

STTNS: Transformer-based model Spatial-Temporal Transformer Networks

SVD: Stopped vehicle detection

SVM: Support Vector Machine

TET: Time Exposed TTC

TGRCN: Time-series Generalised regression Convolutional Neural network

TIT: Time integrated TTC

TN: True Negative

TP: True Positive

TSGRNN: Time Series generalised Regression Neural Network

TTA: Time To Accident

TTC: Time to collision

UAV: Unmanned Aerial Vehicle

UK: United Kingdom

US: United States

VSL: Variable Speed Limits

WCNN: Weighted Convolutional Neural Network

XGBoost: Extreme Gradient Boosting

ZILT: Zero-inflated log count data time series intervened seasonal INGARCH

ZINB: Zero Inflated Negative Binomial

ZIP: Zero Inflated Poisson

# Chapter 1 Introduction

## 1.1 Background

### 1.1.1 Unsafe Traffic Conditions

Unsafe traffic conditions refer to hazardous traffic conditions, including both traffic crashes and traffic conflicts. Causes of unsafe traffic conditions are various: extreme weather (ice, snow), unsafe road infrastructures (flooding, potholes, malfunctioning traffic lights), poor visibility, and distracted driving (drowsy, drunk, anger) are all potential causal factors. Unsafe traffic conditions increase the risk of crashing into other vehicles, objects, or pedestrians. Traffic crashes impose substantial economic and social costs to society, including infrastructure damage and delays. In 2023, there were an estimated 1.19 million fatalities worldwide due to traffic crashes (WHO, 2023), 1,645 fatalities and 29,643 casualties of serious injuries and fatalities in the UK alone (UK gov, 2023). According to the China Statistical Yearbook, in 2019 there were about 248,000 traffic crashes in total, resulting in approximately $0.2 billion in economic losses, 63,000 deaths, and 256,000 injuries. The cost of traffic crashes is high and about half of crashes are related to pedestrians, cyclists, and motorcyclists. Numerous studies have been conducted to investigate the factors contributing to traffic crashes to mitigate the losses from traffic crashes and improve traffic safety. Developing effective crash prediction models can provide early alerts to drivers and enable timely responses from traffic police to prevent traffic accidents. Findings from crash prediction and model interpretation can also provide policy implications to promote overall safety levels. Informative and appropriate explanatory variables are indispensable for building robust and precise crash prediction models. However, effectively extracting real-time traffic parameterss and integrating dynamic factors into crash prediction models to forecast near future crash incident has posed challenges for researchers for a long time and this problem has remained unresolved up to now.

The following “Vision Zero” pyramid demonstrate the concept of road safety theories based on the principle of “analysis - prevention - provision -control - consequence” (MATEC, 2021).

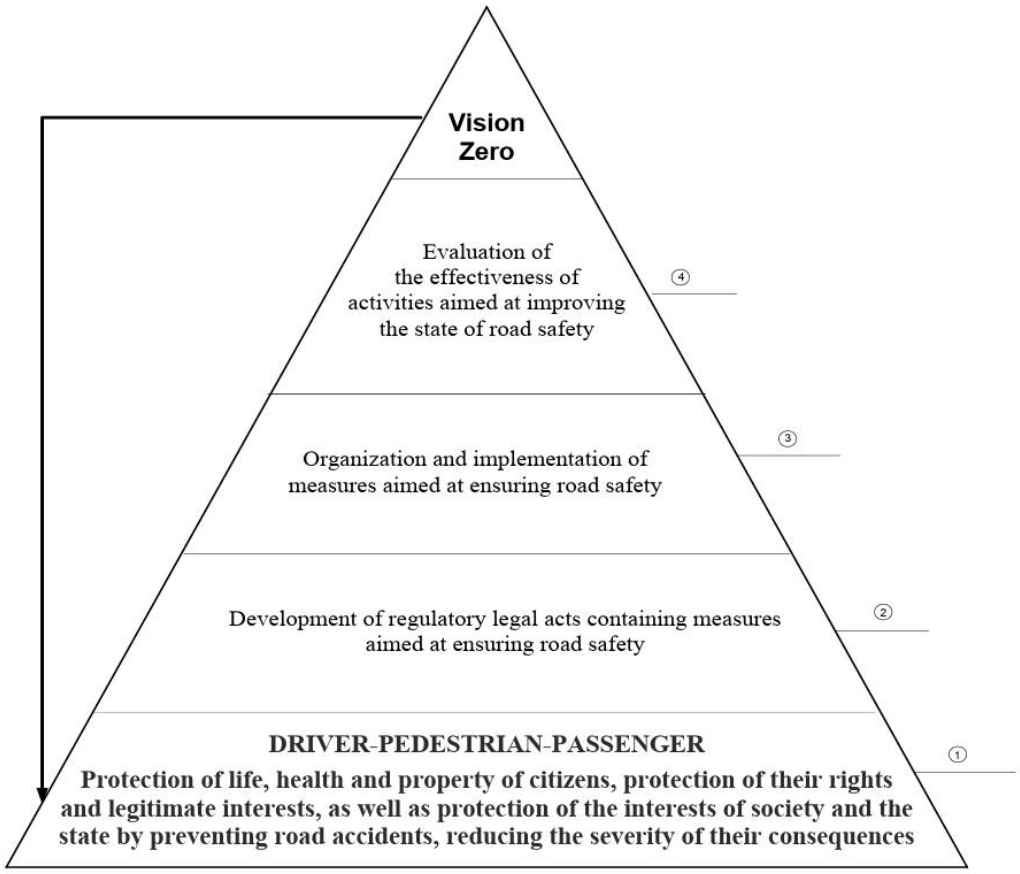



Figure 1.1. Vision Zero Pyramid (MATEC, 2021)

The pyramid theory of road safety is structured as follows:

The base of the Pyramid:

This base level emphasizes the protection of the life, health, and property of citizens, safeguarding their rights and legitimate interests, as well as protecting the interests of society and the state (MATEC, 2021). The primary goal of this level is to prevent traffic crashes and reduce the severity of their consequences (MATEC, 2021).

Second Level:

The second level focuses on the development of measures aimed at ensuring road safety.

These measures include not only the training of vehicle drivers but also the education of all citizens in road safety rules and requirements (MATEC, 2021). This is relevant to all participants in the transport process, regardless of their administrative or legal status (MATEC, 2021).

Third Level:

This level involves the implementation of the measures outlined in the second level, as well as the monitoring of activities carried out by public associations, legal entities, and individuals to prevent road accidents and mitigate their consequences (MATEC, 2021). It encompasses meaningful actions such as the construction, repair, and operation of highways, the installation of traffic management systems, the improvement of vehicle safety standards, and the training of drivers for safe participation in the transport process (MATEC, 2021). The responsibility for implementing these measures lies with various government bodies, such as the Ministry of Transport, and the Ministry of Health, with tasks distributed among their subordinate organizations and institutions (MATEC, 2021).

Fourth Level:

The top of the pyramid involves the evaluation of the effectiveness of the activities implemented to improve road safety (MATEC, 2021). This assessment ensures that the measures taken are achieving their intended goals and identifies areas for further improvement (MATEC, 2021).

The Vision Zero program aligns with this pyramid theory by incorporating principles such as "control and separation," "functional harmony," "predictability and simplicity," and "striving for limitations" (MATEC, 2021). Therefore, to prevent traffic crashes, predictive models and prevention strategies should be implemented accordingly. This thesis will focus on discussing predictive and preventive systems by putting forward crash and conflict prediction models, identifying contributing factors, analysing causal factors, and devising pertinent interventions to reduce crash risk and enhance overall traffic safety levels based on fundamental traffic road safety theories.

Traffic crashes are rare events that occur randomly, and are closely linked to spatial and temporal systematic structures. They have multifaceted causes and exhibit a highly skewed statistical distribution. Numerous factors can influence traffic crashes, including static traffic features, dynamic traffic parameterss, driver conditions, and environmental factors. Static traffic features include road types (mountainous freeway, urban freeway, plain freeway, junction), road grades (freeway, expressway, ordinary ways) and roadway geometry design features. Dynamic traffic parameterss include traffic flow, density, speed, speed variances, lane changes, and vehicle types. Driver conditions refer to factors such as fatigue, road anger, distractions (e.g. phone use), and smoking. Environmental factors encompass precipitation, visibility, wind, and snow. These factors contribute to crash frequency and represent different dimensions in interpreting crash occurrences. Road traffic collisions are complex phenomena involving interactions among road geometry, environmental conditions, traffic dynamics, vehicle and human factors. A significant bottleneck that restricts short-term collision prediction models from achieving high accuracy and having a practical application is the acquisition of real-time traffic operational variables such as speed, traffic flow, and traffic dynamics.

However, near future roadway crashes is a small likelihood event. Collecting crash data in a short period at road segment is extremely hard. In response to the challenge posed by the scarcity of crash data, the concept of traffic conflicts has emerged as a valuable tool for evaluating traffic safety. Traffic crash is defined as an event where a collision involving various road users such as vehicles, motorcycles, and pedestrians, resulting in measurable consequences, such as injuries, disabilities, property damage, or death (Road Traffic Accident, UNDRR). In contrast with traffic crash being an actual collision with measurable consequences, the original definition of traffic conflict is an observable situation in which collision is imminent if their movements remain unchanged (Amundsen and Hydén, 1977). It can also be interpreted as a near-miss situation in which a crash is about to happen but does not actually happen due to an intervention by user or a safety device or by taking immediate and appropriate actions such as braking, or swerving (Formosa, et al., 2020). The disparities

between traffic crashes and conflicts are displayed in the following table for better clarification.

Table 1.1. Distinguishes between traffic crashes and conflicts

| | Consequence | Participants | Collision | Measure |
|---|---|---|---|---|
| Traffic Crashes | Measurable: Damage, Injury, Death | vehicles, pedestrians, or other road users | Actual Collision | Passive Measure |
| Traffic Conflicts | Avoidance. Not actual collision | vehicles, pedestrians, or other road users | Near Miss Events | Proactive Measure |

Conventional crash prediction models are based on police-reported crash data. Reactive crash analytical models are built on historical crash data to establish an association of factors affecting crashes from retrospective perspectives. Proposed road safety improvements are made in reaction to identified safety problems brought to light by crashes that have occurred after the road has been designed, built, and opened to the traveling public (U.S. Department of Transportation, Federal Freeway Administration). However, the effectiveness of reactive crash analysis is faced with the problem of crash data quality such as under-reporting and geo-coding errors, and more importantly, no information regarding pre-crash conditions. Therefore, the reactive approach majorly relies on statistical modelling to analyse association rather than causation. A paradigm shift should be established from a reactive crash approach to a proactive crash approach and to the predictive crash approach eventually. In order to prevent crashes, vehicle kinematics and dynamic traffic operation parameters should be calculated before the event, and the feasibility of crash risk indicators should be investigated to detect the early stages of crash development and further examine the factors affecting crash occurrences (Papazikou et al., 2019).

Surrogate Safety Measures (SSMs) are used in road safety analyses as alternative indicators to quantify various unsafe traffic events. Safety surrogate measures offer a means to assess conflict risk, drawing upon data collected by sensors such as cameras, radars, and Lidars installed on various platforms, including drones, roadside units, and vehicles. With the employment of different SSMs and traffic dynamic variables, statistical machine learning models can be built for conflict prediction in various scenarios. Predicting the probability of a traffic conflict occurring and identifying the contributory factors hold significant implications for roadway operators and vehicle manufacturers, aiding in the development of countermeasures and strategies to detect infrastructure and vehicle-related traffic conflicts.

About 50% of traffic crashes are from pedestrians, cyclists, and motorcyclists and human error contributes to about 90% (WHO 2023). Developed countries are experiencing flat-lining fatality trends. Crash further decline is getting more difficult and requires an in-depth analysis of interactions among vehicles, humans, infrastructure, and the environment. A retrospective study of reactive crash association analysis is not sufficient to reduce fatality rate since the reactive approach is still passive prevention in essential. A complete and immediate 'paradigm shift' in transport should be constructed from approaches of reactive crash association analysis to proactive crash prevention and predictive crash causation. Historical crash data builds the foundation of crash prediction model and investigates the association of contributory factors affecting crash occurrences. Proactive crash prevention integrates near crash indicating factors such as SSMs, vehicle kinematics, and dynamic traffic parameterss to form holistic proactive prevention systems and strategies, such as Active/proactive in-vehicle safety systems (ADAS). Predictive crash models prevent traffic crashes in advance by analysing causation and calculating crash risk probability to promote safety level in general. The following figure depicts crash sequence by matching human error and crash protection in naturalistic driving.

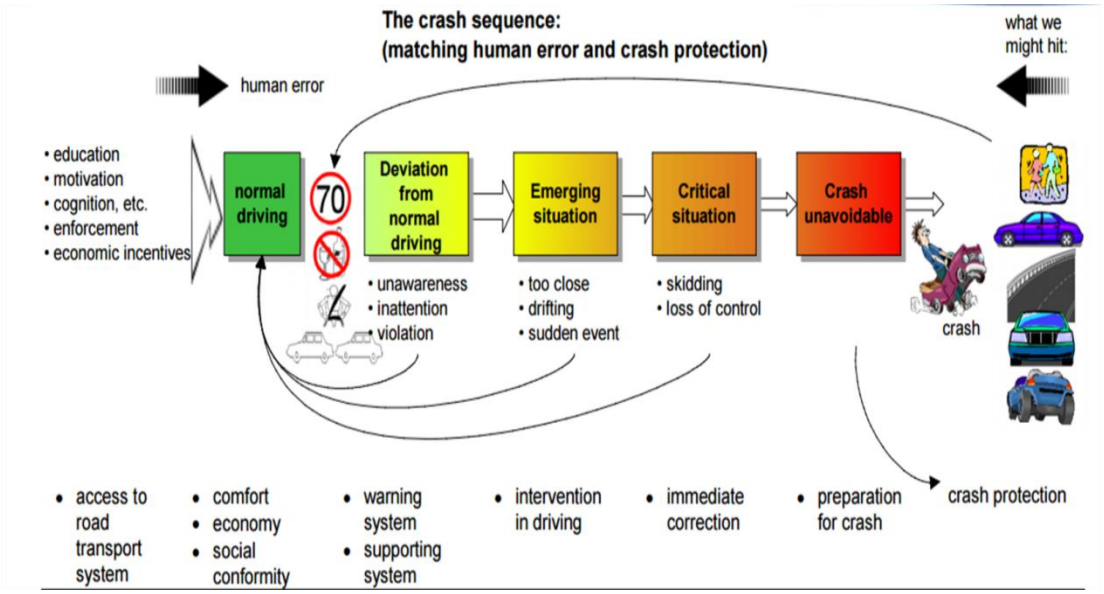



Figure 1.2. The Crash Sequence in Naturalistic Driving Study.

Based on crash and conflict predictive models, proactive system for preventing road crashes and injuries can be built. The following plot shows the key elements of the road crash prevention system.

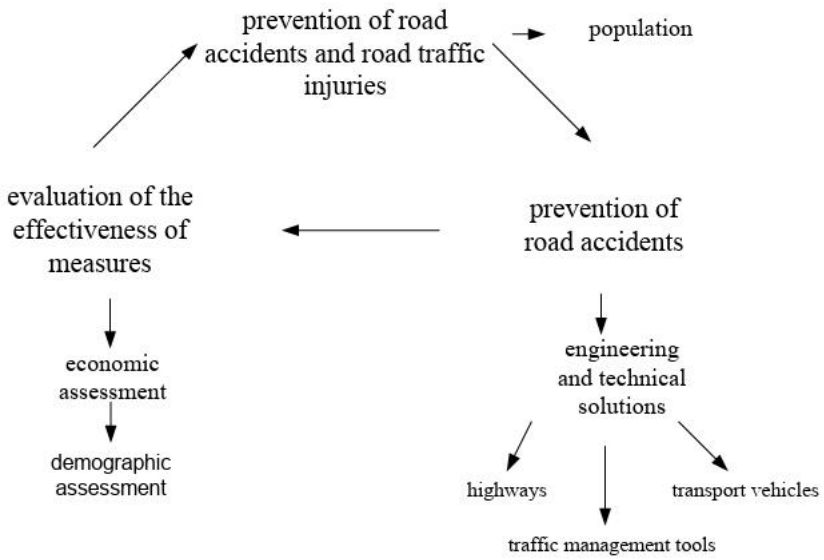



Figure 1.3. Understanding of the road crash prevention system (MATEC, 2021)

### 1.1.2 Sensors in Proactive Traffic Safety Management

Proactive traffic safety management has emerged as a crucial method to reduce unsafe traffic conditions, facilitated by the availability of emerging and better quality data via a plethora of ITS sensors such as inductive loop detectors (ILDs), cameras, radars, and Lidars on roadways (Abdel-Aty et al., 2010). The underpinning technique enabling proactive traffic management is real-time crash prediction (RTCP) to implement measures to reduce the crash risk and bring back the traffic state to a safe situation through the implementation of pertinent interventions.

Existing studies highlight that unstable traffic dynamics contribute significantly to complicated vehicle interactions and subsequent road traffic crashes, particularly on high-speed road networks. Consequently, the ability to predict unsafe hazardous traffic conditions is imperative in establishing a proactive traffic safety system. Such a system could assist network operators to anticipate potential collision locations and times in advance. Once potential collision triggers are identified, operators can implement pertinent interventions (e.g., speed limit adjustments, and other warnings) to alleviate traffic conditions that might lead to collisions.

Conventionally, traffic characteristics like speed, volume, and travel times have been gathered from various sensors and systems, including Inductive Loop Detectors (ILDs), Automatic Number Plate Recognition Cameras (ANPR), and GPS-equipped floating vehicles. However, existing literature has pointed out several issues with these data sources, such as missing observations, aggregated measures (resulting in low sampling frequency), and a lack of detailed individual vehicle data (like speed variance and trajectories).

With advancements in deep learning computer vision technology, typical video sensors such as roadside surveillance cameras, Unmanned aerial vehicle (UAV) drones and in-vehicle forward-facing cameras can be used as a data collecting unit. According to statistics, China alone has approximately 24 million roadside surveillance cameras, and there are estimated to be more than 100 million roadside surveillance cameras worldwide (the south China Morning

Post, 2019). UAV drones and in-vehicle cameras are popular and convenient to use for capturing RGB videos to record traffic conditions. Deep learning computer vision techniques can then be applied to extract dynamic traffic parameterss in real-time base.

Although roadside surveillance cameras cover most of the road segments, especially in freeways, existing techniques for extracting traffic data (e.g. speed measurements of individual vehicles) from videos are not accurate enough to be employed for proactive traffic management systems. Therefore, it is essential to develop new techniques for estimating traffic data from images captured by surveillance cameras. By applying computer vision with deep neural networks to analyse video data, dynamic traffic parameterss can be extracted from in real-time base through detection, tracking, and prediction methods. Highly disaggregated vehicle-based data, including trajectories, speed, and traffic volume, can be transformed into aggregated traffic characteristics such as speed variance (within a lane and between the lanes), average speed and traffic flow. Camera sensors include roadside surveillance cameras, ETC cameras mounted above roads, and UAV drones. These camera sensors capture objects through imaging and video recording. Although image processing algorithms differ across these camera sources, object detection and tracking models remain similar. Extensive traffic data labeling ensures highly accurate detection results. By taking traffic observations from a high-quality LiDAR (Light Detection and Ranging) sensor as 'ground truth', the study from this thesis shows that the developed technique can estimate lane-based traffic volume, speed, vehicle types, etc. at very high accuracy. With real-time traffic dynamic parameters collected from video processing of roadside surveillance cameras and UAV drones, short time crash prediction can be realised by utilising real-time traffic data to build crash prediction models.

### 1.1.3 Prediction Methods for Unsafe Traffic Conditions

Over recent decades, a plethora of Safety Surrogate Measures (SSMs) have emerged as valuable metrics for predicting traffic conflicts. However, existing research predominantly

focuses on conflict prediction at junctions or relies on a single SSM, such as time-to-collision (TTC), for detecting vehicle-related conflicts. This leads to incorrect conflict identification as found by Papazikou et al. (2019) that single-vehicle crash risk was not considered properly. This limitation highlights the challenge of selecting appropriate SSMs for vehicle- or segment-based conflict prediction, considering the diverse range of factors influencing conflict outcomes. To address this gap, this study leverages data collected from various infrastructures and vehicle-based sensors, including drones, lidars, radars, and cameras in China and the UK: urban junctions, motorway segments, and vehicle-based data from instrumented vehicles. Machine learning approaches are employed to manage extensive and disaggregated data, including the development of a stacked ensemble method for classifying traffic conflicts from normal driving maneuvers and vehicle interactions. In-depth analysis is also conducted to evaluate different SSMs' performances across various scenarios. Interpretation of the relationship between traffic conflicts and SSMs will also be discussed in Chapter 8 results analysis.

Unlike traffic conflicts that can be identified by human observers, short-window traffic-crash count data, however, exhibits excessive zeros and serial autocorrelation. Most of the commonly used regression-based models fail to address excessive zeros and temporal structure simultaneously in hourly traffic-collision prediction. Utilising dynamic traffic data, crash prediction models can forecast crashes in different short-term spans (hourly, semi-hourly, and real-time conflicts). Predicting short-term traffic crashes presents significant challenges due to imbalanced datasets characterised by excessive zeros in non-crash counts, random crash occurrences, spatio-temporal correlation in crash counts, and inherent heterogeneity. Existing models, in isolation, struggle to effectively address these distinct characteristics present in crash data. This thesis puts forward both a time series based zero inflated model and a generalised regression based convolutional neural network model to capture crash characteristics and make crash predictions in different time spans.

The findings of this study could be utilised by relevant transport agencies in developing engineering interventions and countermeasures to proactively manage road safety. These

findings hold significant implications for roadway operators and vehicle manufacturers in devising strategies to detect infrastructure and vehicle-related traffic conflicts.

This thesis will introduce computer vision techniques for extracting dynamic traffic data, hourly and semi-hourly crash prediction, traffic conflict prediction, and pertinent interventions to prevent traffic crashes.

## 1.2 Problem Statement

Unsafe traffic conditions refer to hazardous traffic conditions, including both traffic crashes and traffic conflicts. Causes of unsafe traffic conditions are various: extreme weather (ice, snow), unsafe road infrastructures (flooding, potholes, malfunctioning traffic lights), poor visibility, and distracted driving (drowsy, drunk, anger) are all potential causal factors. Unsafe traffic conditions increase the risk of crashing into other vehicles, objects, or pedestrians. Normal traffic conditions are contrary to unsafe traffic conditions in the opposite perspectives. Ribeiro Jr et al. (2012) conducted a manual classification of traffic-related tweets, organizing them into two main categories: traffic conditions and traffic events. Traffic conditions refer to the real-time state of traffic at a particular location and moment, such as descriptions like "slow traffic" or "congestion" (Ribeiro Jr et al., 2012). On the other hand, traffic events pertain to specific incidents or occurrences that have the potential to disrupt or change traffic conditions, such as crashes and conflicts (Ribeiro Jr et al., 2012). While this manual classification approach provides valuable insights, it is inherently time-consuming and labor-intensive, requiring significant human effort (Xu et al., 2018). To overcome these limitations, machine learning techniques have been increasingly employed as a more efficient and scalable alternative for automatically classifying and analyzing traffic-related tweets (Xu et al., 2018).

Normal traffic conditions can be defined from different perspectives. In the scope of this thesis, normal traffic condition is defined based on traffic flow theory and traffic safety

perspectives.

From a traffic flow theory perspective, traffic flow theory generally categorizes traffic states into free flow, stable flow, and unstable flow (congested flow) (Knoop, 2017). Normal traffic conditions usually correspond to free flow or stable flow states.

From a traffic safety perspective, normal traffic conditions are defined by low crash risk, normal driving behavior and good environmental conditions (Malin et al., 2019). To be specific, stable traffic conditions usually with no significant conflict points, no dangerous behaviours (such as frequent lane changes, abrupt braking, etc), and adverse weather factors affect traffic flow (Malin et al., 2019).

Unsafe traffic conditions are random, occasional events with a low likelihood of occurrence, making their characteristics difficult to capture accurately and predict. However, if unsafe traffic conditions could be predicted, timely pertinent interventions could thereafter be implemented to prevent crash occurrences and alert drivers to take evasive actions to avoid collisions. Predictions for traffic crashes are typically classified into long-time period, short-term period, and real-time intervals. Empirically, long-time predictions cover daily, monthly, or even yearly predictions. Short-term predictions span less than or equal to one hour. Real-time base predictions involve immediate forecasting based on traffic conflicts as surrogate indicators for crashes. This thesis primarily focuses on short-term crash prediction and real-time conflict prediction.

Traffic crashes are actual random collisions with sparse distribution and small likelihood. The total number of traffic crashes is very limited and crash events are hard to be collected. Traffic conflicts, however, is the situations where interaction of relevant road users increases the risk of crashes but does not actually result in traffic collisions. The likelihood and frequency of traffic conflicts are much higher than actual collisions. Conflict data collection is also straight forward, which can be identified by independent observers or equipped sensors such as Radar, LiDar, and cameras. Limitations of actual crash data and crash-based methods

have given rise to the study of alternate measures of safety that do not predict on the occurrence of a crash but traffic conflicts instead.

Although traffic conflicts and crashes share the same failure mechanism in the driving process, modeling traffic conflicts presents new challenges because of their distinct characteristics. Traffic conflicts are distinct from traffic crashes in the following three perspectives: safety events continuum, etiological consistency, and crash causality (Zheng et al., 2021; Tarko, 2021). Traffic conflict is treated as a crash precursor for being as a traffic encounter with a considerable probability of harmful collision (Tarko, 2021). However, traffic conflict may or may not lead to crashes. If drivers follow a controlled and comfortable manner and do not violate crash nearness values, then crashes may be avoided (Tarko, 2021). However, if drivers fail to see the hazard and violate and violate crash nearness values, then they may not avoid a collision (Tarko, 2021). Crash nearness values are influenced by driver response time which is largely subject to the relative vehicle speeds. Therefore, the relationship of vehicle operation parameters with traffic conflicts and crashes should be distinct even though they may have some connections. Extracting dynamic vehicle operation parameters is imperative for our research to investigate inherited characteristics and causal effects of traffic conflict and crashes.

However, acquiring real-time traffic motion parameters through high-resolution detectors such as LiDAR, Radar, and Inductive loop detectors may not be practical in many cases. Unlike surveillance cameras, LiDAR, Radar, and inductive loops cover only selected road segments and do not capture all dynamic traffic operational parameters, such as lane change behaviour, vehicle trajectory, detecting fire and lane occupancy. Therefore, utilising abundant roadside surveillance cameras to extract needed traffic parameterss is conducive and important to research in analysing unsafe traffic conditions. With the development of computer vision technologies, statistical machine learning, deep learning, and artificial intelligence are becoming popular used advanced methods in various applications: image recognition, audio recognition, naturalistic language processing, autonomous and connected vehicles, and traffic proactive safety management, etc. Computer vision-based deep learning

methods can also find its applications in extracting dynamic traffic parameterss in civil engineering. Many detection and tracking models such as You Only Look Once (YOLO-v8), Fairness Multiple Object Tracking (FariMOT), and affine matrix transformation for spatial coordinates conversion provide possibilities in capturing traffic variables.

After collecting dynamic traffic operation data through video processing, hazardous traffic situations such as crashes, traffic conflicts, and abnormal events (unexpected stopped vehicles) should be predicted over different periods using real-time traffic data. Designing accurate traffic unsafe condition prediction models is a critical focus of this thesis. Unsafe traffic conditions (conflict, crash) usually exhibit inherent spatial and temporal characteristics. Capturing spatial and temporal structures and identifying appropriate traffic patterns for various roadway scenarios are the prerequisites for crash and conflict prediction. Different statistical machine learning models should be built for different prediction purposes by incorporating relevant traffic features. This study selects hourly crash prediction as long-term prediction period, semi-hourly crash prediction as near future prediction period, and real-time traffic conflicts as crash surrogates for immediate prediction. Once traffic hazardous condition prediction models have been built, important factors contributing to conflict or crash occurrences will be investigated and the relationship between unsafe traffic conditions and traffic and vehicle dynamic operational data will be studied. Discussions on implementing pertinent interventions based on unsafe traffic condition prediction results to prevent and alleviate traffic collisions will also be included in this thesis.

Therefore, several challenges hinder the realisation of such a safety system:

(i) Lack of highly detailed and disaggregated traffic data,

(ii) Inconsistent availability of this data across segments over time,

(iii) Techniques to predict unstable traffic conditions and determine causal factors simultaneously and

(iv) Strategies to devise interventions to prevent potential collisions.

This PhD thesis aims to overcome these limitations by developing:

(i) Novel methods to acquire highly detailed real-time traffic data,

(ii) Robust computer vision models to detect, track, and classify video objects, and calculate dynamic traffic data in the meantime,

(iii) Leveraging deep learning for forecasting unstable traffic conditions, including crashes, conflicts, and

(iv) Utilising causal analytical methods to identify factors contributing to hazardous traffic situations.

This thesis meticulously analyses the mechanisms of crash occurrence, the characteristics of traffic crashes, the characteristics of traffic conflicts, crash surrogate safety measures, key contributing factors influencing traffic crashes, and their importance scores. Based on deep learning techniques and mathematical statistical analysis, it constructs semi-hourly and hourly traffic accident prediction models, as well as a real-time traffic conflict prediction model. The development of these models will benefit transport engineers engaged in traffic safety analysis, traffic engineering, and intelligent transportation systems. Transport engineers can be benefited from this PhD thesis to gain a better understanding of the mechanisms and causes of unsafe traffic conditions (crashes and conflicts). Additionally, the traffic crash and conflict prediction models provided in this thesis are easy for transport engineers to replicate. The input includes historical traffic crash data, traffic operation variables such as vehicle speed, speed variance, lane-specific flow, vehicle type, truck to car ratio, weather conditions (cloudy, sunny, rainy, snowy), and road geometry. The output consists of short-term traffic crash predictions and the causal factors of unsafe traffic conditions along with their influencing factors.

In the future, the author plans to develop traffic crash analytic and prediction software based on the models provided in this thesis. Traffic engineers will be able to predict unsafe traffic conditions through simple software operations. By predicting future traffic crashes, transport engineers can better grasp traffic operation trends and causal factors. Furthermore, by utilising the methods provided by this thesis, traffic engineers can calculate corresponding traffic risk values based on the predicted number of crashes and their probabilities, enabling

proactive roadway traffic safety management in real applications. Applying initiated models and analytical methods in this thesis, transport engineers can utilise available sensors, such as various types of roadside cameras, for instant extraction of dynamic traffic parameterss, build intelligent traffic conflict and crash prediction models for the near future, devise pertinent interventions to prevent unsafe traffic conditions, and make recommendations for policy formulation.

## 1.3 Research Importance

Despite significant progress achieved, there is still serious concern regarding road safety with more than1.35 million people dying annually worldwide and a further 50 million people suffering injury due to road crashes. The concept of measuring crash risk over very short time window in the near future has been gaining more practicality due to the recent advancements in the fields of information systems and traffic sensor technology. real-time safety prediction approaches, which aim at monitoring traffic in real-time, identifying unsafe traffic dynamics, and implementing suitable interventions, play a crucial role for the development of proactive road safety management systems.

### 1.3.1 Importance of Computer Vision Recognition

Timely traffic operation information provides operational parameters for predicting crashes in real-time. The development of video detection techniques facilitates the collection of data such as vehicle types, real-time vehicle trajectories that are hard to obtain from other sources (e.g. ILDs), such as. Compared to non-intrusive detection systems such as Automatic Vehicle Identification (AVI) and Remote Traffic Microwave Sensors (RTMSs), video analysis based on roadside camera recordings is more cost-effective and provides access to real-time traffic data from multiple perspectives. According to statistics published by the south China Morning Post, there are more than 200 million surveillance cameras of the ‘SkyNet System’ in China alone. This large volume of video cameras provides a vast amount of valuable recording data.

Exploring and analysing information contained in the data enable the capture of real-time traffic conditions and make an estimation of future traffic system behaviours.

Different from calibrated speed cameras or radar-equipped cameras, the methodology proposed in this research puts forward a more general technique that can process videos for extracting necessary traffic operation information with known parameters of surveillance camera height and lane width and is not restricted from further calibration or auxiliary facilities installed. The availability of such rich data from roadside cameras enhances the reliability of travel time estimation and route guidance systems. However, the utilization of these data is currently limited in the context of proactive safety management systems. By integrating real-time traffic operation parameters into statistical or deep learning model, near future crash incidents can be predicted more precisely.

### 1.3.2 Importance of Predicting Unsafe Traffic Conditions

Safety field theory is applied in the road-user context by conceptualizing each individual as carrying an inherent risk of a crash by their motion and recognizing that they actively try to minimize their crash risk to maintain an acceptable level of safety (Arun et al., 2022). Traffic theory analysis involves using theoretical statistical models to explore the contributing factors, mechanisms, and patterns of crashes and conflicts in order to identify crash hotspots for enhancing road safety measures and developing effective prevention strategies (Shahi, et al., 2023). The relationship between standard behaviour to conflicts, and crashes can be explained by the following plot.

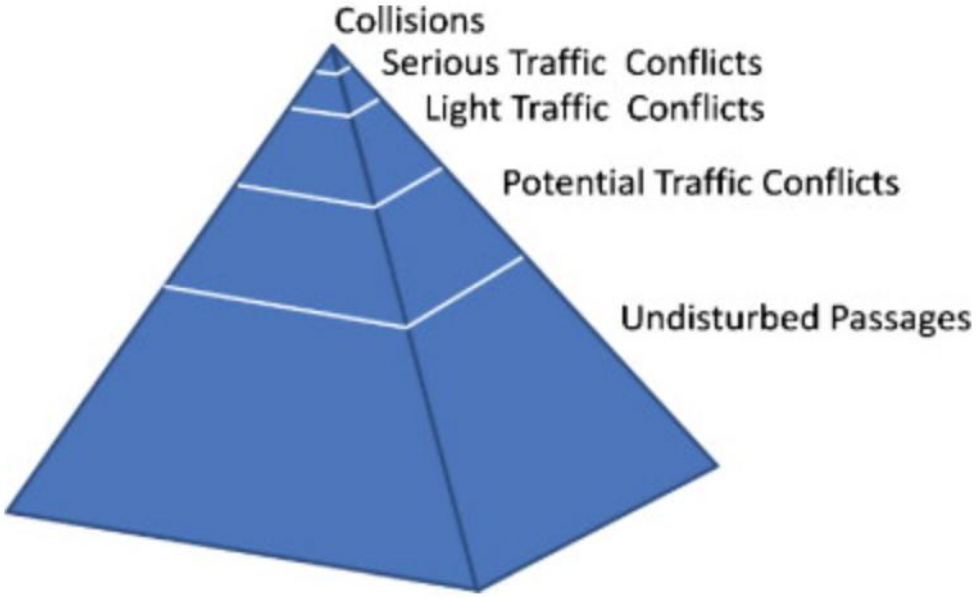



Figure 1.4. Pyramid of traffic events—based on Hyden (1987).

A different layer represents a class of events of similar severity and the volume shows the frequency of these events (Hyden, 1987). Investigating the relationship among various traffic operation parameters and modeling the movements of road users is essential for estimating the likelihood of crashes. The traffic safety continuum concept suggests that all traffic events, ranging from normal interactions to actual crashes, are part of a shared causal chain (Arun et al., 2023). Even seemingly minor traffic incidents may hold valuable safety insights (Hydén, 1987; Laureshyn et al., 2010; Sobhani et al., 2010). Therefore, the identification of contributing factors to unsafe traffic conditions and investigation causality of traffic crashes are indispensable for reflecting traffic safety theory and improving road safety levels. For instance, the relationship between traffic conflicts and crashes is highly context-specific. Factors such as the traffic environment, which varies by geographic location, and the data collection method (e.g., manual observations, video-based measurements, or naturalistic driving studies) can greatly affect the strength and reliability of this relationship (Arun et al., 2023).

Tarko (2012) further formalized this idea by introducing a sequential model of traffic safety

events, which uses information from earlier events to predict subsequent safety-related occurrences. This plot also depicts the relationship between normal interactions with unsafe traffic conditions, showing the evolution from road user normal interaction, to risky events (conflict), and to the different severity levels of traffic crashes.

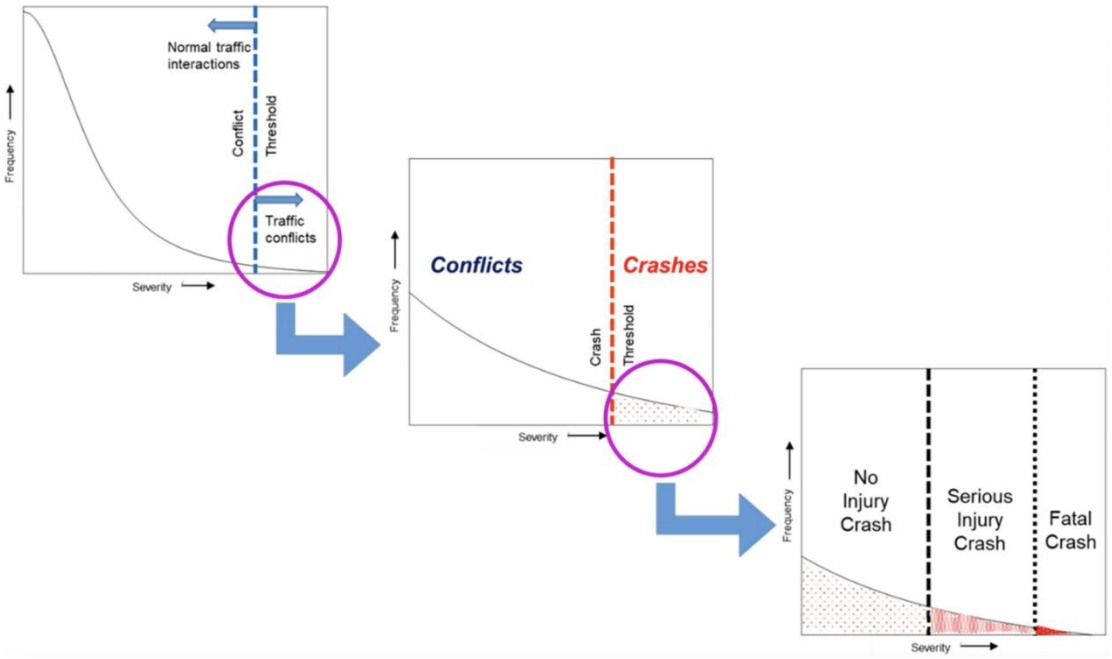



Figure 1.5. Sequential traffic safety assessment (Tarko, 2012)

As discussed, unsafe traffic conditions prediction encompasses long-term crash prediction, short-term crash prediction, and real-time conflict prediction using conflicts as crash surrogates practically. Long-term predictions forecast trends beyond one hour. Short-term, equivalent near future crash prediction refers to forecast period within an hour. Real-time conflict prediction refers to the forecast period in real-time base or less than 5 minutes. Long-term prediction can help stakeholders to see crash trend in the future. Near future crash prediction can inform traffic police to devise pertinent intervention strategies to prevent accidents. Real-time conflict prediction is essential to autonomous vehicles and connected vehicles, transmitting information on risky driving maneuvers and vehicle interactions. One common definition of traffic conflict is that a conflict occurs when two or more road users come into proximity in both space and time, creating a situation where a collision is likely unless their current paths or speeds are altered (Svensson, 1998). Prediction of traffic conflicts precisely can prevent traffic crashes from occurring to a large extent by reducing risky

behaviours through the implementation of pertinent interventions.

Traffic crashes involve complex interactions among various external factors, such as road environments, traffic dynamics, and human behaviours. Therefore, beyond extracting traffic parameterss, this thesis will investigate deeper into optimising deep learning and statistical modelling structures to consider not only spatio-temporal crash features, but also the comprehensive influence of traffic parameterss on crash occurrences. This study will propose different statistical and machine learning methods to predict hourly crashes and near future crashes (semi-hourly) by using real crashes data collected both in China and the United Kingdom. For traffic conflict prediction, relevant machine learning methods will be applied to classify traffic conflict using different safety surrogate measures (SSMs) and vehicle motion parameters utilising infrastructure based motorway, urban junction, and vehicle based motorway data from China and the UK.

Variable importance is also analysed across different scenarios. For crash prediction, Local Interpret Model-agnostic Explanation (LIME) method is used to analyse contributing factors and variable importance of short-term crash incident in this study for deep learning CNN model. For traffic conflict prediction, Recursive Feature Elimination (RFE) algorithm is used to rank the most significant factors including both SSMs and traffic dynamic data, in identifying conflicts across different road environments.

## 1.4 Research Aim and Objectives

To achieve this aim, specific research objectives have been outlined:

- To analyse factors affecting unsafe traffic conditions.
- To develop computer vision algorithms to extract traffic features.
- To create an ensemble learning model to predict traffic conflicts in real-time.
- Apply statistical machine learning to predict near future crashes.
- Formulate policy implication to prevent unsafe traffic conditions.

The primary purpose of this PhD thesis is to utilise available sensors, especially various types of roadside cameras, for instant extraction of dynamic traffic parameterss, build intelligent traffic conflict and crash prediction models for the near future by making use of the acquired traffic parameterss as independent variables, devise pertinent interventions to prevent unsafe traffic conditions, and make recommendations for policy formulation.

This PhD thesis will present the development of deep learning computer vision algorithms in extracting dynamic traffic parameterss through video processing in freeway road segments and urban junctions respectively, the building of stacked hierarchical ensemble learning model in classifying real-time traffic conflicts, and the establishment of a new time-series model in predicting hourly and semi-hourly traffic crashes.

Upon the detection of traffic conflicts in real-time, this PhD thesis will also discuss pertinent interventions to prevent unsafe traffic conditions. It will introduce instances of traffic police departments and freeway management companies in dealing with traffic crashes, abnormal scenarios, and post crash situations. Abnormal scenarios such as congestion, retrograde, unexpected stopped vehicles, pedestrian walking in the motorway, etc, are treated as crash harbingers and will increase risk of occurring unsafe traffic conditions to large extent. Retrospective on how traffic control centre dealing with unsafe traffic conditions and formulating relevant regulations provide references and recommendations to researchers for investigating suitable interventions in reducing traffic crash risk and promoting traffic safety level by making pertinent policies and management regulations.

## 1.5 Research Design

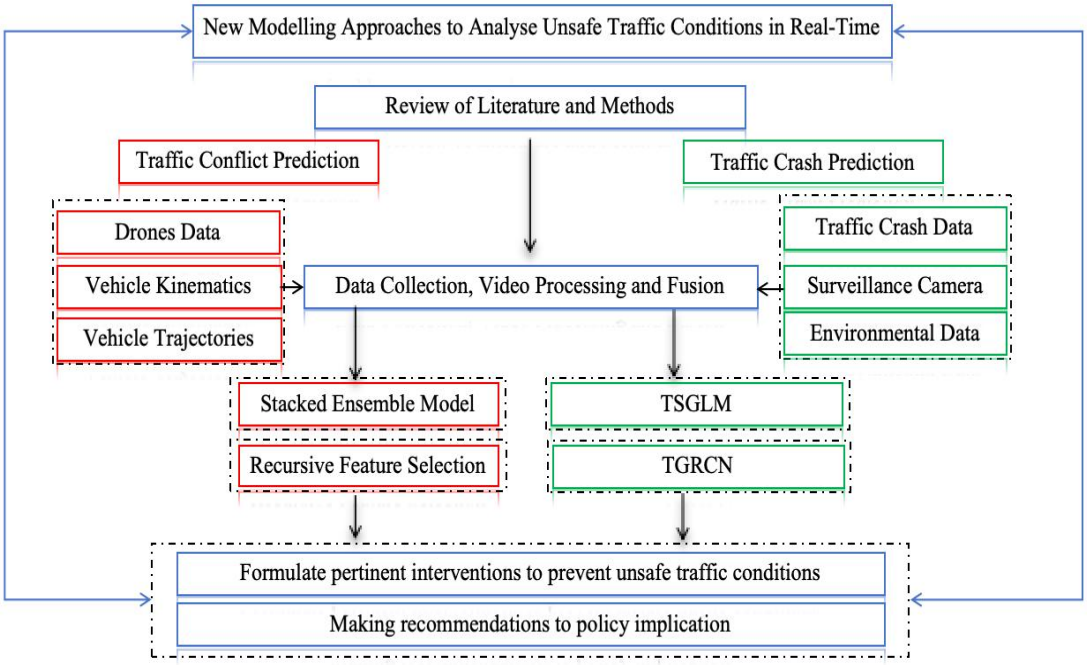
The research objectives are achieved through data collection and methodologies outlined in Table 1.1.

Table 1.2 Research Design

| Seq | Objectives | Approach | Chapter | Outcome |
|---|---|---|---|---|
| 1 | Analyse factors affecting unsafe traffic conditions. | Literature review | 2 | A series of contributory factors in predicting unsafe traffic dynamces (both crashes and conflicts) |
| 2 | Develop computer vision algorithms to extract traffic features. | Literature review and a new video analysis technique | 4 | A new computer vision algorithm to obtain traffic flow conditions on a roadway |
| 3 | Create an ensemble learning model to predict traffic conflicts. | Developing a new technique to integrate multiple machine learning methods | 2, 3, 5, 8 | An ensemble machine learning model |
| 4 | Apply statistical machine learning algorithms to predict near future crashes. | Literature Review, Methodology, Results Analysis | 2, 3, 6, 8 | A model for predicting short-term (i.e. 30-minute and 1 hr) traffic crashes |
| 5 | Formulate policy implication to prevent unsafe traffic conditions. | Discussions and Conclusion | 9, 10 | A set of recommendations to enhance traffic safety by preventing traffic crashes (predictive approaches to road safety) |

The following flow chart depicts the overall outline of this PhD thesis, illustrating the

relationships between different components, independent variables, methodologies, and objectives.




ZILT: Zero-inflated log count data time series intervened seasonal INGARCH model

TGRCN: Time-series Generalised regression Convolutional Neural network model

Figure 1.6. Overall Thesis Methodology

## 1.6 Thesis Outline

This thesis consists of ten chapters.

Chapter one is the Introduction. The main idea of this chapter is to state the background, limitations, research importance, and objectives of the PhD project. It briefly introduces the proposed methods and technical routes to solve existing problems, provides the foundation, meaningfulness, and necessity of having this research, and describes thesis outlines and how the document is structured.

Chapter two presents traffic crash characteristics, influencing factors, and traffic parameterss extraction through computer vision. This chapter is composed of two parts. The first part

discusses inherent characteristics of traffic crashes, traffic influencing factors, and driver conditions that may lead to crash occurrences. It introduces the inherent characteristics such as excess zeros and spatial temporal structures in crash data and explains their relationship to traffic dynamic features in both short and long-term window. The second part introduces the effectiveness of various types of visual sensors used in different scenarios, a new affine transformation from the image space to the world space, detection and tracking methods based on deep learning, and explains the real application of computer vision techniques in this study.

Chapter three presents time series methods, spatial statistics, machine learning classification methods, and deep learning neural network methodologies that are used in real-time traffic conflict classification and traffic crash prediction. This chapter also introduces surrogate safety measures for conflict detection.

Chapter four describes the development of computer vision techniques in extracting traffic dynamic features. In contrast to Chapter two - introduction of computer vision techniques and sensors, this chapter focuses more on the specific technical routes and deep learning models used in this study to extract traffic parameterss in different scenarios. This chapter also includes results analysis and findings discussion in the application of computer vision techniques in different scenarios.

Chapter five presents traffic conflict classification and causal analytic method. This chapter is composed of two parts. The first part initiates a new stacked ensemble learning method to predict traffic conflict in real-time. This method integrates both machine learning and deep learning models to build strong classifiers in conflict classification. The second part introduces feature importance algorithms for analysing contributing variables in explaining causal factors of crash occurrences. It compares different causal factors for traffic crashes and traffic conflicts respectively and then analyses the importance of influencing factors in different scenarios.

Chapter six states the development of traffic crash forecasting methods, which is the main focus of methodology development in this thesis. It introduces Zero-inflated log count data time series intervened seasonal INGARCH (ZILT) Model innovatively proposed in this study to extract crash features and make predictions based on time series. It then introduces the time series generalised regression CNN model and compares its performance with other deep learning based methods such as Graph Neural Network (GNN), Multilayer Perception (MP), and Long short-term Memory Model (LSTM). Finally, it evaluates and assesses the advantages and drawbacks of different methods in the given scenarios.

Chapter seven covers data collection, cleaning, and processing. This chapter describes the data collection process in both China and the United Kingdom. For data collection in China, Sutong Bridge freeway, urban city junctions in Shanghai and Suzhou are accomplished. For data collection in UK, London M1 motorway crash data is processed.

Chapter eight presents the results analysis of application of different types of prediction models in different scenarios. It includes traffic conflict prediction results analysis, traffic crash prediction results analysis, and model interpretation for analysing influencing contributing factors for each scenario.

Chapter nine is the discussion. This chapter discusses challenges in making short-term crash predictions, compares pros and cons of different models, and describes other potential factors that may be overlooked in traffic crash prediction modelling. It also discusses how to implement pertinent interventions to prevent and alleviate traffic collisions.

Chapter ten is the conclusion. This chapter summarizes the entire thesis, discusses its contributions and innovations to traffic safety, describes the potential limitations of this research, and make recommendations for future development.

The following figure is the flow chart for technical route of this thesis. It depicts the relationship between different prediction methods, the data sources, the independent variables

used in building prediction models, and the model interpretation methods.

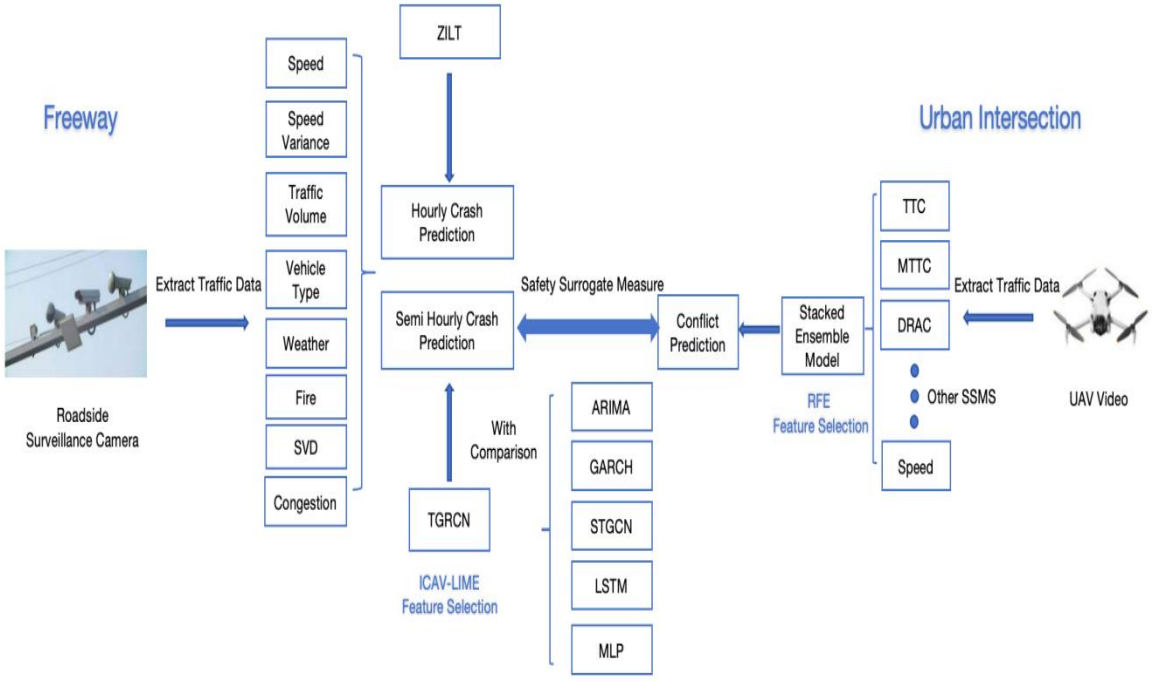



Figure 1.7. Flow chart for technical route of this thesis

Acronyms:

SVD: Stopped vehicle detection

ZILT: Zero-inflated log count data time series intervened seasonal INGARCH

ARIMA: Autoregressive integrated moving average

GARCH: generalised autoregressive conditionally heteroscedastic

STGCN: Spatio-temporal graph convolutional network

LSTM: Long-short-term Memory

TGRCN: Time-series Generalised regression Convolutional Neural network

MLP: Multi-layer perceptron

TTC: Time to collision

MTTC: Modified time to collision

DRAC: Deceleration Rate to Avoid a Crash

# Chapter 2 Literature Review of Factors Affecting Unsafe Traffic Conditions

This chapter is literature review section for thesis, discussing unsafe traffic condition characteristics, including crashes and conflicts. It builds research foundation for variable selection, methodologies, and statistical analysis. It also provides references to technical approaches and informs thesis structure. For traffic crashes, this chapter discusses real-time crash characteristics, near future crash characteristics, and crash prediction methods in different time spans by reviewing past studies in crash analysis and prediction. For traffic conflicts, it introduces factors affecting conflicts, application of surrogate safety measures in traffic conflicts analysis, and empirical traffic conflict classification methods.

## 2.1 Traffic Crash Characteristics

### 2.1.1 Real-time Crash Characteristics

The causes of traffic crashes are multifaceted, but previous studies have demonstrated that factors such as road environment and geometry, traffic dynamics, vehicle characteristics, and human behaviour significantly contribute to these incidents (Abdulhafedh, 2017; Treat, 1977; Sabey and Staughton, 1975). Moreover, evidence indicates that traffic crash data exhibits serial correlation over time, suggesting that temporal factors must be considered when predicting traffic crashes (Abdulhafedh, 2017).

Near future crashes along with near crashes are usually considered “safety critical events” (Farmer et al., 2015). Crashes are defined by consequences such as fatality, injury, and property damage, while near crashes are just proxy for crashes defined by driver maneuvers (Seacrist et al., 2020). Although near crashes increas the precision of odds ratio estimates and allow for statistically significant estimation that would not be doable with the analysis of

crashes individually, the validity of linking near crashes to actual crashes is skeptical (Seacrist et al., 2020). Contributing factors for near crashes and actual crashes have been studied to be different (Guo et al., 2010). Seacrist et al (2020) pointed out that besides crash severity, frequency, incident type, driver maneuvers, crash avoidance behaviours, and even vehicle kinematic data significantly differed from those of actual near future crashes. Therefore, studying the characteristics of near future actual crashes and investigating corresponding interventions of driver, police, and road management centres are more meaningful than just collecting analysis on crash proxy data even though they are more easily collected. Modern statistical and computer technologies make near future crash analysis and prevention to be pragmatic.

The rise of radar systems and high-resolution detectors has significantly enhanced the data available for analysing traffic crashes, including metrics like traffic flow, vehicle speed, weather conditions, and the truck-to-car ratio. This wealth of data improves the accuracy of traffic crash predictions and facilitates real-time forecasting. Most recent studies in this domain focus on real-time crash prediction, often aiming to provide alerts at 5-minute intervals (Hossain and Muromachi, 2012; Cai et al., 2020; Liu and Chen, 2017; Abdel-Aty et al., 2005).

However, while 5-minute warnings can be valuable, they may not provide sufficient time for emergency services and traffic management systems, particularly in developing countries where intelligent transportation systems (ITS) are still in their infancy. In these contexts, hourly traffic crash predictions can be more beneficial, allowing relevant agencies—such as Departments of Transportation—ample time to implement necessary measures to mitigate potential economic losses, injuries, and fatalities. By adopting a longer prediction timeframe, stakeholders can enhance preparedness and response strategies, ultimately improving road safety and resource allocation.

### 2.1.2 Hourly Crash Characteristics and Trends

Traditional traffic crash prediction can be categorized into two main types: real-time crash prediction and temporal crash prediction for specific time units within designated road segments. Real-time crash prediction focuses on forecasting traffic crashes and analysing influencing factors at short intervals, typically every 5 minutes (Hossain and Muromachi, 2012; Cai et al., 2020; Abdel-Aty et al., 2021; Qin et al., 2006). This approach allows for immediate response and resource allocation.

In contrast, other studies adopt a broader temporal perspective, predicting traffic crashes and examining contributing variables over longer time units, such as hourly or daily intervals (Chen et al., 2018; Martin, 2002; Ivan et al., 2000; Xing, 2019). This longer-term analysis can provide valuable insights into patterns and trends in traffic safety, allowing agencies to implement proactive measures to enhance roadway safety and reduce accidents.

Conventional crash frequency studies even conducted research with long-run aggregated traffic information on at yearly or monthly base for not being able to collect instant traffic data (Chen et al., 2018). Martin (2002) & Qin et al. (2006) and Ivan et al. both showed that the influence of hourly traffic intensity on the number of crashes is significant (Martin, 2002; Ivan et al., 2000; Qin et al., 2006). Similarly, Chen, et al. (2018) also highlighted the impacts of the driving conditions, including road surface, traffic conditions, and weather on the occurrence of traffic crashes each hour. Therefore, even though traffic crashes can be recorded at any time intervals, weather and environmental data are usually collected in one-hour intervals.

In practice, predicting traffic crashes is to provide instant information to traffic police to prevent crashes. Reasonable time interval should be reserved for traffic police to receive messages and take effective actions to prevent crashes in advance. Short time interval such as 5-min to 10-min is not enough for traffic police to react. Half an hour and more are reasonable time interval for traffic police or road management office to implement pertinent

interventions accordingly.

## 2.2 Factors Affecting Traffic Crashes

### 2.2.1 Speed and Speed Variances

Speed is a key traffic kinematic parameter in traffic safety management, which is considered the main causal factor to traffic crashes (Quddus, 2013; Wang et al., 2013; Theofilatos and Yannis, 2014). As speed increases, vehicle control becomes more challenging for drivers, resulting in more serious injuries and increased crash rates (Quddus, 2013; Wang et al., 2015; Wang et al., 2018). Many studies have found that speed is associated with crash frequency and severity. Finch et al. (1994), employ a linear model showing that a 1 mph increase in speed could lead to a 4.9% rise in the accident rate on rural roads. Higher speed or larger speed variations lead to higher crash frequencies (Garber and Gadiraju, 1989; Solomon, 1964; Oh et al., 2001). Taylor et al. (2002) similarly illustrated that a 10% increase in mean speed could result in a 26% increase in accidents across all categories, based on an analysis of 174 road segments from rural single-carriageway roads in the UK.

Average speed is influenced by the driving environment and varies between peak/off peak hours, rural/urban arterials, and freeway/rural roadways (Wang et al., 2018). Therefore, the speed effect on crash occurrences may vary from different conditions. For example, driving during nighttime tends to be riskier than during the day (NHTSA, 2007). Despite nighttime traffic comprising only about 25% of total traffic volume, the nighttime crash rate has consistently remained high over the past decades, generally around 1.6 times higher than the daytime rate (Hawkins, et al., 2008). Moreover, the fatality rate for nighttime crashes is significantly higher compared to daytime crashes. In 2011, 13,861 fatal crashes occurred at night, accounting for nearly half of all fatal crashes in the US. Although there was a 1.8% decrease in the fatality rate from 2010 to 2011, the number of fatal crashes increased by 0.5%. Doecke et al. (2020) conducts a study to investigate the association between impact speed and

the likelihood of serious injury in crashes involving light vehicles. Data was gathered and analysed from the National Automotive Sampling System - Crashworthiness Data System in the US, between 2011 and 2015, including cases where impact speed was recorded by an event data recorder (EDR) and where the injury outcome was known. Doecke et al. (2020) finds that the speed of impact has a strongly significant positive correlation with the risk of serious injury across all types of impacts studied: the risk of serious injury reaches 1% at 28 km/h for head on impacts, 51 km/h for side impacts, 64 km/h for front impacts, and 67 km/h for rear impacts (Doecke et al., 2020).

Besides average speed that has been intensively studied so far, factors such as heterogeneity of road segments and different signal spacing density can affect speed consistency (Wang et al., 2018). Variation of speed brings risk to traffic flow stability and therefore influences traffic collisions. Speed variance is defined as the variation of operating speeds among vehicles and across lanes (Solomon, 1964). Solomon (1964) and Cirillo (1968) demonstrated that crash rates increase as speeds deviate from the traffic stream's average speed, with higher speeds correlating with more severe crashes. Lave (1985) also concluded that speed deviation is significantly correlated with crash fatality rates on both rural and urban arterials. Precedent research also shows that speed variance is a more important causal factor than average speed in predicting traffic crashes (Garber and Gadiraju, 1989; Quddus, 2013). The reason can be ascribed to the consistency of speed can ensure safer driving, resulting in less unexpected traffic accidents (Warren, 1982). Wang et al. (2018) found that higher average speed is associated with higher crash frequency but correlation among speed, speed variation, and crashes is subject to time of the day, urban and rural environment, freeway and rural roads, etc. Wang et al. (2018) also emphasized the importance of reducing speed deviation among vehicles as an active traffic management strategy for proactive arterial safety interventions to promote overall traffic safety.

### 2.2.2 Traffic Volume

Traffic volume serves as an indicator of traffic risk, with higher volumes generally correlating with higher crash rates (Marchesini and Weijermars, 2010). However, the increase in crash rates may not be proportional to the increase in traffic volume due to lower individual crash risks at higher traffic intensities compared to lower ones (Marchesini and Weijermars, 2010). The relationship between traffic volumes and safety outcomes is mixed. Zhou and Sisiopiku (1997) studied a 26 km segment of Interstate I-94 in Detroit, USA, and found a positive correlation between hourly crash rates and hourly traffic volume, but noted that the crashes were less severe in the situation. In contrast, Lord et al. (2005) found the opposite pattern where crash risk decreases as traffic volume increases on the freeway segment investigated in Montreal, Canada. Tanner (1953) proposed a non-linear relationship between crashes and traffic volume: $Y = \alpha F^{\beta}$, where Y denotes crashes per year, F is the traffic volume, $\beta$is set to be values less than 1. It indicates that crash count increases at a decreasing rate with increases in traffic volume (Lord et al., 2005). Abbas (2003) also concluded that crash predictive models of traffic volume followed a power relationship in most cases by investigating more than 200 predictive models for rural roads. Some other researchers have found that hourly crash rates follow a U-shaped relationship with hourly traffic volume (Martin, 2002; Cedar and Livheh, 1982). Hoye and Hesjevoll (2020) pointed out that the link between traffic volume and crash rates changes as volumes increase, with different relationships observed at low volumes compared to volume approaching capacity.

While there are inconsistent findings regarding how traffic flow characteristics affect the safety of both rural and urban freeway segments, the importance of traffic volume in traffic safety analysis is evident. The impact of traffic volume on crashes may be confounded by road environment (rural/freeway), weather condition, vehicle types, vehicle operating speed, singe or multiple crash types and other traffic flow characteristics. Therefore, previous research has yielded contradictory results regarding the relationship between crash rates and traffic volume.

### 2.2.3 Vehicle Types and Environmental Factors

Compared to sedans, trucks and buses are associated with more severe crash injuries. The fatality rate caused by truck and bus accidents is significantly higher than for typical cars (Li et al., 2020). Heavy vehicle drivers, in particular, truck drivers have a higher rate of crash involvement with moving vehicles in transport than car drivers (Li et al., 2020; Duke et al., 2009). Baker and Reynolds (1992) discovered that during heavy storms in the UK, nearly 50% of accidents were overturning accidents, with 66% of these accidents involving large trucks, indicating a heightened risk. It is probably due to visual sight limitation in surrounding environments where blind spots existed and the joint influence of declination of decision making by fatigue driving. Therefore, truck drivers are at a higher risk of crashing than drivers of lighter vehicles.

Environmental factors have the potential to influence traffic crash occurrences and its frequencies, and severity (Wang et al., 2013; Theofilatos and Yannis, 2014; Wang et al., 2017). Environmental surrounding factors include roadway geometric design, weather conditions (rainy, snowy, cloudy, foggy, temperature, pressure, humidity, wind, etc), and lighting conditions. Environmental factors along with human factors and traffic dynamic parameters, are found to have a significant association with traffic crashes (Wang et al., 2013; Theofilatos and Yannis, 2014). Fierce weather condition increases the probability of having traffic crashes (Wang et al., 2017). Study shows that fatal crashes in rain are three times more likely compared to sunny conditions (Wang et al., 2017). Snowfall impacts traffic safety by altering roadway surfaces and reducing visibility, leading to an increased occurrence of crashes, spinouts, and breakdowns (Seeherman and Liu, 2015). Snowy and icy weather pose even greater dangers than rainy conditions (Wang et al., 2017). Nighttime driving also increases the risk of drivers involvement in crashes due to impaired vision and reduced decision-making abilities (Wang et al., 2017). Research also suggests that drivers' compensatory actions can mitigate the effects of weather conditions (Andrey and Yagar, 1993; Khattak et al., 1998). Hence, it is essential to investigate traffic-related factors under diverse weather conditions to comprehensively grasp their influence on hazardous situations.

Being as important contributing factors according to the reviews on precedent literature, vehicle types and weather related conditions are involved in the modelling procedure and crash analysis throughout the thesis.

### 2.2.4 Driver Factors

Driver characteristics are closely related to crash rates. Age is recognised as a critical influencing factor in crashes (Regev et al., 2018). Studies show that younger male drivers and older drivers are populations who are more likely involved with traffic crashes (Li et al., 2020). Younger male drivers are more careless and more radical compared to experienced middle age drivers. They tend to underestimate crash risk and are not disciplined to follow traffic rules (Regev et al., 2018; Li et al., 2020). Older drivers, while more disciplined and more experienced than younger drivers, decline in vision, hearing, attention, and decision-making capabilities, increasing their crash risk (Horswill et al., 2010).

Driving distractions, fatigue, speeding, drunk driving, and road rage are all contributing factors to increased crash risk. According to the NHISTA 2019 report, speeding contributed to 26% of all crash fatalities in the United States in 2017. Distracted driving behaviours such as cell phone use, texting, talking, eating food, and looking around are primary factors in traffic crashes. Statistics indicates that around 71% of young drivers involved in fatal crashes had experience with texting or phone use while driving (NHISTA 2019). Road anger is one of the most leading causes to vehicle crash-related conditions.

Driving anger, commonly referred to as road rage, has emerged as a significant concern in traffic psychology, characterized by feelings of annoyance, fury, or rage experienced while driving. It is a major contributor to risky driving behaviours and motor vehicle crashes, which rank among the leading causes of morbidity and mortality on roadways (Underwood et al., 1999; Zinzow & Jeffers, 2018). Defined as a specific emotional response triggered during

driving, driving anger encompasses a range of feelings and thoughts associated with frustration (Deffenbacher et al., 1994).

Research indicates that driving anger can adversely affect driving performance, particularly due to heightened arousal and negative emotional states (Zepf et al., 2020). Drivers experiencing anger tend to exhibit risky behaviours such as strong acceleration, higher speeds, and a greater likelihood of running yellow lights (Abdu et al., 2012; Roidl et al., 2014). Additionally, anger can impair critical driving skills, leading to more errors in lane keeping and adherence to traffic rules (Jeon et al., 2014).

Preventing road anger is crucial for enhancing overall traffic safety and reducing fatality rates. As motorization has increased, road traffic crashes have become a leading cause of death in many regions. Notably, nearly 90% of traffic accidents are linked to driver behaviours, with driving anger being a prominent factor. This emotional agitation can be more dangerous than typical distractions while driving, as aggressive driving behaviours significantly increase risks on the road.

Mitigating the risks associated with road rage is essential for improving traffic safety. Strategies to address driving anger may include educational campaigns, stress-reduction techniques, and fostering a more respectful driving culture. By tackling the root causes of driving anger, we can work towards safer roadways and reduced crash rates.

Driver fatigue resulting from prolonged driving is another critical factor in traffic crashes. Significant variations in fatigue levels exist among drivers, with cumulative fatigue having a pronounced effect on individual performance (Wang et al., 2024). According to statistics, driving fatigue related fatalities numbered 684 in 2021, 21% of fatal crashes attributed to driver fatigue (Stewart, 2023; Tefft, 2014). Although various fatigue alarming systems developed by technology companies use computer vision techniques and eye tracking sensors to detect driver fatigue, make alerts, and take interventions, the practical effectiveness of driver monitoring systems (DMS) still needs to be evaluated (Wang et al., 2024).

## 2.3 Traffic Conflicts Characteristics

Traffic collisions were responsible for 1.19 million deaths worldwide in 2023 (World Health Organization, 2023). However, collection of actual crash data is limited to lack of time efficiency, under-reporting, unobserved heterogeneity, sampling issues of representatives, blurred records (such as unclear location and severity), and scarce of amount, which gives rise to the study of alternate safety measures (Lord and Mannering; Zheng et al., 2021).

Safety surrogate measures (SSMs) offer a means to assess conflict risk, drawing upon data collected by sensors such as cameras, radars, and lidars installed on various platforms, including drones, roadside units, and vehicles. The extraction of pertinent information from raw data, including vehicle positioning, speed, and acceleration, necessitates sophisticated computer vision and data processing techniques, enabling the computation of diverse indicators essential for comprehensive safety evaluation.

Surrogate Safety Measures (SSMs) assess hazardous interactions by detecting critical actions to reflect collision causality (Archer, 2005; Tarko et al., 2009; Nadimi et al., 2016). SSMs include time based variables and kinematic variables, which are derived from time related traffic motion parameters such as speed, flow, density, relative distance, occupancy, and acceleration in the context of unsafe traffic patterns (Wang et al., 2013). In addition to SSMs, traffic, human, weather, and vehicle-related factors play pivotal roles in predicting critical incidents, shaping strategies to enhance traffic safety (Wang et al., 2015). Papazikou et al. (2017) observe that critical Time-to-Collision (TTC) values vary with different roadway speeds, which fluctuate during adverse weather. Integrating traffic, human, weather, and vehicle-related factors into SSMs within proactive safety systems could thus yield significant benefits in predicting and mitigating traffic conflicts.

Previous studies in transportation have examined how various traffic and weather conditions

correlate with accident probabilities (Xu et al., 2013c). Unsafe traffic conditions usually occur during traffic operations, and weather conditions can significantly alter the dynamic environment. Therefore, understanding the interaction between traffic factors and diverse weather conditions is crucial for assessing their impact on hazardous situations. To be more specific, the influences of various factors on traffic conflicts may also be subject to roadway conditions and traffic environments. Apparently, many in-depth analyses are still lack of to investigate the relationships between traffic conflicts and various contributing factors with conditions on different roadway environments. Once specific relations of these factors to traffic conflicts have been explored, effective conflict prediction models can be built to provide valuable perspectives for predicting real-time traffic conflicts.

## 2.4 Factors Affecting Traffic Conflicts

Laureshyn et al. (2010) highlighted the challenges in identifying a common indicator that connects the various levels of the sequential traffic safety model. One major issue is the highly context-dependent relationship between traffic conflicts and crashes (Arun et al., 2022). Factors such as the traffic environment in different locations, traffic operation parameters (speed, acceleration, lane change behaviours), traffic flow variables (traffic volume, density, traffic flow by lanes), driving behaviours (fatigue, anger, phone use), road user interactions (vehicle to vehicle, pedestrian to vehicle, etc), and roadway geometric design can significantly influence the strength and reliability of this relationship. Additionally, most traffic conflict indicators do not account for critical factors like road user reaction times or vehicle maneuvering capabilities (e.g., braking and steering) (Arun et al., 2022). As a result, variations in road user behaviour and vehicle characteristics can significantly affect the relationship between traffic conflicts and crashes.

Furthermore, individual conflict indicators provide only a partial view of the overall safety situation, while multiple conflict indicators could be used to gain a more comprehensive understanding, applying several metrics to each traffic interaction can be impractical (Arun et

al., 2022). Arun et al. (2021c) provides an overview of traffic conflict safety assessment methods and is displayed in the following graph.

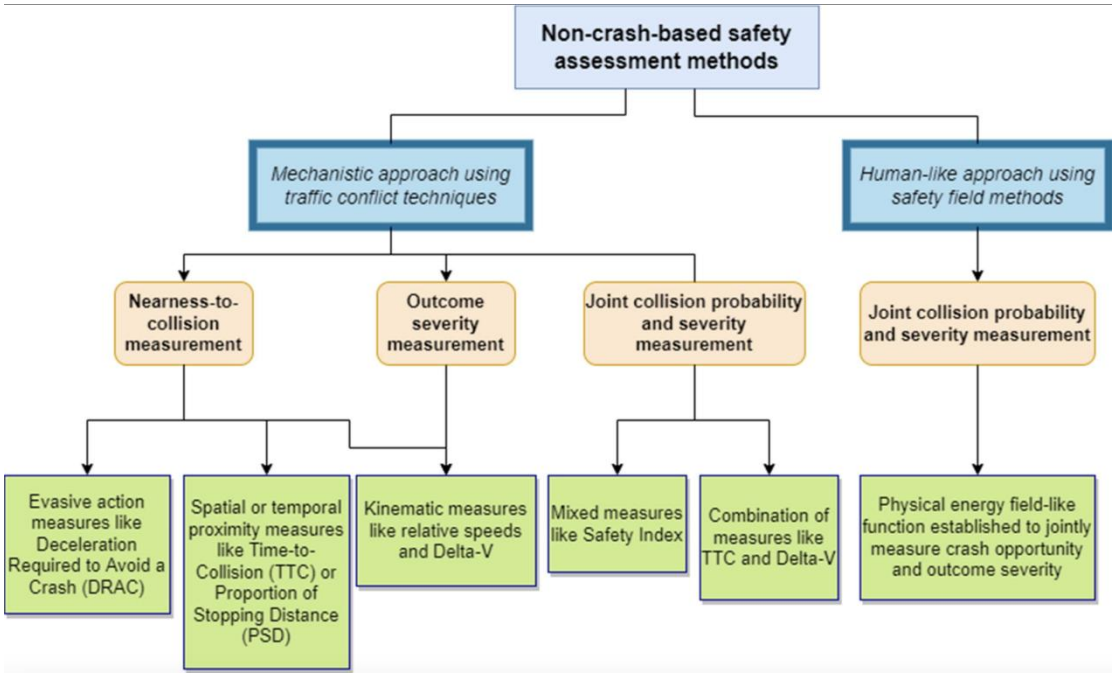



Figure 2.1. Overview of conflict assessment methods (Arun et al., 2021c).

It can be seen from the flow chart that non-crash based safety assessment methods can be divided into mechanistic approach and human-like approach. Various indicators contribute to explaining the occurrences of traffic conflicts. However, the interaction between conflict indicators and individual contributing factors to traffic conflicts in different scenarios is still lack of discussion, which will be discussed in this thesis.

### 2.4.1 Surrogate Safety Measures in Traffic Conflict Analysis

Existing studies have assessed the performance of several risk metrics derived from longitudinal maneuvers against four evaluation criteria: accuracy, timeliness, robustness and efficiency (e.g. Lu et al. 2021). They demonstrated that not a single measure performs well in predicting a traffic conflict reliably. For instance, they found that metrics performing better in prediction accuracy such as Time-To-Collision (TTC) or single-step Probabilistic Driving

Risk Field (S-PDRF) performed weakly in timeliness. Indeed, the literature contains mixed conclusions on best performing SSMs based on the context. For instance, Tak et al. (2020) found that deceleration-based metrics perform better for rear-end conflicts than Time-To-Collision (TTC) and distance-based metrics whereas He et al. (2018) found that modified TTC (MTTC) outperformed TTC and Deceleration Rate to Avoid a Crash (DRAC). A significant research gap in literature is the absence of studies evaluating SSMs performance in different road environments and SSM selection justification for specific context-dependent applications (Arun et al., 2021). Moreover, studies that include vulnerable road users and that consider other road types than signalised intersections are lacking in the literature (Arun et al., 2021) . The transferability of common model architectures for conflict prediction across different road scenarios has not been examined and is essential for industrial deployment of predictive models.

Several studies have examined the performance of Safety Surrogate Measures. Lu et al. (2021) assessed the performance of six risk metrics for longitudinal maneuvers against four evaluation criteria: accuracy, timeliness, robustness, and efficiency. They demonstrated that no measure performs well in all performance dimensions. For instance, they found that metrics performing better in prediction accuracy such as Time-To-Collision (TTC) or single-step Probabilistic Driving Risk Field (S-PDRF) performed weakly in timeliness. Johnsson et al. (2021) explored a relative approach to validate the effectiveness of SSMs in a case study of six intersections in the northern Europe and found that TTC indicator was in line with the ground truth of bicycle infrastructure. Wang et al. (2021) identified limitations and opportunities of SSM application in Connected and Automated Vehicles (CAV) including SSM for CAV trajectory optimization and SSM for individual vehicles and vehicle platoon. Similarly, Xie et al. (2018) also found that conventional SSM such as TTC may not be a good indicator in CAV scenarios because TTC neglects the potential risk of car-following scenarios where the following vehicle's speed is slightly less than or equal to the leading vehicle's but the spacing between two vehicles is relatively small. Nadimi et al. (2021) thinks it is unclear

which SSM indicators can reflect danger more precisely. Novel methods should be developed to make comparison by taking the advantage of statistical analyses of SSM datasets. Therefore, comparing different types of SSMs and identifying the most effective ones in specific scenarios is important to improve the precision and accuracy of conflict prediction and safety evaluations without crash data.

Studies often distinguished between urban and motorway road environments. Regarding motorways, different findings on the best performing SSM are present in the literature. Tak et al. (2020) found that deceleration-based metrics perform better for rear-end conflicts than TTC and distance-based metrics. The study evaluated three SSMs and performed a comparative analysis between collision risk and driver behaviour based on two different car-following theories: the action point model and the asymmetric driving behaviour model. He et al. (2018) found that MTTC outperformed TTC and DRAC using the statistical relationship between crash records and the safety measures. Regarding urban environments and more particularly intersections, few studies have comparatively evaluated the performance of SSM while accounting for different road users. Deceleration-based SSM have been proven to be more appropriate for unsignalized intersections from the literature (Bonela and Kadali, 2022) . Simulation models have also been employed extensively to assess the performance of SSMs at intersections such as a study comparing the performance of the Aggregate Conflict Propensity Metric compared to other SSM for 12 signalised intersections (Wang and Stamatiadis, 2014) . However, most of the studies are limited by the number of SSMs studied and compared as well the single road environment considered.

The thesis selected thirteen commonly used SSMs from total of 28 SSMs in the literature review due to lack of data availability in real scenarios such as mass of vehicles, the released energy that may affect vehicle occupants, and the change in total kinetic energy before and after the crash, etc. The selected SSMs involve time-based, distance-based and deceleration-based measuring metrics which are presented in Table 2.1. The time-based

metrics include Time-To-Collision (TTC), modified TTC (MTTC), Post-Encroachment Time (PET), Time integrated TTC (TIT), Time Exposed TTC (TET), Headway (H), and Gap Time (GT). Among the selected distance-based metrics are headway, Proportional Stopping Distance (PSD) and Difference of Stopping distance and Safety distance (DSS). Deceleration-based metrics employed are Deceleration Rate to Avoid a Crash (DRAC), Potential Index for Collision with Urgent Deceleration (PIUCD) and Crash Index (CAI). Every SSM is calculated between two vehicles at a specific instant in time.

Table 2.1. Definition of the selected Safety Surrogate Measure

| Selected SSM | Definition | Equation |
|---|---|---|
| Time-To-Collision (TTC) | The time left to a collision assuming constant speed and direction. | $TTC(t) = \frac{D}{\Delta V}$ |
| Modified TTC (Ozbay et al., 2008) | Modified to consider acceleration discrepancies to account for all potential longitudinal scenarios. | $MTTC(t) = \frac{-\Delta V \pm \sqrt{\Delta V^2 + 2\Delta a D}}{\Delta a}$ |
| Post-Encroachment Time (PET) (Allen et al., 1978) | The period between the leading vehicle departure and the following vehicle arrival to a conflict area. | $PET = t_4 - t_2$ $t_4$ is arriving time at a conflict point of the 2nd vehicle and $t_2$ is the time of the 1st vehicle departing |
| Time integrated TTC (TIT) (Minderhoud and Bovy, 2001) | TTC integrated over the period under a TTC threshold. | $TIT(t) = \sum_{n=1}^{N} [\frac{1}{TTC_{it}} - \frac{1}{TTC^*}] \Delta t$ $TIT^* = \sum_{n=1}^{N} TIT(t)$ |

| | | |
|---|---|---|
| Time Exposed TTC (TET) (Minderhoud and Bovy, 2001) | Summation of every instant where the TTC is below the threshold value. | $TET(t) = \sum_{n=1}^{N} \delta_t \Delta t,$ $\delta_t = \begin{cases} 1, 0 < TTC(t) < TTC^* \\ 0, otherwise \end{cases}$ $TET^* = \sum_{n=1}^{N} TET(t)$ |
| Headway (Vogel, 2003) | The time between the front of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point. | $H(t) = t_2 - t_1$ $t_2$ is the arrival time of leading vehicle to a point on the roadway; $t_1$is the arrival time of following vehicle to the same point. |
| Gap time | The time between the arrival of two vehicles to the conflict location. | $G(t) = t_3 - t_2$ Where $t_3$ is the expected arrival at the potential point of collision, provided that the vehicle maintains the original approach speed and direction. $t_2$ is the time from the end of encroachment. |
| Proportion of stopping distance (PSD) (Astarita et al., 2012) | Proportion of the remaining distance to a collision point and the minimum acceptable stopping distance. | $PSD(t) = \frac{D}{\frac{v_f^2}{2MADR}}$ |
| Difference of stopping distance and space distance (DSS) (Okamura et al., 2011) | Difference between the distance between vehicles and the stopping distance. | $DSS(t) = (\frac{v_l^2}{2\mu g} + D) - (v_f^2 \Delta t + \frac{v_f^2}{2\mu g})$ |
| Deceleration rate to avoid a crash (DRAC) (Saccomanno et al., | Deceleration rate needed to avoid a collision with the ratio between the difference in speed and | $DRAC(t) = \frac{\Delta V^2}{2D}$ |

| | | |
|---|---|---|
| 2008) | their closing time | |
| Potential Index for Collision with Urgent Deceleration (PIUCD) (Uno et al., 2002) | Distance separating two vehicles if they have completely stopped with emergency braking. | $PIUCD = \frac{v_l^2 - v_f^2}{2MADR} + D - v_f \Delta t$ |
| Crash index (CAI) (Ozbay et al., 2008) | Impact of speed on a potential collision's kinetic energy | $CAI = \frac{(v_f + a_f MTTC)^2 - (v_l + a_l MTTC)^2}{2} *$ |

With $D$ corresponding to the distance between two vehicles, $\Delta V$ and $\Delta a$ the difference in speed and acceleration between two vehicles, $v_l$ and $v_f$ the velocity of the leading and following vehicles respectively, , $a_l$ and $a_f$ the acceleration of the leading and following vehicles respectively, $\Delta t$ the time step, $TTC^*$ the threshold value of TTC, $MADR$ the maximum deceleration rate, $\mu$ is the friction coefficient and $g$ is the gravity acceleration constant.

## 2.4.2 Other Factors Affecting Traffic Conflicts

The severity of conflicts arises from intricate interactions involving roadway and environmental features, as well as vehicle dynamics (Xu et al., 2024). It is beneficial to comprehend how and to what degree roadway and other road users affect a vehicle during a conflict. This understanding aids in analysing the root causes of collisions and offers insights into enhancing roadway safety through effective countermeasures (Xu et al., 2024). In addition to Surrogate Safety Measures as traffic conflict indicators. Vehicle dynamic variables (such as speed, and acceleration), traffic operation parameters (such as traffic volumes, speed variances, and traffic density), weather conditions (such as precipitation, temperature, wind, and humidity), and human factors (age, gender, anger, fatigue, distraction)

are all significant contributing factors to traffic conflicts. Not only SSMs are derived from traffic parameterss and vehicle kinematics, but some variables are causal factors to traffic crashes. Many studies have validated the importance of involving dynamic traffic parameterss and environmental factors in traffic conflict analysis.

Basso et al. (2024) builds logistic regression to understand the variables' contribution on the probability of conflict occurrence and shows that the probability of a conflict increases with contributing factors such as vehicle speed, traffic flow, speed variances, average speed difference, and straightness. However, the probability of conflict decreases with the driver's age, the vehicle's age, and the passed vehicle speed just before the ego vehicle (Basso et al., 2024). Time of the day also impacts conflict probability. Daytime conflict probability is higher than that of nighttime (Basso et al., 2024). Male drivers also have a higher likelihood of getting traffic conflicts than female drivers (Basso et al., 2024). Kassu & Hasan (2019) utilises principal component analyses to identify principal factors that influence traffic accidents, revealing that number of lanes, prevailing weather, and the pavement surface condition (wet, dry, snow), lighting condition, the driver's age, and gender are closely related to crashes on urban and rural interstate freeway segments. Xu et al. (2024) develops a path analysis model to determine the relationship between roadway-to-vehicle, vehicle-to-vehicle interactions, and conflict severity. The findings suggest that both the features of the road and the environment contribute directly and indirectly to the severity of conflicts. In terms of indirect influence, the kinematics of the vehicles involved in conflicts, including average speed and speed variability, act as intermediaries linking road conditions to the outcomes of conflicts (Xu et al., 2024). More than 90% crashes are caused of human factors. Wang et al. (2024) uses state space model to detect driving fatigue with consideration of individual differences and time cumulative effect. It also points out that fatigue is an important cause of traffic conflicts (Wang et al., 2014). Effectively detecting fatigue can reduce conflicts and prevent crash occurrences. Similarly, Cai et al. (2019) builds CNN model to recognise driver anger in real-time and concludes that driving anger is related to traffic safety, proactive management will promote overall traffic safety level. Other than human factors, weather condition also impacts traffic conflicts by changing the driving environment within a short

period. According to (FHWA, 2013), over 22% of the total accidents are related to weather conditions. Karkowski and Chung (2007) indicates that precipitation, strong winds, and extreme temperatures can all influence drivers' abilities, including their behaviour, vehicle performance, and traffic flow, ultimately affecting the risk of conflicts. Under bad weather conditions, drivers tend to have longer response times, longer braking distances, and less control of vehicles. Therefore, extreme weather such as snow, heavy rain, strong wind, and fogy, may all increase traffic conflict probability and jeopardize driver driving safety.

## 2.5 Summary

This chapter consists of two parts. The first part discusses traffic crash inherent characteristics, traffic safety influencing factors, and driver conditions that may lead to crash occurrences. It introduces inherent characteristics such as excess zeros and spatio-temporal structures in crash data and explains their relation to traffic dynamics over both short and long-term periods. Crash inherent characteristics include randomness, low likelihood, multifaceted nature, and highly skewed distributions. Therefore, capturing real-time crash characteristics is the key problem that is being studied throughout this research.

Crash influencing factors primarily encompass dynamic traffic parameterss, including vehicle types, density, traffic flow, lane changes, speed, speed variances, and driver status. This chapter explores how these traffic parameterss relate to crash occurrences based on a literature review. While previous studies have demonstrated that traffic parameterss are influential to crash occurrences, their significance in predicting crashes has been under-researched. Subsequent chapters will delve deeper into the ranking of variable importance among crash influencing factors. Conducting a literature review of traffic crashes enhances understanding of the causation of traffic crashes, the relationship between traffic crashes and their affecting factors, near future crash prediction methods, and model interpretation.

The second part introduces traffic conflict characteristics, including factors affecting conflicts, the application of surrogate safety measures in traffic conflict analysis, and traffic conflict classification methods. Traffic conflicts are treated as proper crash surrogates as they can evaluate the safety implications of road and traffic conditions. Traffic conflicts are influenced by driving maneuvers and between vehicle interactions. Traffic conflicts are reflections of hazardous vehicle to vehicle interactions and aggressive single vehicle driving behaviours. Conducting a literature review of traffic conflicts enhances understanding of the causation of traffic conflicts, the relationship between traffic conflict and their affecting factors, real-time conflict prediction methods, and model interpretation.

# Chapter 3 Statistical Machine Learning Methods in Unsafe Traffic Condition Modelling

This chapter introduces statistical machine learning methods in unsafe traffic condition modelling. It classifies models into three categories: statistical models, machine learning models, and deep learning neural network models. Statistical models include the ARIMA model, INGARCH model, Bayesian conditional autoregressive model, zero inflated count data model, etc. Machine learning models include random forest, support vector machines, stacked ensemble learning model, artificial neural networks, etc. Deep learning neural network models include LSTM, DNN, CNN, Transformer, Graph Neural Network, RNN, Generalised regression neural network, etc. These models constitute the methodology foundation of the proposed thesis but different models have different utilities. Some models are used for regression based prediction. Some models are used for classification problems. Some models are used for model interpretation and causal analysis. Crash and conflict predictions as indispensable components of reactive and proactive traffic safety approaches, providing fundamental information on the relationship between independent and dependent variables, making forecasts to near future traffic conditions, and helping to design predictive accident prevention strategies. This chapter will introduce model structure and compare strengths and weakness of each model, and also discuss their applications in real crash and conflict prediction scenarios.

## 3.1 Overview of Statistical Learning Unsafe Traffic Condition Prediction Models

### 3.1.1 ARIMA Model

Traffic crash prediction can generally be categorized into two primary approaches: real-time crash prediction and crash prediction for specific temporal units within designated road segments. Real-time crash prediction typically operates at 5-minute intervals, aiming to identify potential crashes and analyse contributing factors (Hossain and Muromachi, 2012; Cai et al., 2020; Abdel-Aty et al., 2005; Lee et al., 2003). In contrast, some studies focus on predicting crashes over longer time frames, such as hourly or daily intervals. Research indicates that hourly traffic intensity significantly influences crash occurrence (Martin, 2003; Ivan et al., 2000; Qin et al., 2006), and factors like road surface conditions, traffic density, and weather conditions also play crucial roles (Chen et al., 2018).

To improve the accuracy of traffic crash predictions, a variety of models have been developed and applied, ranging from probabilistic approaches and regression models to machine learning and deep learning techniques. Examples of traditional regression models include those developed by Ma et al. (2008), Rakha et al. (2008), and Caliendo et al. (2007). In addition, machine learning methods such as Support Vector Machines (SVM) and Random Forests, as well as deep learning techniques (Cai et al., 2020; Iranitalab and Khattak, 2017; Zhang et al., 2018; Theofilatos et al., 2019; Dong et al., 2018), have gained traction in crash prediction. Although traffic crash data is frequently treated as time series data, the application of traditional time series models presents limitations. Early research primarily relied on autoregressive integrated moving average (ARIMA) models for crash prediction (Quddus, 2008; Chen et al., 2007), but these models are unsuitable for crash data, as it is nonnegative integer-valued and does not follow the normal distribution of errors assumed by ARIMA (Quddus, 2008).

To overcome this issue, Quddus (2008) proposed the integer-valued autoregressive (INAR)

Poisson model, which better accommodates the Poisson distribution and handles the serial correlation present in spatial and temporal data. More recently, hybrid models that combine ARIMA with machine learning or deep learning techniques have demonstrated improved crash forecasting accuracy. For example, Sun et al. (2015) introduced a hybrid model integrating ARIMA with Support Vector Regression (SVR), while Barba et al. (2014) combined ARIMA with neural networks to enhance prediction performance. Additionally, Shao et al. (2019) developed a time series prediction model that merges ARIMA with Backpropagation Neural Networks and Support Vector Machines. These developments represent an ongoing effort to enhance crash prediction methodologies and increase the reliability of forecasts in real-world traffic applications.

### 3.1.2 Bayesian Statistical Modelling

Bayesian models, particularly those using the Monte Carlo Markov Chain (MCMC) method, have been extensively applied to crash-frequency modeling and identifying contributing factors due to their ability to handle complex models (Satria et al., 2020). These models use MCMC simulation techniques to generate samples from the posterior distribution, enabling effective model estimation (Satria et al., 2020). For instance, Song et al. (2006) utilised a Multivariate Conditional Autoregressive (CAR) model to incorporate spatial effects and provide spatial priors for Bayesian multivariate hierarchical models, ensuring posterior propriety even under non-informative priors. Given the high heterogeneity and strong spatial correlation observed in road crash frequencies at the segment level, Aguero-Valverde and Jovanis (2008) proposed using the inverse of adjacency (proximity) as a weight in the CAR model. This adjustment accounts for spatial correlation and helps reduce bias associated with model misspecification (Satria et al., 2020).

The Bayesian CAR model can model spatial relationships by introducing a spatial weight matrix and account for spatial random effects through a mean regression equation (Satria et al., 2020). The Bayesian CAR model is a spatio-temporal structured model, which is usually

applied to make predictions on road crash data at segment base where spatial correlation is the problem (Satria et al., 2020). It includes a time-coefficient to consider temporal impacts, a CAR random impact to include space-time interactions (Satira et al., 2020).

The Bayesian CAR model structure proposed by (Aguero-Valverde, 2011) is as follows.

$$Y_{it} \sim \text{Poisson}(\theta_{it}) \qquad (1)$$

Where $Y_{it}$ are the observed number of crashes in segment i at time t,

$\theta_{it}$ are the expected Poisson rate, which is the crash frequency expectation for segment i at time t.

The Poisson rate is modeled the log-normal distribution:

$$\text{Log}(\theta_{it}) = \beta_0 + \sum_k \beta_k x_{itk} + \varepsilon_{it} \qquad (2)$$

Where $\beta_0$ is the intercepts, $\beta_k$ is the coefficient for the k th covariate, and $x_{itk}$ is the value for the k th covariate for segment i at time t and $\varepsilon_{it}$ is the error term for segment i at time t (Satria et al., 2020).

### 3.1.3 Ensemble Learning Methods

Ensemble learning, commonly used for accident prediction, includes two different tree-based methods, Random Forest model class including Bagging and Random Forest and Boosting model class including AdaBoost, Gradient Boosting Machines (GBM), XGBoost, LightGBM. Random Forest is a robust ensemble algorithm employing Bagging for random selection, effectively avoiding overfitting (Zolfaghari and Golabi, 2021). Compared to neural networks and SVMs, Random Forest offers stable training results, fewer parameters, and good generalisation performance.

XGBoost and GBM/Light GBM are two widely used Boosting models in traffic accident analysis. Parsa et al. (2020) employed XGBoost for real-time accident detection based on actual data. XGBoost is an exceptionally flexible and effective multi-layer perceptron solution, enhancing forest techniques for improved computational resource levels. Developed primarily to boost neural network model performance and computational efficiency, XGBoost achieved a 79% detection rate, demonstrating high performance in accident prediction. Sorum and Pal (2024) compares twelve machine learning algorithms in predicting the driver injury severity using ten years of accident data (from 2011 to 2020) with 693 accidents obtained from Shilong, India and find that Light GBM model has the best prediction accuracy. Wen et al. (2021) introduced a novel Light GBM method to model crash counts and identify key risk factors for various types of roadway segment crashes. Their study concluded that Light GBM outperforms XGBoost in predicting crashes based on a dataset of vehicle crashes in Texas from 2015 to 2017. Ahmad and Abdel-Aty (2013) applied a Stochastic Gradient Boosting Machine (SGB) to enhance the reliability of real-time crash risk assessments, using automatic vehicle identification and remote traffic microwave sensor data. They highlighted one of SGB's key advantages: its ability to model complex nonlinear relationships. Additionally, SGB can handle various types of predictors, manage missing data without the need for prior transformation, and is suitable for real-time applications. Schlogl (2019) compared Random Forest and XGBoost for hourly road accident prediction, finding that while XGBoost provided superior accuracy, it exhibited lower sensitivity (with a maximum sensitivity of 0.69), suggesting significant room for improvement in prediction accuracy.

## 3.2 Overview of Deep Learning Neural Networks

### 3.2.1 Deep Neural Network

Deep Neural Networks (DNN) are built from units called perceptrons (ptrons). Ptrons are composed of one or more inputs, an activation function, and an output. DNN combines ptrons in structured and connected layers, and the ptrons are independent of each other in the given

layer (Portilla, 2016). The DNN used in the study has three hidden layers, with 5, 3, 3 ptrons respectively. A feedforward and resilient back propagation algorithm is used to train and update the weights.

Feed-word function:

$$\mathrm{Output_n} = \mathrm{Activation}(\mathrm{Weights_{n-1}} \cdot \mathrm{Output_{n-1}}) \quad (3)$$

Back propagation:

$$\mathrm{E_{n-1}} = \mathrm{W_n^T} \cdot \mathrm{E_n} \quad (4)$$

Weight updating:

$$\mathrm{W_n} = \mathrm{W_n} \cdot \mathrm{L_r} \cdot \frac{\delta \mathrm{E_{n+1}}}{\delta \mathrm{W_n}} \quad (5)$$

In the equations, $\mathrm{L_r}$ represents the learning rate, which is 0.1 in our study. E is our error function and W represents the weights. As the learning iteration (epoch) goes up, the weight is updated according to the slope of the derivative of the error function.

DNN is used for traffic conflict prediction as a component in the stacked ensemble model. The loss function used for DNN is binary Cross-Entropy for two classes (non-conflict and conflict). The formula is as follows.

$$\mathrm{L}(\mathrm{y}, \hat{\mathrm{y}}) = -(\mathrm{y}\log(\hat{\mathrm{y}}) + (1-\mathrm{y})\log(1-\hat{\mathrm{y}}))$$

Where y is the true label (0 or 1) and $\hat{\mathrm{y}}$ is the predicted probability of the positive class.

### 3.2.2 Long short-term Memory Model

Long short-term memory (LSTM) model is developed to address the gradient vanishing problem that existed in the conventional recurrent neural netowrk (RNN) (Hochreiter and Schmidhuber, 1997). LSTM is consisted of a cell to retain information over extended periods, an input gate and an output gate to control the flow of information into and out of the cell, a forget gate to discard information from the previous state (Hochreiter and Schmidhuber, 1996). LSTM is effective at handling long-term dependencies regardless of the length of time

gaps (Hochreiter and Schmidhuber, 1997 ).

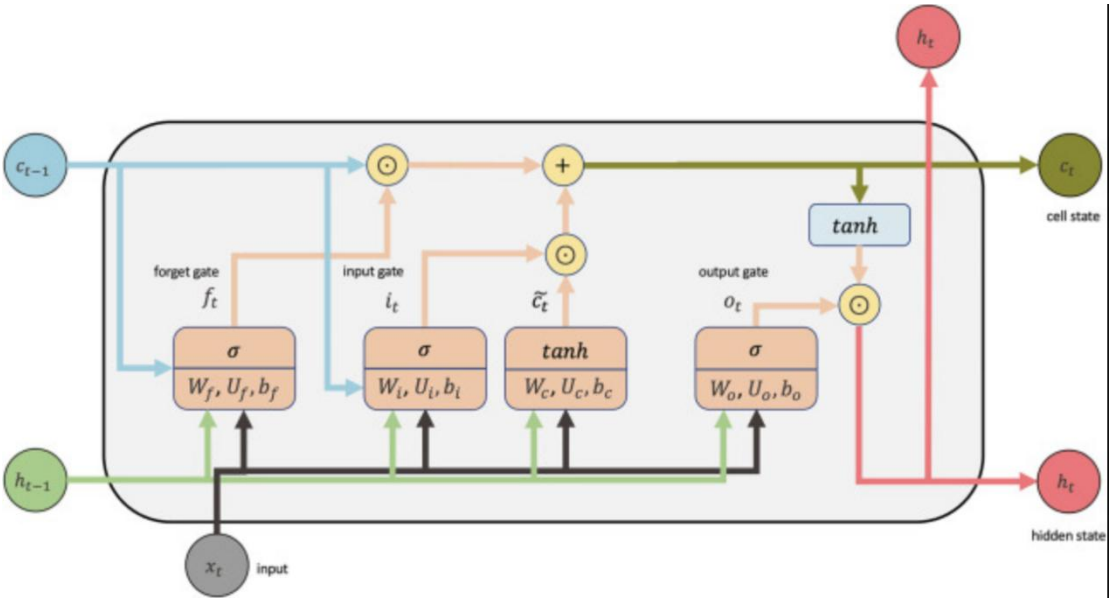



Figure 3.1. A basic cell of LSTM

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (6)$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (7)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (8)$$

$$\tau_t = \sigma(W_c x_t + U_c h_{t-1} + b_c) \quad (9)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (10)$$

$$h_t = o_t \odot \tanh(c_t) \quad (11)$$

Input gate vector $i_t$ is calculated by linear transformation of input $x_t$ and the hidden state $h_{t-1}$ and by activation funciton $\sigma$. Each element in $i_t$ is a real number ranging between 0 and 1, which determines the proportion of information allowed to pass through the gate in each dimension (Gopaluni et al., 2023). $W_i$, $U_i$, and $b_i$ are the parameters of the input gate, which needs to be learned in the training process. The calculation of the forgetting gate $f_t$ and the output gate $o_t$ is similar to the input gate $i_t$, and they have their own parameters *W*, *U*, and *b*. The transition of the cell state from the last moment $c_{t-1}$ to the current moment

$c_t$ is jointly controlled by the input gate, candidate cell state and the forget gate (Gopaluni et al., 2023). The hidden state $h_t$ is determined by output gate $o_t$ and cell state $c_t$. The input gate determines how much of the input information at the candidate cell state $\tilde{c}_t$ is stored in the cell state (Gopaluni et al., 2023). The forget gate determines how much of the cell state information at the previous cell state $c_{t-1}$ is forgotten, and the final cell state unit is obtained by adding two gate signals (Gopaluni et al., 2023). It can be seen that in the LSTM, there is a linear self-circulation relationship between the internal cell state units $c_{t-1}$ and $c_t$. The linear self-circulation between the cell state units can be seen as the sliding processing of information at different moments (Gopaluni et al., 2023).

### 3.2.3 Convolutional Neural Network

Convolutional neural networks (CNNs) are primarily employed in image processing, object detection, and classification tasks as deep learning technique (Chollet, 2018). The layers in a CNN consist of neurons arranged in three dimensions: the spatial dimensions of the input (height and width) and the depth (Chollet, 2018; Cai et al., 2021). Neurons in a given layer are connected only to a small, localized region of the preceding layer, which is convolved with filters (Chollet, 2018; Cai et al., 2021). CNNs are typically composed of three types of layers: convolutional layers, pooling layers, and fully connected layers (Chollet, 2018).

The convolutional layer computes the output of neurons connected to local regions of the input by calculating the scalar product between their weights and the corresponding region of the input volume (Chollet, 2018; Cai et al., 2021). The pooling layer performs down-sampling along the spatial dimensions of the input, reducing the number of parameters and the computational complexity of the activations (Chollet, 2018; Cai et al., 2021). The fully connected layers generate class scores from the activations, which are used for classification tasks (Chollet, 2018; Cai et al., 2021).

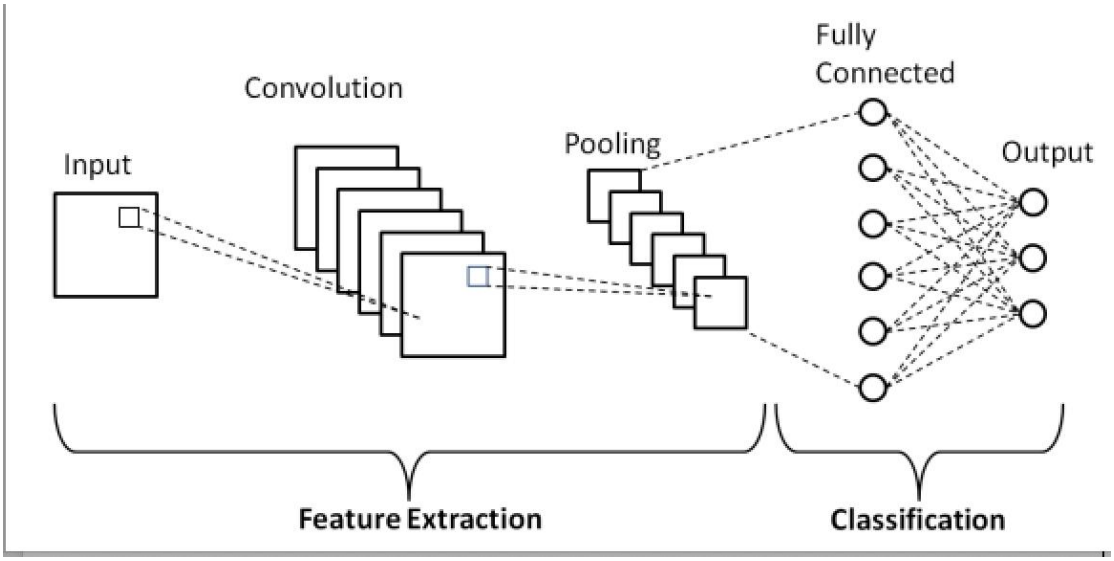



Figure 3.2. Typical CNN architecture (Phung and Rhee, 2019)

During training, the input to a CNN is usually an RGB image. The RGB pixel grids are converted into floating-point tensors, and the mean RGB value is subtracted from each pixel. The pixel values are then rescaled from the original range of 0 to 255 to a normalized range of [0, 1]. To mitigate overfitting, data augmentation techniques are applied to generate additional training data from existing samples, ensuring that the model does not encounter the same image twice during training. Additionally, feature-wise standardized normalization is applied by dividing the inputs by the standard deviation of the dataset (Cai et al., 2021).

In this thesis, CNNs were utilised to process traffic videos and extract dynamic traffic operation parameters. Images were passed through a series of convolutional layers with small 3×3 filters to capture spatial features such as left/right, up/down, and centre orientations at the smallest scale (Cai et al., 2021). The convolution stride was set to 1 pixel, and padding was set to 1 pixel for the 3×3 convolutional layers (Cai et al., 2021). Max-pooling was performed over a 2×2 pixel window with a stride of 2 (Cai et al., 2021). The rectified linear unit (ReLU) activation function was used for all hidden layers in the convolutional layers. Through convolutional and down-sampling operations, the CNN transforms the input layer by layer, ultimately producing class scores for classification and regression tasks (Cai et al., 2021).

### 3.2.4 Spatio-temporal Graph Neural Network

Spatio-Temporal Graph Convolutional Nerual Network (STGCN) is composed of several spatio-temporal convolutional blocks and each block is composed of two gated sequential convolution layers and one spatial graph convolution layer in between (Yu et al., 2020). To deal with the gradient overdispersion issue and reduce network load, residual connection and bottleneck strategy are applied within each block (Yu et al., 2020). The input $\mathbf{v}_{t-M+1}$, ..., $\mathbf{v}_t$ is uniformly processed by spatio-temporal blocks to handle with spatial and temporal dependencies coherently. Output layer fuses comprehensive features to generate the final prediction (Yu et al., 2020).

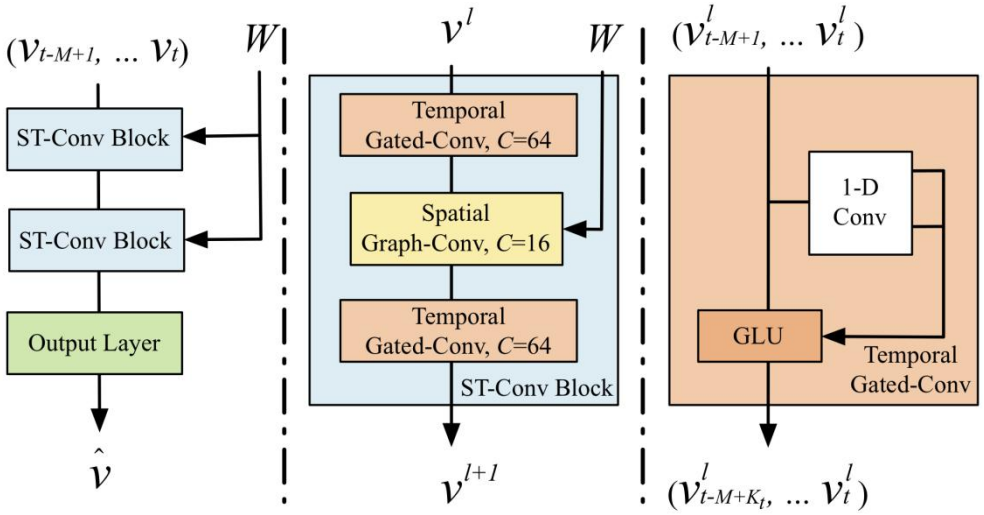



Figure 3.3. Structure of STGCN

Transformer-based model Spatial-Temporal Transformer Networks (STTNS) is built with reference to Xu et al. (2020). STTNS designs a Graph Neural Network (GNN) variant - spatial Transformer to dynamically model directed spatial dependencies with self-attention mechanism to capture real-time conditions and traffic directions (Xu et al., 2020). Xu et al. (2020) defines short-term temporal range to be less than 30 minutes, and long-term temporal range to be larger than 30 minutes. STTNS jointly leverage dynamical directed spatial dependencies and long-range temporal dependencies to improve the accuracy of long-term traffic condition prediction (Xu et al., 2020). With application of STTNS model to London

M1 motorway short-term crash prediction, STTNS cannot predict crash incidents effectively. STTNS performs inferior to STGCN in terms of crash prediction. One explanation is that although Transformer based model is widely used to predict traffic patterns, such as traffic flows, speed, traffic crash is a small likelihood incident with highly uncertainty and randomness. Transformer related model may not be suitable to deal with imbalanced classification problems. Very rare literature was found to be related to usage of GNN or Transformer related networks for short-term traffic crash.

## 3.3 Methods in Traffic Crash Analysis

### 3.3.1 Review for Statistical Crash Prediction Methods

Road traffic crashes are counted as non-negative, integer-based random events (Zheng et al., 2010). Common models for predicting crashes utilise statistical spatio-temporal methods, including Bayesian inference, machine learning techniques, and deep learning neural networks. Bayesian dynamic logistic regression adjusts model parameters by combining new instances with existing prior knowledge (Cai et al., 2023; Yuan et al., 2019). A significant benefit of this approach is that, in contrast to traditional extrapolation—which typically provides only a prediction equation and a probability value—Bayesian analysis offers a range of interpretative possibilities. The Bayesian hierarchical structured model addresses issues of non-stationarity and unobserved heterogeneity in extreme situations to improve prediction accuracy (Sabey and Staughton, 2019). Bayesian Belief Networks include variables such as ramp flow and ramp location speed. Hossain and Muromachi (2011) incorporated vehicle trajectories into their analysis to explore the factors influencing crash occurrences. Wang and Feng (2019) applied an Autoregressive Integrated Moving Average with Explanatory Variables (ARIMAX) model to examine road crashes in Nigeria. Traditional ARIMA frameworks enable projections based solely on the historical performance of the forecasted variable, assuming a strong correlation between past values and the magnitudes of prior probabilities. The ARIMAX model effectively captures short-term data characteristics and

predicts near-future trends. Christofuorou et al. (2011) demonstrated that ARIMA utilises prior time series analyses for forecasting consumption. While ARIMA is a univariate approach, ARIMAX integrates historical consumption data from multiple datasets, such as climatic conditions (Christofuorou et al., 2011). Dong et al. (2018) used multivariate probit models to link crash types with existing traffic conditions. Hu et al. (2018) employed a Multivariate Negative Binomial (MVNB) model within a supervised fine-tuning module as a regression layer to tackle unobserved heterogeneity in traffic crash prediction. Zhang et al. (2020) proposed a Long short-term Memory (LSTM) combined with a Gradient Boosting Regression Trees (GBRT) model to enhance the LSTM classifier by incorporating boosting regression trees. Gradient boosting builds progressively weaker algorithms, each attempting to predict the residual left by the previous one, which can lead to rapid overfitting. Hu et al. (2018) introduced a Grey Neural Network model to reduce data distortion caused by small sample sizes. He et al. (2009) utilised a Back Propagation Neural Network to manage nonlinear mappings and complex internal mechanisms.

Count data models, such as Negative Binomial (NB) and Poisson models, are commonly employed to analyse traffic accident data, adhering to the underlying distribution assumptions (Quddus, 2008). However, cross-sectional or panel count data models may overlook the temporal structure inherent in time series data, potentially skewing modeling results when variables are highly correlated. The Autoregressive Integrated Moving Average (ARIMA) model, a quantitative method, leverages time series data to understand number sets or forecast future patterns. ARIMA predicts potential trends based on historical data, a process termed autoregressive, and the Seasonal Autoregressive Integrated Moving Average (Seasonal ARIMA) includes a consistent term specifically designed for periodic unitary series data. ARIMA is widely utilised in temporal analysis of time series data exhibiting serial correlation. Both ARIMA and Seasonal-ARIMA models have been extensively applied to time series count data (Quddus, 2008). Various traditional statistical methods, along with machine learning and deep learning techniques, can be applied to accident prediction. A developed logistic regression model explores the connection between traffic flow and accident occurrences (Abdel-Aty et al., 2004). Yu et al. employed an Artificial Neural Network (ANN)

and a Support Vector Machine (SVM) to forecast accident duration (Yu and Abdel-Aty, 2013). Bao et al. utilised a Convolutional Neural Network (CNN) to predict short-term citywide accident risks (Bao et al., 2019). Schlogl et al. treated accident prediction as a binary classification task, finding that tree-based models performed effectively (Schlogl et al., 2019). Within the field of machine learning, ensemble learning, count data models for traditional statistical regression, and deep learning methods are the most commonly used approaches for predicting accidents.

Crash frequency data are non-negative integer-based random counts (Quddus, 2008). To meet the underlying distribution assumptions, traffic crash data frequently utilise count-data modeling techniques, such as the Poisson model (Quddus, 2008). The Negative Binomial model, an extension of the Poisson regression model, is applied to address potential over-dispersion issues (Lord and Mannering, 2010), which are often due to excess zeros in crash data. Since traffic crash data are generally collected as time-series, models like Autoregressive Integrated Moving Average (ARIMA) and Seasonal-ARIMA are commonly used to model time-series count data and have gained prominence in recent years for analysing time-series data with serial correlation (Quddus, 2008). Nonetheless, the ARIMA model is not suitable for non-negative integer-valued data, such as traffic accidents, because its error assumptions are normally distributed. Even when the dataset does not contain lower values, theoretically, the ARIMA framework can generate negative predictions (Quddus, 2008). To effectively model the distribution of traffic accidents and account for the temporal structure in time series, this study proposes a time-series count data model that incorporates multi-source data as covariates for forecasting crash occurrences.

### 3.3.2 Review of Machine Learning Crash Prediction Methods

In addition to traditional statistical modeling, machine learning, and deep learning algorithms have become increasingly popular for predicting crash frequency. Common approaches for forecasting freeway car crashes include Artificial Neural Networks (ANNs) and Bayesian

Neural Networks (BNNs). These networks are structured hierarchically, with interconnected nodes arranged in layers: an input layer, one or more hidden layers, and an output layer. In this framework, the neural network weights are considered fixed but adjustable (Abdelwahab and Abdel-Aty, 2002; Riviere et al., 2006; Xie et al., 2007). Hierarchical neural networks are typically seen as providing improved crash forecast approximations, though their ability to generalise still requires further exploration (Wu and Wang, 2020).

Machine learning techniques based on statistical learning theory, such as Support Vector Machines (SVMs), offer the potential for better generalisation and increased interpretability. Wu and Wang (2020) compared Support Vector Regression (SVR) and Back Propagation Neural Networks for traffic accident prediction, finding that SVR yielded superior accuracy and better generalisation.

The AdaBoost-CNN method integrates multiple base estimators using a weighted linear combination (Taherkhani et al., 2020). In contrast to sequential forecasting approaches like Long short-term Memory (LSTM) and Recurrent Neural Networks (RNNs), AdaBoost-CNN employs Convolutional Neural Networks (CNNs) to extract crash characteristics. During the training phase, sample weights are adjusted after each round based on the accuracy of predictions (Freund and Schapire, 1996). A less representative sample that is relevant to crash prediction will be given greater weight. As a result, AdaBoost-CNN can partially address issues related to imbalanced data. However, since CNNs do not incorporate temporal information, their effectiveness in crash prediction is contingent upon specific scenarios.

To enhance the representativeness of crash samples, the Synthetic Minority Oversampling Technique (SMOTE) is commonly utilised to mitigate the effects of data imbalance. SMOTE operates by identifying instances that are close to each other in the feature space, creating a line connecting these instances, and generating a new synthetic sample at a random point along that line. Nevertheless, the synthetic data generated through this technique is often highly correlated with existing samples and lacks temporal information.

A newly developed Graph Neural Network includes a generalised version that features a spatial-temporal block. This spatial-temporal block encompasses temporal gate convolution, spatial gate graph convolution, and temporal attention mechanisms, enabling the network to learn both local and global features of regional data. Unlike CNNs, Graph Neural Networks operate on graphs with directional edges, allowing them to model road network graphs for constructing macro-level regional graphs. However, this study focuses specifically on a segment of the G15 freeway bridge, which limits the inclusion of broader macro feature road maps.

## 3.4 Review for Methods in Traffic Conflict Analysis

Conflict modelling includes both conflict frequency and conflict severity models (Zheng et al., 2021) . This study will focus on frequency to predict conflicts in real-time as a binary classification problem. There exists a plethora of statistical and data-driven conflict prediction methods. The most common algorithms used for conflict prediction are Neural Networks (NN) with Long Short-Term Memory NN, Convolutional NN, Deep NN and Feed Forward NN, Support Vector Machine, and Bayesian Networks (Marcillo et al., 2022). Random forest (RF) is a widely used strong classifier that combines multiple decision trees to obtain a classification result through a voting mechanism. Random forest outperforms decision trees by handling well overfitting problems in which each decision tree will not grow deep and different trees are trained to learn different features. RF is an improvement over bagged decision trees that combines predictions from multiple models in ensembles and performs best if the predictions from the sub-models are uncorrelated or weakly correlated (Berk, 2016). RF changes the bagging algorithm with learned subtrees resulting in less correlation in the subtrees' prediction. RF has been widely used in traffic conflict prediction for having strong classifying ability, identifying and ranking influencing factors affecting traffic conflicts or crashes, and extracting latent features of traffic data. Yan and Shen (2022) built random forest model with Bayesian optimization to predict traffic accidents and identify influencing factors

affecting unsafe traffic conditions. Zhao et al. (2022) utilised deep convolutional neural network and random forest model to initiate a risk analytic model to predict traffic accident severity. Wang et al. (2021) built a random forest model to avoid congested road and choose high-speed routes to avoid traffic congestion.

Gradient Boosting Machine (GBM) is an ensemble method sequentially combining the predictions of multiple weak learners and decision trees. Contrasting with random forests that rely on simple averaging of multiple models to make predictions, boosting methods use a different approach for forming ensembles (Natekin and Knoll, 2013). Boosting involves adding new models to the ensemble sequentially. At each iteration, a new weak base learner is trained to address the errors made by the ensemble up to that point (Natekin and Knoll, 2013). GBM builds models sequentially and the subsequent models reduce the errors of the previous model through minimizing loss function with optimal gradient descent in each iteration step. Similar to Random Forest, the basic prediction model used for GBM is decision trees (Hastie et al., 2001).

In gradient boosting machines (GBMs), the learning process involves sequentially fitting new models to improve the accuracy of the response variable estimate. GBM algorithm creates new base learners that are highly correlated with the negative gradient of the loss function, which reflects the errors of the entire ensemble (Natekin and Knoll, 2013). GBM combines multiple weak prediction models, often decision trees, in a sequential process to improve prediction accuracy (Natekin and Knoll, 2013; Hastie et al., 2001). Each subsequent model in the sequence focuses on correcting the errors made by its predecessor, resulting in a stronger, more robust model. GBM is particularly effective for predicting the likelihood of traffic conflicts by analysing factors such as vehicle speed, distance, and lane changes (Zhang and Haghani, 2015; Niyogisubizo et al., 2023). Compared to simpler models, GBM offers greater precision in identifying potentially risky traffic situations (Zhang and Haghani, 2015; Niyogisubizo et al., 2023).

SVM (Support Vector Machine) is a supervised machine learning algorithm which is mainly

used to classify data into different classes (Berk, 2016). Unlike most algorithms, SVM makes use of a hyperplane which acts as a decision boundary between the various classes (Berk, 2016). A main advantage of SVM is that it can be used for both classification and regression problems. In general, SVM is used for classification problems, and the SVR (Support Vector Regressor) is used for regression problems.

SVM can be used for classifying non-linear data by using the kernel trick. The kernel trick means transforming data into another dimension that has a clear dividing margin between classes of data (Berk, 2016). A kernel can be used to transform data into another dimension that has a clear dividing margin between classes of data. Kernel functions offer the user the option of transforming nonlinear spaces into linear ones. The kernel trick enables the identification of the optimal hyperplane between various classes of data (Hemsi, et al, 2020; Hofmann et al., 2008). Therefore, a complicated non-linear classification problem can be solved by finding a suitable hyperplane in a higher dimension by using the kernel trick. Orsini et al. (2021) used a support vector machine as classifier, and Monte Carlo cross-validation to improve model robustness to make real-time traffic conflict prediction within 5 minutes time duration and achieved 93% accuracy. SVM can also be used to analyse causalities along with traffic conflict prediction. Zhong and Du predict traffic casualties using SVM with heuristic algorithms based on collision data of urban roads in China (Zhong and Du, 2023).

A Deep Neural Network (DNN) is a type of artificial neural network characterized by having multiple layers between the input and output layers, including neurons, synapses, weights and biases, and activation functions. These layers and components enable DNNs to model complex relationships and patterns in data effectively. DNN is widely used in transportation and can be designed to predict potential collisions or near-misses on the road by analysing real-time traffic data, including vehicle positions, speeds, and trajectories (Tang et al., 2019; Xiao, 2019). By leveraging its ability to identify complex patterns and relationships in data, a DNN can detect indicators of high-risk scenarios and provide early warnings (Formosa et al., 2020; Formosa et al., 2023). This capability enables proactive interventions to mitigate risks and enhance road safety, making it a valuable tool for real-time traffic management and

collision prevention systems (Formosa et al., 2020; Formosa et al., 2023).

Zheng et al. (2023) develops non-parametric models: Multilayer Perceptron (MLP), Support Vector Regression (SVR), and Random Forest (RF) with Bayesian optimization approach to optimize the model hyper-parameters to predict traffic conflicts at signalized intersections at the signal cycle, and makes comparison with traditional Safety Performance Function (SPF). Results show that MLP model performs better than SVR and RF models, and all three Bayesian optimized machine learning models outperform the traditional SPF in conflict prediction accuracy. Islam & Abdel-Aty (2023) utilises previous instance trajectory data of individual vehicles to predict potential conflict in 9 s in the future with the application of the LSTM model. Similarly, Cao et al. (2021) establishes a multilayer LSTM model of turning left, going straight, and turning right to predict the trajectory of the target vehicle through the unsignalized intersections. Formosa et al. (2020) uses Regional Convolution Neural Network (RCNN) to identify traffic conflicts from images captured by a single front facing camera and develops a series of Deep Neural Network (DNN) models to predict traffic conflicts with TTC, speed, weather, and traffic density as independent variables. Ding et al. (2024) applies k-means, GMM, and Mclust models to identify traffic conflicts with various SSMs as independent variables. It reveals that the heterogeneity of thresholds of SSMs is exhibited across traffic state transitions (Ding et al., 2024). Ge et al. (2020) develops Negative Binomial model to predict traffic conflict severity based on TTC thresholds, which reveals that TTC within (0, 1.3s) means traffic conflict is serious. Similarly, Hu et al. (2022) builds combined methods of Zero truncated Poisson regression and ordered logit regression to assess conflict frequency and severity with short-term (30-second time interval) traffic characteristics.

The stacking method is also considered as an Ensemble Learning Method. It employs a meta-learning algorithm to determine the optimal way to combine predictions from two or more base machine learning models. The advantage of stacking is that it leverages the strengths of various high-performing models for a classification or regression task, resulting in predictions that often outperform those of any individual model in the ensemble. Cai et al. (2024) utilised the Stacked Ensemble Learning model by combining Random Forest, Support

Vector Machine (RBF), and Deep Neural Network as the first layer, and Gradient Boosting Machine as the second layer to make prediction of traffic conflicts in real-time using Shanghai urban junction data, achieving 98% accuracy. Tang et al. (2019) uses a two-layer stacking framework with RF, AdaBoost, and GBDT as the first layer, and the Logistic Regression model as the second layer to predict crash injury severity. Tang et al. (2019) also compares its prediction accuracy with multiple traditional models such as SVM (RBF), MLP, Random Forest, and concludes that the proposed Stacked Ensemble model performs best in prediction accuracy. The discussion of Ensemble Learning methods will be elabourated in this Chapter 3.

## 3.5 Summary

This chapter introduces methodologies for traffic crash prediction and traffic conflict prediction, including time series models: ARIMA, INGARCH, Count Data Model; Machine Learning models: Random Forest, Boosting, KNN, SVM, Stacked Ensemble Learning; Deep Learning models: RNN, LSTM, CNN, STGNN. These models are widely used in regression, forecasting, classification, and other applications.

A unique challenge in crash prediction is that traffic crashes are random, low likelihood events, making their occurrence difficult to predict. This chapter conducts reviews for statistical analytical models and machine learning methods for short-term crash prediction. It compares the effectiveness and predictive ability of different model frameworks in capturing spatial temporal crash characteristics and utilising dynamic traffic operation parameters in making near future crash prediction. In general, machine learning and deep learning based models perform better than conventional statistical methods in terms of prediction accuracy, but statistical methods have more model interpretability and result in explanatory ability in real applications. More elabouration on traffic crash prediction will be introduced in Chapter 6 Development of Traffic Crash Prediction Models.

Traffic conflicts are considered surrogate measures for crashes because real-time traffic crashes are relatively rare. In order to well quantify and better measure traffic conflicts, Safety Surrogate Measures (SSMs) are commonly employed for conflict detection. There are over forty different SSM measures, which can be classified into three categories roughly: Time-based factors, Distance-based factors, and Deceleration-based factors. This chapter introduces all three types of SSMs and explores which ones are most suitable for traffic conflict detection in the different given scenarios. This chapter also introduces a stacked ensemble learning model to capture conflict features and make real-time conflict predictions. The stacked ensemble model is composed of gradient boosting trees, deep neural networks, and support vector machine as the first layer, with random forest as the meta layer. More elabouration on traffic conflict prediction will be introduced in Chapter 7 Development of Traffic Conflict Prediction Models.

# Chapter 4 Techniques In Extracting Traffic Dynamic Features

This chapter is the main chapter to introduce computer vision techniques in extracting dynamic traffic data. It contains three parts: literature review, methodology, and analysis of detection results. Literature review part reviews various types of road sensors in transportation and also conducts an overview of video processing techniques and their applications in real use cases. In methodology part, it introduces the structures of commonly used deep learning models such as YOLO, FairMOT, CNN and their generalised versions. It offers a comprehensive exploration of the technical methodologies and challenges involved in extracting traffic parameterss (speed, acceleration, traffic volumes, etc) from video data using computer vision. It also emphasizes the need for adaptable approaches capable of accommodating real-world complexities. The results analysis part compares test results from different deep learning computer vision models and analyses pros and cons of different detection and tracking models with application to the collected video data of roadway scenarios. Additionally, it suggests future research endeavors to improve the effectiveness of deep learning methods for traffic crash prediction, accident analysis, and proactive traffic management.

## 4.1 Various Types of Road Sensors in Traffic Studies

Unstable traffic dynamics, which can lead to road traffic collisions, are influenced by a complex interplay of factors, including road geometry, environmental conditions, traffic dynamics, vehicle characteristics, and human behaviour (Sabey and Staughton, 1975). Traditional freeway crash prediction models often fall short in incorporating real-time traffic dynamics—such as speed, speed variance, traffic flow, and vehicle types—due to challenges in data collection.

However, atypical changes in direction and speed, as indicated by traffic dynamics, can significantly increase the risk of collisions for other road users (Hossain and Muromachi,

2012). Research has demonstrated that traffic conflicts often serve as precursors to crashes, highlighting the critical relationship between traffic dynamics and crash occurrences (Zheng et al., 2021).

The advent of high-resolution detectors has provided a wealth of data on vehicle speed, lane traffic flow, vehicle types, and environmental conditions, paving the way for more accurate and timely crash predictions. By leveraging this data, it is now possible to incorporate real-time traffic dynamics into predictive models, enhancing our ability to forecast and mitigate potential collisions on roadways.

LiDAR: LiDAR sensors employ pulsed lasers for object detection. A typical LiDAR device consists of a laser, scanner, and specialized GPS receiver (Velodyne LiDAR, 2016). Key specifications for selecting a model include laser channels, vertical field of view, and vertical resolution of laser beams. Effective installation is crucial for optimizing performance in roadside LiDAR applications; it involves integrating technical features of the chosen LiDAR model with application objectives (Zhao et al., 2019).

Users can customize the rotation frequency (typically 5–20 Hz) of LiDAR sensors. A single data frame is generated after the sensor completes a 360°, three-dimensional (3D) scan using a line scan pattern, and the captured point clouds are stored in pcap format (Velodyne LiDAR, 2016). Data file sizes depend on the duration of data collection and the number and complexity of surrounding objects, averaging about 2–3 megabytes per second per unit in our experiments. Output data from LiDAR sensors include the precise location (X, Y, Z coordinates) of each point, their distance from the sensor, intensity, laser ID, azimuth, adjusted time, and timestamp. By using the GPS location of the LiDAR sensor and a reference point, all points can be accurately matched to their real-world locations.

Radar: The term "radar" originates from the acronym for "radio detection and ranging." Radars utilise radio waves to ascertain the distance and velocity of detected targets. Typically, a radar system includes a transmitter for emitting radio signals and a receiver to capture

reflected energy from targets. Radar now serves as a traffic counter that are used in a variety of applications in traffic engineering, especially in capturing accurate speed and traffic data. With the use of Radar data, it helps to survey traffic and road usage, curb speeding violations, and improve overall traffic safety level.

Inductive Loop Detectors: Inductive loop detectors are a type of traffic sensor utilised to classify vehicles by detecting the induced current from a wire loop embedded in the pavement. They are widely deployed on freeways due to their high accuracy and cost-effectiveness. Inductive loops are activated when a heavy metal object or vehicle passes over a loop embedded in the pavement. As the vehicle moves across or stops on the loop, it induces a vortex current that decreases the loop's inductance. This reduction in inductance triggers the output relay of the electronics component, sending a signal to the controller to indicate the presence of a vehicle. Therefore, inductive loops are usually used for traffic volume calculation.

Acquiring real-time traffic motion parameters using high-resolution detectors like LiDAR, radar, and inductive loop detectors (ILDs) can often be impractical for several reasons. Firstly, unlike surveillance cameras, these technologies typically cover only key road segments, leaving many areas without monitoring. Secondly, the installation of LiDAR, radar, and ILDs is both costly and labour-intensive, while extracting traffic motion parameters from roadside surveillance cameras is more efficient and straightforward. Moreover, these high-tech systems are unable to capture certain critical motion parameters, such as lane change behaviour, vehicle trajectories, lane occupancy, and incidents like fires.

Given these limitations, it would be advantageous to directly extract various traffic motion parameters through video processing techniques. There is a vast network of roadside surveillance cameras, with China alone having approximately 626 million cameras, of which around 24 million are positioned on roadways (IHS Markit, 2016). However, less than 2% of these cameras are equipped with smart technology capable of detecting vehicle speeds and traffic violations (IHS Markit, 2016). Most of the existing roadside cameras were not installed

with the intention of extracting detailed traffic operating features. Instead, they are typically operated manually, allowing users to tilt, pan, and zoom, which complicates the calibration necessary for accurate speed and volume estimation (Formosa et al., 2020).

Despite these challenges, recent advancements in deep learning and computer vision techniques present a promising opportunity to extract real-time traffic operating parameters from standard roadside cameras. These technologies can identify traffic incidents, monitor traffic flow, detect abnormal scenarios, estimate speeds, and even recognise weather conditions, congestion, and vehicle types. By leveraging such timely traffic information, it becomes feasible to create an intelligent alert system that not only informs traffic management centres of current conditions but also develops predictive capabilities for anticipating potential crashes. This approach could significantly enhance traffic safety management and response strategies.

## 4.2 Overview of Video Processing

Roadway traffic safety management, particularly in the context of accident detection, is gaining significant attention due to its critical role in reducing collision risks and enhancing traffic flow. Vehicle collisions on freeways can obstruct lanes, leading to increased traffic volume on remaining lanes and a heightened risk of subsequent accidents (Retallack and Ostendorf, 2020). Various factors contribute to traffic accident risks, including environmental conditions and temporal-spatial patterns.

Previous studies have highlighted the impact of specific factors on accident rates and have developed predictive models based on available data. Many traditional proactive accident detection methods rely on sensor-recorded data or environmental conditions, such as precipitation, traffic volume, and road geometry (Duivenvoorden, 2010; Eisenberg, 2004; Shefer and Rietveld, 1997). Additionally, some research has focused on non-physical patterns, examining the spatio-temporal correlations of traffic accidents and the non-uniform

distribution of traffic risks over time, which has informed predictive modeling efforts (Milton and Mannering, 1998).

However, existing models often fall short in providing real-time cumulative risk assessments. Environmental factors, such as road design and spatio-temporal patterns, are typically static relative to traffic flow and may not effectively reflect the current traffic conditions relevant to risk inference (Milton and Mannering, 1998). Furthermore, many models depend on sensor-collected data, which can be limiting.

Despite the extensive research on sensor-dependent detection methods, significant challenges hinder their widespread implementation. The high costs associated with hardware installation can render these approaches impractical for large-scale use (Ren et al., 2018). This issue is exacerbated by vehicle-based detection systems that require data from sensors installed on individual vehicles to function optimally (Heyns et al., 2019).

To address these challenges, there is a growing need for innovative solutions that leverage existing resources—such as roadside cameras and video analytics—to enhance traffic safety management without the prohibitive costs associated with sensor-dependent systems. This approach could facilitate more effective real-time monitoring and accident detection, ultimately improving roadway safety.

### 4.2.1 Computer Vision Detection Methods

Video-based detection methods excel in financial efficiency and hardware optimization, making them particularly suitable for integration into existing traffic surveillance systems. With an estimated 24 million traffic cameras installed in China—yet less than 1% equipped with smart monitoring algorithms (IHS Markit, 2016)—automating detection processes can significantly enhance operational efficiency while reducing reliance on manual monitoring.

In contrast to sensor-based systems, which often have limited applications and are typically designed for specific tasks (such as radar systems that focus solely on distance measurement) (Nithya et al., 2020), video-based methods provide a comprehensive analysis of traffic conditions. These methods can identify anomalies (e.g., traffic accidents, improperly parked vehicles), track vehicle movement, and analyse traffic density without the need for multiple specialized sensors (Ajao et al., 2020).

Various studies have highlighted the advantages and potential applications of video-based algorithms. For instance, Sable et al. (2020) introduced an online vehicle contour-based density measurement method. Damulo et al. developed a traffic camera-focused density detection approach using the Haar Cascading algorithm within a specified Region of Interest (ROI) (Dailey et al., 2021). Additionally, research has addressed common deficiencies in vision-based methods, such as small object detection and environmental impacts (Nguyen et al., 2020).

Tian et al. (2019) proposed a traffic accident detection system that leverages neural networks and Cooperative Vehicle Infrastructure Systems (CVIS). Their YOLO-CA network, which incorporates multi-scale feature fusion, enhances the detection of smaller or distant objects, addressing typical challenges in vision-based detection.

Wang et al. (2020) tackled low-visibility conditions by employing Retinex Image Enhancement, which minimizes the effects of severe weather on detection outcomes. This enhanced image input undergoes object detection, followed by accident probability assessment using a decision tree.

Yao et al. (2019) explored the feasibility of vehicle-based autonomous detection methods, creating a first-person risk evaluation system that analyses motion inconsistencies among front vehicles. Huang et al. (2020) utilised the extensive information from cameras to develop a two-stream convolutional network architecture aimed at near-accident detection.

Overall, these studies illustrate the versatility and effectiveness of video-based detection methods, positioning them as a compelling alternative to traditional sensor-dependent systems in traffic management.

### 4.2.2 Object Tracking Algorithms

Slow inference speed and high computational costs are significant challenges in vision-based approaches for traffic analysis. However, recent advancements have made notable improvements in these areas. For instance, Dailey et al. (2021) introduced a novel method for estimating traffic speed using sequences of images from uncalibrated cameras. This approach leverages the geometric relationships present in images, employing frame differencing to isolate moving edges and track vehicles across frames. It also utilises parameters from vehicle length distributions to enhance accuracy.

Ozbayoglu et al. (2016) developed a predictive visual accident detection model aimed at minimizing delays caused by network inference speed. They evaluated the model using resource-efficient techniques like nearest neighbour and regression trees, thus addressing computational demands while maintaining functionality.

Agrawal et al. (2020) tackled these issues by selectively dropping frames based on histogram differences between consecutive images, thereby reducing unnecessary processing. They utilised a support vector machine to predict accidents after extracting features with ResNet50 and K-Means clustering, achieving a balance between speed and accuracy.

Zu et al. (2014) employed a mean-shift algorithm for vehicle tracking and motion evaluation, producing accident predictions with a Gaussian Mixture Model for vehicle identification, showcasing a computationally efficient tracking method.

These studies suggest that conventional image processing techniques can often outperform neural network-based methods regarding speed and computational efficiency. To mitigate the

speed limitations of neural networks in real-time scenarios while preserving accuracy, innovative iterations of object detection algorithms have been developed, specifically tailored for online applications.

Vehicle detection is a hot topic that has been studied for a long period of time and enjoys wide application in fields such as safety analysis, traffic monitoring, autonomous vehicle, intelligent connected vehicles, etc. Conventional detection technical route include one-stage detection, and two-stage detection. two-stage detection methods was proposed before one-stage detection, common methods include R-CNN, Fast R-CNN, Faster R-CNN, SPP-NET, etc. CNN is the fundamental neural network used for two-stage detection. Within the two-stage detection, the first stage is generating a candidate box regions (Zhang et al., 2022). The second stage is discriminating against the contents of the candidate box and then classifying boxes into different labels (Zhang et al., 2022). R-CNN (Regions with CNN features) is the first proposed model in two-stage detection by Girshick et al. (2014). R-CNN uses CNN to extract features in candidate regions and then detect classified objects. SPP-Net was proposed by He et al. (2014) to initiate a spatial pyramid pooling method to accelerate detection speed. Faster R-CNN optimized detection speed of R-CNN with the use of a Region Proposal Network (RPN) instead of selective search to generate candidate boxes (Zhang et al., 2022).

One-stage methods integrate candidate box generation and detection into a single step, with the YOLO series model serving as a prominent example. Redmon et al. introduced the You Only Look Once (YOLO) network structure for object detection and identification, which offers a significant advantage in computational time compared to earlier detection models, such as sliding-window or region-based algorithms, thanks to its one-pass detection capability (Redmon et al., 2016; Redmon and Farihadi, 2018; Wojke et al., 2017). Consequently, YOLO is frequently incorporated into vehicle-tracking models that require high performance as the object detector. A common pairing for object tracking is YOLO integrated with Deep Simple and Online Real-time Tracking (SORT) (Wojke et al., 2017). This integration consists of two-stages: object detection using YOLO followed by object tracking via deep SORT.

Although YOLO enables rapid video object recognition, the deep SORT stage can slow down the overall processing speed when it needs to re-identify objects by calculating their similarities.

Multi-object tracking is a crucial task in computer vision. Similar to the YOLO model, Zhang et al. (2020) developed the Fairness Multi-object Tracking (FairMOT) network, which combines detection and re-identification stages to achieve high efficiency and effectiveness in object tracking tasks. The FairMOT network structure can be utilised for tracking vehicles and generating their trajectories (Zhang et al., 2020). Unlike Deep SORT, where the re-identification task is heavily dependent on the detection stage, FairMOT optimizes both detection and re-identification stages jointly, based on an anchor-free object detection architecture known as centreNet (Zhang et al., 2020). To enhance the re-identification capability of FairMOT in traffic scenarios, Cai et al. (2023) proposed a modified version of FairMOT that employs CSPDarknet53 (Cross Stage Partial Dark Network with 53 layers). This modification optimizes the FairMOT network by utilising the CSPDarknet53 structure to improve its performance in detecting and tracking vehicles in traffic scenarios. In this approach, bounding boxes are generated by applying a non-max suppression process to the predictions from the encoder-decoder network within FairMOT. By integrating CSPDarknet53 and retaining the DLA structure in FairMOT, aggregated features can be fused. The modified FairMOT effectively associates the same vehicle across different frames, allowing for the calculation of screen-space distance offsets for each vehicle (Wojke et al., 2017). Additionally, Cai et al. (2023) incorporated a Proportional Integral Derivative (PID) controller as a kernel function $\sigma$ to reduce sporadic noise in speed measurements, which can occur due to precision limitations arising from low resolution.

### 4.2.3 Camera Calibration for Speed Calculation

There are many ways to calculate vehicle speed in videos. Cvijetic et al. (2023) uses Yolo algorithm for vehicle detection and tracking, and applies a one-dimensional convolutional

neural network for speed estimation by calculating the area of the bounding box frame to frame as the vehicle approaches the camera. Luo et al. (2024) uses the combined method of Yolov5s and Deep SORT to detect and track passing vehicles. Luo et al. (2024) then utilises known references in the image (lane markers and contour labels) to infer actual coordinates, reaching around 90% accuracy in speed estimation. Without camera calibration, speed estimate is not accurate.

Some researchers calibrate camera in advance by drawing reference lines in images and measure corresponding length and width in actual coordinates. They then calculate speed when vehicle passes the calibrated test zone (Luo et al., 2024). This approach can get highly accurate speed estimation but is labourious by calibrating every video in each scenario. Once the corresponding scenario cannot be actually measured, the recorded video cannot proceed either since not having the necessary parameters. The above mentioned approach is considered as hard calibration that estimates both the intrinsic and extrinsic parameters of the camera manually (Luo et al., 2024).

Finding an automatic camera calibration method and calculating image speed using inferred actual coordinates not only reduces calibration time but also enhances the precision of speed calculations. Numerous scholars have investigated camera calibration techniques for deriving actual speed from video processing. For instance, Lai (2000) focused on using road lanes, camera height, and tilt angle to establish world coordinates in terms of ground distance (Lai, 2000). Bas and Crisman employed the vanishing point of the road edge to determine the camera's focal length and pan angle (Bas and Crisman, 1997). However, many conventional camera calibration methods rely on predefined camera height and tilt angle or necessitate specialized calibration patterns in traffic scenes, which can be difficult to obtain (Bewley et al., 2016).

Fung et al. (2003) introduced a camera calibration method that establishes the relationship between image coordinates and world coordinates by considering parameters such as pan angle, tilt angle, swing angle, focal length, and camera distance. Their study proposed a

transformation matrix to convert image coordinates into world coordinates (Fung et al., 1980). utilising these parameters, vehicle speed can be calculated by projecting image pixel speed into real speed based on the established world coordinates.

### 4.2.4 Application of Drones to Collect Traffic Data

As an emerging new technology, drones provide a wider view, high flexibility and reliability for analysing traffic flows and safety conditions (Chen et al., 2020). Taken from an eagle perpendicular view, objects are less occluded, videos are less distorted, and as a result, detection, tracking, dynamic data estimation are much higher than road side surveillance cameras Drones deployment in urban junction or freeway segment provide solutions to extract dynamic traffic parameterss and monitor traffic movements in real-time. Many studies collected drone-based datasets and conducted analysis on traffic congestion, flow rate, and vehicle speed estimation by detecting, tracking, and counting vehicles (Bisio et al., 2022). Benefits are apparent with deployment of drones to solve traffic issues:

i) High resolution video data can be captured from a higher altitude (Bisio et al., 2022);
ii) Individual vehicle kinematic data and traffic operation status can be gathered and monitored by drawing trajectories, calculating speed, acceleration, lane change information, and vehicle to vehicle interaction;
iii) Implementation of deep learning technique to detect abnormal scenarios and unprecedented traffic issues (Zhang et al., 2019).

Ozguven et al. (2021) provides a feasibility analysis on the deployment of drones with computer vision to take images of crosswalk, extract microscopic traffic data at urban intersections, and investigate the fatal pedestrian involved crashes near intersections. Chen et al. (2020) utilises drones to fly over urban junctions to detect small objects in real-time through a Concatenated Bi-Fusion feature pyramid network. Ashqer et al. (2022) evaluated signalized intersection performances using UAV drones and indicated using drones to

congested intersections to investigate issues, mitigate traffic condition. Zong et al. (2022) leveraged drones' capabilities for traffic collision risk assessment at urban road junctions. Samandar et al. (2022) captured drones videos in urban junctions and roundabouts, extracted necessary dynamic parameters, calibrated simulation model parameters, and analysed the adjustment for signalized intersections so that queue dynamics and delays are matched (Zong et al., 2022). Mansour (2020) introduced using deep learning computer vision methods to extract traffic data from drones in the selected intersection. Bouassida et al. (2021) evaluated the impact of drone signaling in crosswalk scenarios. Reis et al. (2024) used YOLOv8 network to do object detection on more than 40 different classes from drones view and then performed transfer learning with learned parameters on more representative of "real world" environments.

Other deployments of drones include traffic intersection signal control and guiding, drones spraying pesticides, traffic flow and congestion analysis, vehicle interaction analysis, dynamic traffic data extraction for near future crash prediction, and making prompt corresponding interventions, etc.

## 4.3 Introduction of Computer Vision in Traffic Detection

### 4.3.1 You Only Look Once (YOLO)

Different from two-stage method such as R-CNN that uses a classification for the probabilities and a regression for boxes coordinates, YOLO is the one-stage end-to-end detection method using straight forward output based only on regression to predict the detection objects that surpasses many other methods by its efficiency, fast speed, and precise detection with light weight in real-time object detection field (Terven and Cordova-Esparza, 2024). The evolving timeline of YOLO versions is displayed in the following graph.

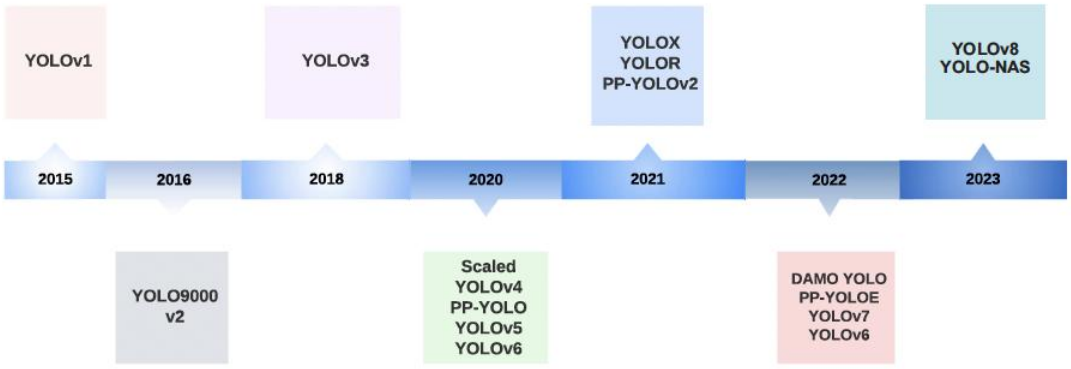



Figure 4.1. Development of YOLO versions

YOLOv1 has a simple architecture but puts forward one-shot regression to fasten processing speed. YOLOv3 was invented in 2018, which includes significant changes and improvements from YOLOv1 and YOLOv2 to its structures. YOLOv3 uses multi-scale detetction architecuture, introducing Darknet53 backbone and Convolution-BatchNorm-Leaky ReLU blocks into the structure, making YOLOv3 to be on par with the state-of-the-art whicle keeping real-time performance and lighter weight (Terven and Cordova-Esparza, 2024). YOLOv3 is also deemed to be a classical network that lays the foundation of YOLO series. YOLOv5 was released in 2020 used a modified CSPDarknet53 backbone followed by convolutional layers to extract image features (Terven and Cordova-Esparza, 2024) and incorporated a spatial pyramid pooling fast (SPPF) layer to accelerate computation. YOLOv5 model was also the first detection method used by this thesis. The architecture is displayed as follows.

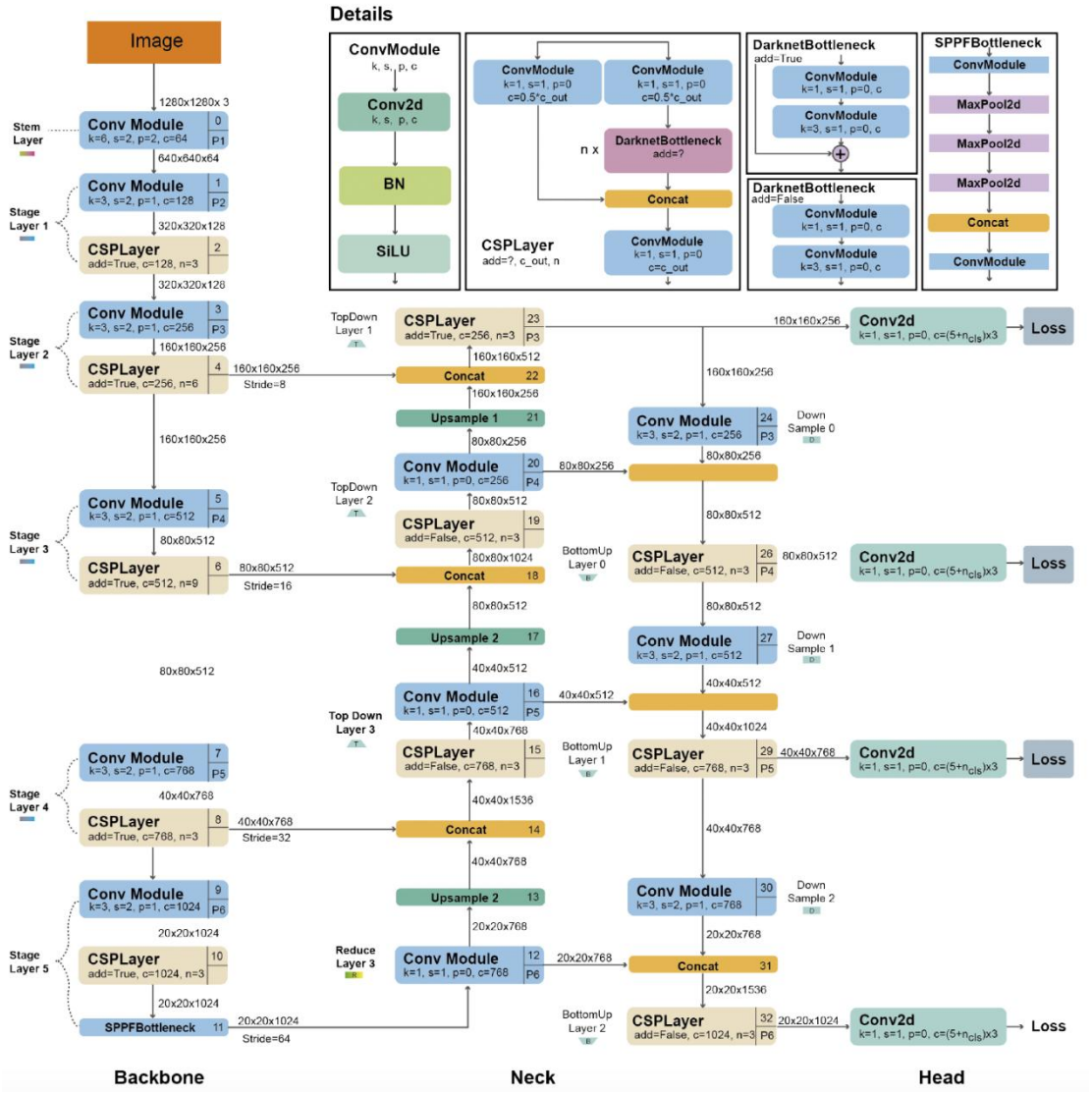



Figure 4.2. Architecture of YOLO v5

YOLO v5 mainly consists of input, Backone, Neck, and Prediction.

(1) Backbone: A convolutional neural network that aggregates and forms image features at different image granularity.

(2) Neck: A series of network layers that mix and combine image features and pass image features to the prediction layer.

(3) Head (Prediction): Predict image features, generate bounding boxes, and predict categories.

In 2023, YOLOv8 was released by the company Ultralytics, which also created YOLOv5 in

2020. In contrast with YOLOv5, YOLOv8 made some changes on CSPLayer to combine high-level features with contextual information to improve detection accuracy (Terven and Cordova-Esparza, 2024). YOLOv8 uses an anchor-free model with a decoupled head to process object detection, classification, regression, and tracking tasks. YOLOv8 also provides YOLOv8-Seg model to do semantic segmentation tasks, which is convenient for users to apply the same model in multi-task applications. The architecture of YOLOv8 is as follows.

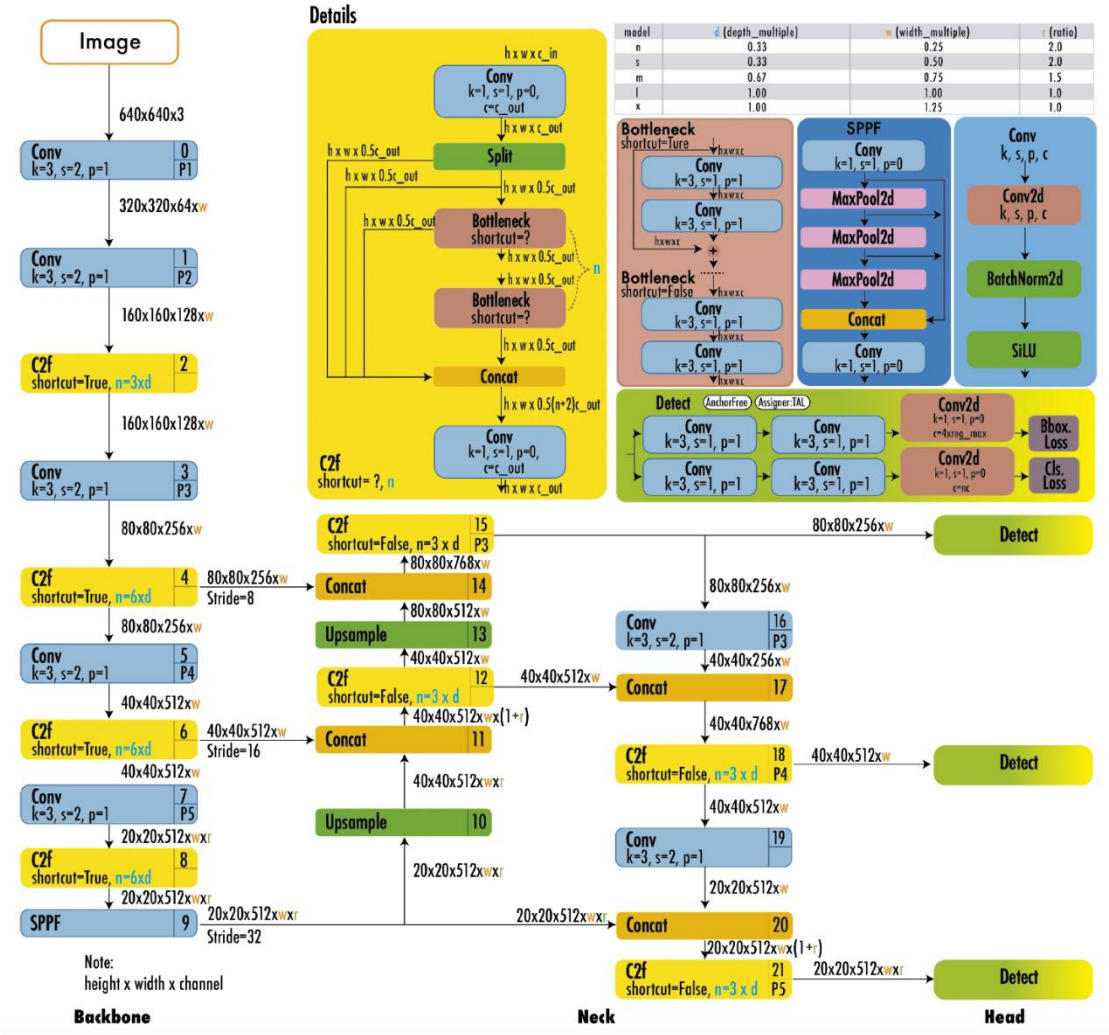



Figure 4.3. Architecture of YOLO v8 model

YOLOv8 offers several scales versions: YOLOv8n (nano), YOLOv8s (small), YOLOv8l(large), and YOLOv8x to support different usage purposes for different sizes to choose from.

### 4.3.2 mFairMOT

This study aims to develop a new approach for analysing videos from surveillance cameras to extract dynamic traffic parameterss. The core model utilised is a modified FairMOT (mFairMOT), which features an Encoder-Decoder neural network as its backbone architecture.

The mFairMOT generates detection frames and re-identification (re-ID) outputs. The detected frames are processed to assess real-time traffic volume and identify abnormal scenarios using logical algorithms. For re-identification, a spatial transformation matrix is computed to convert video coordinates into real-world coordinates, enabling accurate tracking of vehicles. Additionally, the speed of moving objects is calculated based on the distance they cover within a specified time interval. This process ensures a comprehensive analysis of traffic dynamics.

Figure 4.4 illustrates the proposed detection logic flowchart, highlighting the key steps in the detection and analysis process. This approach not only enhances the efficiency of traffic monitoring but also facilitates proactive traffic management by identifying potential issues in real-time.

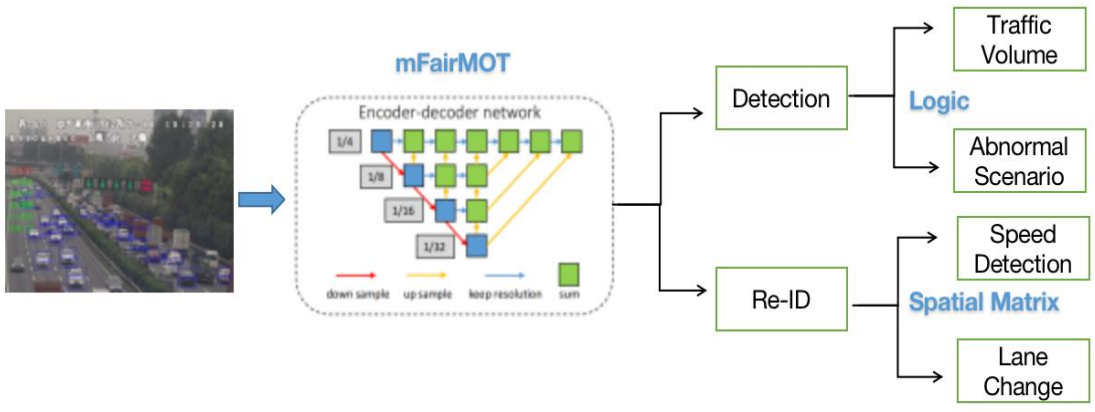



Figure 4.4. Flowchart of Detection Logic

The Fairness Multi-object Tracking (FairMOT) network was recently developed to efficiently combine detection and re-identification (re-ID) tasks, achieving impressive performance in

object tracking (Zhang et al., 2020). This study proposes a modified version of FairMOT, utilising CSPDarknet53 (Cross Stage Partial DarkNet with 53 layers) to enhance its ability to track vehicles and generate their trajectories.

Traditional tracking methods often rely on batch-based algorithms, which can struggle to meet real-time requirements, especially in scenarios with numerous objects. This limitation arises from (i) the lack of feature sharing and (ii) the repetitive nature of the re-ID process. FairMOT addresses these issues by enabling cross-frame object association, thus improving processing speed. However, certain challenges remain that necessitate modifications to effectively detect and track moving vehicles, including:

- Simultaneous detection and re-ID tasks
- Effective fusion of aggregated features
- Differentiating between person re-ID and vehicle re-ID
- Faster learning capabilities
- Generation of high-quality re-ID features

The modified FairMOT presented in this thesis aims to address these challenges. One key advantage of the FairMOT architecture is its ability to jointly integrate detection and re-ID tasks. For detecting moving objects, the anchor-free centreNet method is incorporated into FairMOT (Zhang et al., 2020). The original backbone network, ResNet34 with Deep Layer Aggregation (DLA), is particularly effective for person re-ID but requires enhancement for vehicle detection. Thus, it is replaced with Darknet53, which employs densely connected layers for improved feature extraction (see Figure 4.5) (Zhang et al., 2020).

The integration of CSPNet into the Darknet53 framework maximizes the differences in gradient joints and prevents different layers from learning redundant gradient information. This modification addresses two significant issues: (i) excessive computation and (ii) gradient diffusion, thereby enhancing the learning capability of the network. Additionally, DLA is utilised to fuse aggregated features, further improving the generation of high-quality re-ID features.

The modified FairMOT (mFairMOT) network is designed to efficiently track various moving objects, including vehicles and people. As a state-of-the-art tracking model for multi-object detection, mFairMOT enhances generalizability in tracking diverse object types. The schematic structure of mFairMOT is illustrated in Figure 4.5.

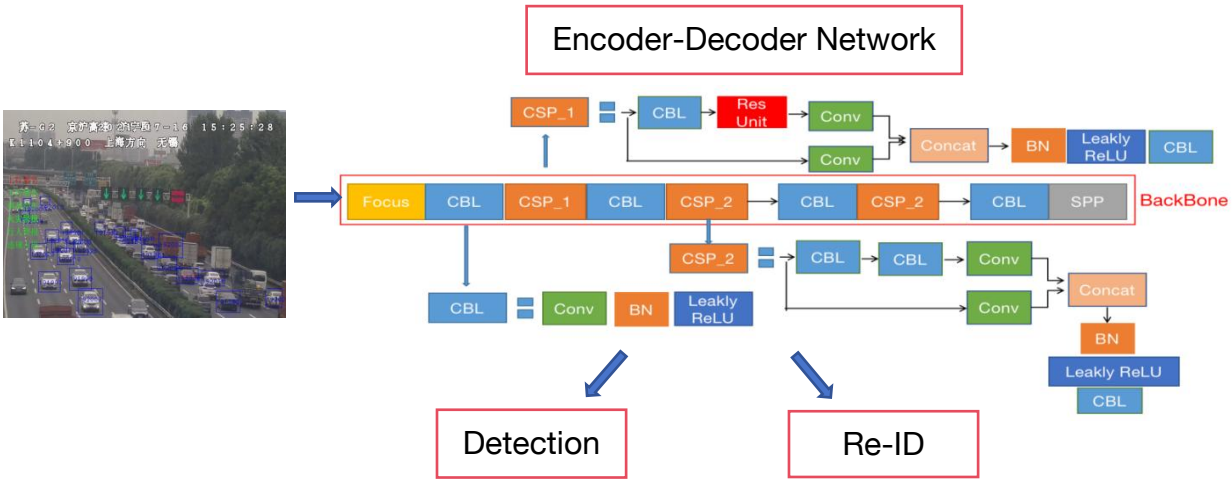



Figure 4.5. Modified FairMOT (mFairMOT) Network Structure

(in which CBL: Block for Convolution+Batch Normalization+Leaky_Relu; Res Unit: Residual Block Unit; Leaky Relu: an activation function; BN: Batch Normalization; CSP: Cross Stage Partial Network; SPP: Spatial Pyramid Pooling)

As illustrated in Figure 4.5, the input image is initially processed by an encoder-decoder network to extract high-resolution feature maps. This encoder-decoder network consists of densely connected layers, incorporating a Focus layer, CBL blocks (which include Convolution, Batch Normalization, and Leaky ReLU activation), a CSP (Cross Stage Partial) network, and ReLU activation functions. Following this, two parallel branches are introduced: one for object detection and the other for extracting re-identification (re-ID) features. The detection branch is responsible for generating frames with detected objects, while the re-ID branch assigns a unique ID to each tracked object, allowing for trajectory depiction. The features at the predicted object centres are utilised for tracking purposes.

Table 4.1. Comparison of modified FairMOT with other conventional methods.

| Model Comparison | Goodness | Drawback |
|---|---|---|
| Visual Average Speed Computer and Recorder of OpenCV (VASCAR) [7] | Light computing. | Intensively relies on object detection. If the first crossing point with the reference line or the exiting point appears earlier or later, speed will be calculated differently. |
| Yolo+DeepSORT [8] | Resolves the time difference problem by not setting a reference line. | Suffered from the segregation of detection and tracking process. The overall speed detection accuracy is influenced by small disturbance. |
| FairMOT [6] | Combine detection and re-ID process together | Re-ID accuracy should be improved to be more robust. |
| Modified FairMOT | Can be adopted to track vehicles and their trajectory generation | Not apparent drawback. |

The Modified Fairness Multi-Object Tracking (mFairMOT) network is used to improve the standard FairMOT model's performance in detecting and tracking traffic scenarios. By integrating mFairMOT with a spatial affine transformation matrix, the system can detect a range of traffic parameterss, such as vehicle speeds, traffic flow, vehicle types, and abnormal events like fires, congestion, and illegal parking.

This algorithm is versatile, capable of extracting real-time traffic data as well as analysing historical video footage without requiring further calibration.

## 4.4 Extraction of traffic parameterss from Surveillance Camera

### 4.4.1 Vehicle Kinematics Calculation

To address potential variations in height and orientation among different traffic camera installations, it is essential to perform installation-specific calibration to achieve precise vehicle position detection prior to system deployment. An affine transformation is derived to map the image space to the world space. A projection matrix is constructed based on road markings to represent the position offset of each vehicle relative to the camera, which is subsequently utilised for speed assessment (Fung et al., 2003).

To facilitate accurate calibration for each camera installation, a marker indicating the projected surface of a road segment must be provided. This marker should be in a quadrilateral shape, encompassing the outline of the road segment and representing a rectangle on the road surface. A sample of the preset marker is depicted in Figure 4.6.

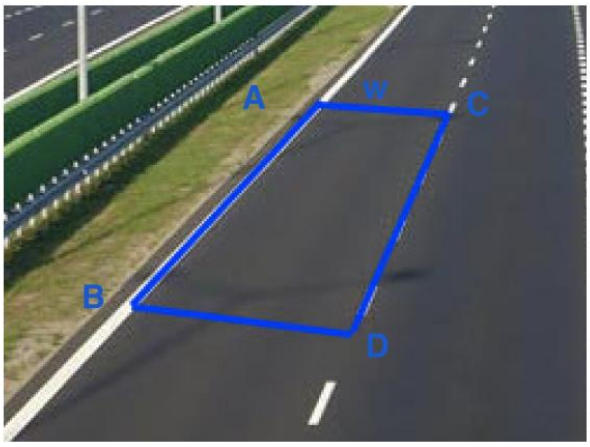



Figure 4.6. Road Marker Label

The marker deduction approach assumes that the road is approximately straight with parallel lanes, as well as a constant slope as flat roads with no change in elevation throughout the view frustum of the camera is preferred, as the slope of an elevating road surface is seldom uniform, introducing projection error and decreasing the model's accuracy (Fung et al., 2003).

Assume a camera model in the world space with positional parameters x, y and z, yaw y (i.e. the horizontal angle of the forward axis of the camera with respect to the world Y axis), pitch p, roll r, tilt angle t, and projection parameters focal length f and camera length l, vehicle world coordinate Cworld $\in R^3$ and image space coordinate Cscreen $\in R^2$ (representing position vectors in the vertical homogeneous coordinate form), the transformation function: $R^2 \in R^3$ maps the given screen coordinate vector p to world coordinate given road marker data m via perspective transformation (Haralick 1980). The perspective projection process is defined as (Fung et al., 2003; Haralick, 1980):

$$Cscreen = P \times R \times T \times Cworld \quad (12)$$

P represents the projection matrix, while T and R represent the matrices responsible for the position and rotation of the viewport in world space respectively. This affine transformation can be inverted to obtain the world coordinate from the screen coordinate of the vehicle:

$$Cworld = P^{-1} \times R^{-1} \times T^{-1} \times Cscreen \quad (13)$$

Excluding conversion of camera properties from road markers, the transformation matrices are defined as:

$$T = \begin{bmatrix} 1 & 0 & 0 & -x \\ 0 & 1 & 0 & -y \\ 0 & 0 & 1 & -z \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$R = \begin{bmatrix} \cos y & -\sin y & 0 & 0 \\ \sin y & -\cos y & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos p & 0 & \sin p & 0 \\ 0 & 1 & 0 & 0 \\ -\sin p & 0 & \cos p & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos r & -\sin r & 0 \\ 0 & \sin r & \cos r & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & \frac{1}{f} & 0 & 0 \end{bmatrix} \quad (14)$$

The camera position can be inferred from the rotation and the camera length:

$$x = l * \sin y * \cos p$$

$$y = -l * \cos y * \cos p$$

$$z = -l * \sin t \quad (15)$$

The road marker's geometry is labeled as shown in Fig. 4.6.

Trivially, the label's on-screen width w, along with other dimensions can be determined by (Fung, Yung, and Pang 2003):

$\alpha(A,B) = X_B - X_A$

$\beta(A,B) = Y_B - Y_A$

$\Upsilon(A,B) = X_A * Y_A - X_B * Y_A$

$$\omega = \beta(A, C) \tag{16}$$

$\omega$ is usually set to be 3.75m and 3.5m for freeway and urban road respectively.

The camera parameters can then be determined as (Fung, Yung, and Pang 2003):

$$l = \frac{\omega(f\mathrm{Sinp}+x_A\mathrm{CospSinr}+y_A\mathrm{CospCosr})*(f\mathrm{Sinp}+x_C\mathrm{CospSinr}+y_C\mathrm{CospCosr}}{-(f\mathrm{Sinp}+x_A\mathrm{CospSinr}+y_A\mathrm{CospCosr})*(x_C\mathrm{CosySinr}-x_C\mathrm{SinySinpCosr}+y_C\mathrm{CosyCosr}+y_C\mathrm{SinySinpSinr}) + (f\mathrm{Sinp}+x_C\mathrm{CospSinr}+y_C\mathrm{CospCosr})*(x_A\mathrm{CosySinr}-x_A\mathrm{SinySinpCosr}+y_A\mathrm{CosyCosr}+y_A\mathrm{SinySinpSinr})} \tag{17}$$

$$f = \frac{\gamma(B,D)\mathrm{Cosy\ Cosp}}{\beta(B,D)\mathrm{Siny\ Cosr} - \beta(B,D)\mathrm{Cosy\ Sinp\ Sinr} + \alpha(B,D)\mathrm{Siny\ Sinr} + \alpha(B,D)\mathrm{CosySinpCosr}} \tag{18}$$

$$\tan y = \frac{\mathrm{Sinp}*(\mathrm{Sinr}*(\beta(B,D)\gamma(A,C)-\beta(A,C)\gamma(B,D))+\mathrm{Coss}*(\alpha(A,C)\gamma(B,D)-\alpha(B,D)\gamma(A,C)}{\mathrm{Sinr}*(\alpha(B,D)\gamma(A,C)-\alpha(A,C)\gamma(B,D))+\mathrm{Cosr}*(\beta(B,D)\gamma(A,C)-\beta(A,C)\gamma(B,D))} \tag{19}$$

$$\mathrm{Sinp} = -\mathrm{Sqrt}\left(\frac{[(\alpha(B,D)\gamma(A,C)-\alpha(A,C)\gamma(B,D))\mathrm{Sinr}+(\beta(B,D)\gamma(A,C)-\beta(A,C)\gamma(B,D))\mathrm{Cosr}]}{[(\alpha(C,D)\gamma(A,B)-\alpha(A,B)\gamma(C,D))\mathrm{Sinr}+(\beta(C,D)\gamma(A,B)-\beta(A,B)\gamma(C,D))\mathrm{Cosr}]}\right) \tag{20}$$

$$[(\alpha(B,D)\gamma(A,C)-\alpha(A,C)\gamma(B,D))\mathrm{Sinr}+(\beta(B,D)\gamma(A,C)-\beta(A,C)\gamma(B,D))\mathrm{Cosr}]$$
$$[(\alpha(C,D)\gamma(A,B)-\alpha(A,B)\gamma(C,D))\mathrm{Sinr}+(\beta(B,D)\gamma(C,D)-\beta(C,D)\gamma(A,B))\mathrm{Sinr}]$$
$$[(\beta(B,D)\gamma(A,C)-\beta(A,C)\gamma(B,D))\tan r+(\alpha(A,C)\gamma(B,D)-\alpha(B,D)\gamma(A,C))\mathrm{Cosr}]$$

$$\tan r = \frac{\begin{array}{l}-\beta(A,B)\beta(A,C)\gamma(B,D)\alpha(C,D)+\beta(A,C)\alpha(B,D)\beta(A,B)\gamma(C,D)\\+\beta(C,D)\gamma(A,B)\beta(B,D)\alpha(A,C)-\beta(A,B)\gamma(C,D)\beta(B,D)\alpha(A,C)\\-\beta(C,D)\beta(B,D)\gamma(A,C)\alpha(A,B)-\beta(A,C)\gamma(A,B)\alpha(B,D)\beta(C,D)\\+\beta(A,B)\gamma(A,C)\beta(B,D)\alpha(C,D)+\beta(C,D)\beta(A,C)\gamma(B,D)\alpha(A,B)\end{array}}{\begin{array}{l}-\beta(A,B)\gamma(A,C)\alpha(B,D)\alpha(C,D)+\beta(A,C)\gamma(A,B)\alpha(B,D)\alpha(C,D)\\-\beta(A,C)\alpha(B,D)\alpha(A,B)\gamma(C,D)-\alpha(A,C)\gamma(B,D)\beta(C,D)\alpha(A,B)\\-\alpha(C,D)\gamma(A,B)\beta(B,D)\alpha(A,C)+\beta(A,B)\alpha(A,C)\gamma(B,D)\alpha(C,D)\\+\alpha(A,B)\gamma(C,D)\beta(B,D)\alpha(A,C)+\alpha(B,D)\gamma(A,C)\beta(C,D)\alpha(A,B)\end{array}} \tag{21}$$

The calculation of vehicle speeds is compromised by positional inconsistencies stemming from inaccuracies in object detection and tracking. Specifically, two main issues arise: vehicle orientation and the presence of missing frames in vehicle detection.

One significant factor contributing to these inconsistencies is the oscillation of bounding

boxes generated during predictions from the mFairMOT network (Zhang et al., 2020). Since FairMOT operates independently of preceding and succeeding frames during the prediction process, it does not impose penalties for geometric consistency in the predicted bounding boxes, leading to noise in the vehicle positioning data.

Additionally, mFairMOT faces challenges in detecting vehicles amidst complex spatial interactions, occlusions, and indistinct object borders. This issue is particularly pronounced on road segments that are not aligned with the forward vector of the camera frustum, where vehicles may become partially obstructed by other objects or nearby vehicles. As a result, there are instances where the object detector fails to register the vehicle. Although these frame losses are infrequent, they can lead to significant inaccuracies in footage captured on such road types.

To alleviate such deficiency, a custom interpolation filter Fi was incorporated to adapt to bounding box oscillations and frame skips for vehicle i. Each vehicle is assigned to a data tracker during its life-time (exposure as an object in the footage). In evaluating speed S at the current frame, σ denotes the generalised kernel function for interpolating between two (often adjacent) footage frames:

$$S = \sigma_F(i, C_{world}, \Delta t_i) \quad (22)$$

Δti denotes the time since the previous frame where the vehicle is detectable, and imposes no distinction between delay from frame rate and delay of skipped frames. Speed per second is computed with abs(Ci-Fi,prev)/Δti (approximating with a linear interpolation over a missing frame), and transformed with Proportional-integral-derivative (PID) controller to reduce positional noise generated by the object detector. PID controller is usually used in automatic control, but when applied to computer vision, it can accelerate optimization convergence process by reducing overshoot problem in stochastic gradient descent (SGD) momentum of weights updating (Bewley et al., 2016). PID has three components, which need to be specified beforehand, $O_P$, $O_I$, $O_D$. Specifications for the controller in this study are as follows:

$O_P = 0.51$

$O_I = 0$

$O_D = 0.103$ (23)

Proportional coefficient: adjusts the strength of the control signal so that the system responds to errors more quickly.

Integral coefficient: reduces the steady-state error of the system so that the system tracks the expected value more accurately.

Differential coefficient: used to improve the dynamic performance of the system and make the system respond to changes more quickly.

The PID controller in this context is incorporated as a filter for speed updating instead of as a 'control' algorithm. The controller output specifies the internal adjusted speed of a vehicle in the context frame, while the set point (SP) and process variable (PV) are the estimated vehicle speed (inputted from the projection transformation) and the internally predicted speed from the previous frame. Since the SP experiences shift throughout the process, the integral component (OI) is mostly irrelevant.

Vehicle speed is calculated by the distance that vehicle has passed in unit of time. In our study, the unit of time is defined as one second which is 30 frames. Modified FairMOT model is used to track vehicle and assign unique ID to the detected object. The distance that a vehicle has passed in one second then is calculated by converting pixels to actual distance in the world coordinates through equations (6) to (16) as shown above.

### 4.4.2 Traffic Volume Calculation

To compute traffic volume, a virtual box is created within each lane (see Figure 4.7). As a vehicle passes through, it intersects with the virtual box, creating a shadow area. When the shadow area grows from 0% to over 70% and then reduces back to 0%, it indicates that a

vehicle has passed through. The traffic volume is then incremented by one. The choice of 70% as threshold is empirical based. Figure 4.7 shows the traffic volume detection logic through virtual box and shadow area movements when a vehicle passing through.

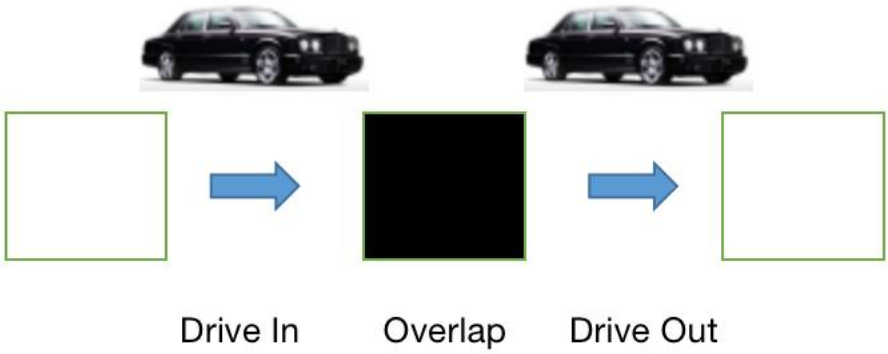



Figure 4.7. Virtual box and shadow area movements when a vehicle passing through

## 4.5 Extraction of traffic parameterss from UAV Drones

YOLOv8 model is used for vehicle detection and tracking in video processing. Since videos are recorded by drones and camera captures videos from perpendicular eagle view, no further coordinate calibration is needed to do spatial matrix transformation from image coordinates to world coordinates. Once the lane width is known, which is usually fixed to be 3.5 meters for urban junctions, vehicle kinematic data can be derived by detection and tracking process. The following table displays dynamic traffic data that can be extracted from drones and are used in our study.

Table 4.2. Dynamic Traffic Data used in the study

| Dynamic Traffic Parameters | |
|---|---|
| Vehicle ID | |
| Object Types | car, bus, truck, motor,person |

| | |
|---|---|
| Vehicle speed | km/h |
| Vehicle acceleration | |
| Acceleration decomposition | X, Y axis |
| Vehicle trajectory (pixel) | pixel |
| Vehicle trajectory (meters) | meter |
| front angle | degree |
| signal control | |

In addition, static junction parameters can be measured by laser rangefinder or taken from local surveying and mapping bureau, which are also used in our study.

Table 4.3. Static roadway parameters used in the study

| Static Roadway Parameters | |
|---|---|
| Road Elevation | Need Measurement |
| Longitude/Latitude | Need Measurement |
| Lanes | |
| Width | Need Measurement |
| Land Markings | |
| Weather | |
| Road Operation Condition | One way/No Turn/No Stoppng |

Application of YOLOv8 model to drones detection is explained in the Figure 4.8.

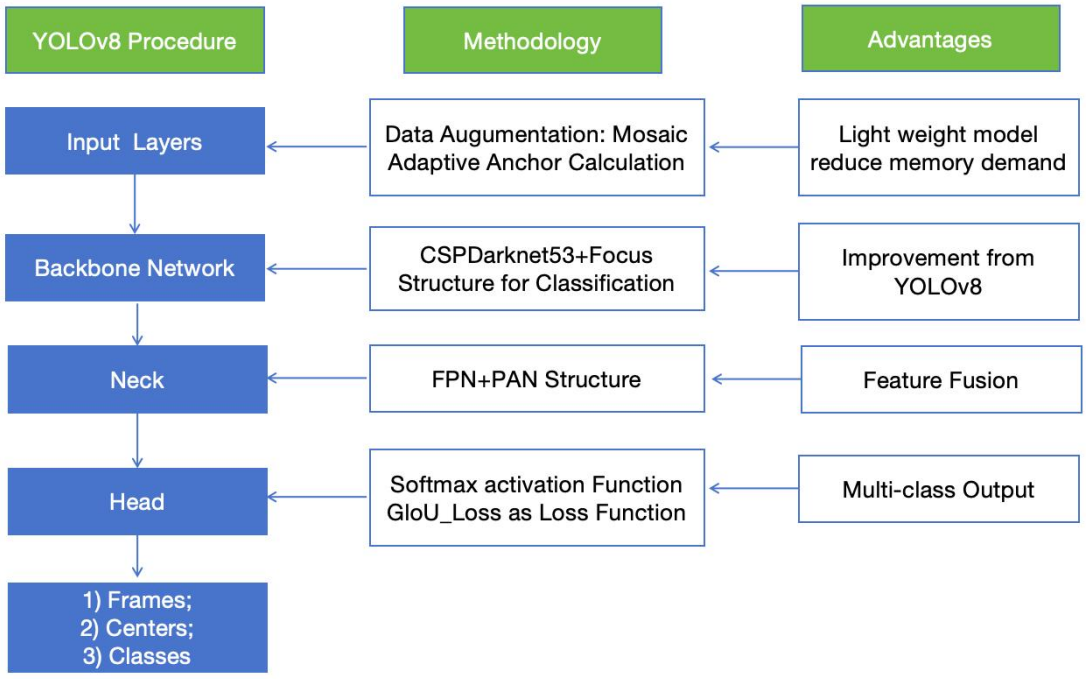



Figure 4.8. Detection logic of drones

However, for any tracking models, once the target object is covered for a certain of time period, it is possible to lose its ID. To solve with this problem, this study designs strategy by calculating similarities between two closest object with same class. Once the similar scores is larger than threshold, they will be treated as same object (re-ID procedure) and the speed of this object in the past disappeared time will be taken as average (smoothing procedure).

The following flow chart exhibits the whole procedures including detection, tracking, smoothing, and parameter calculating to get the needed data from drones.

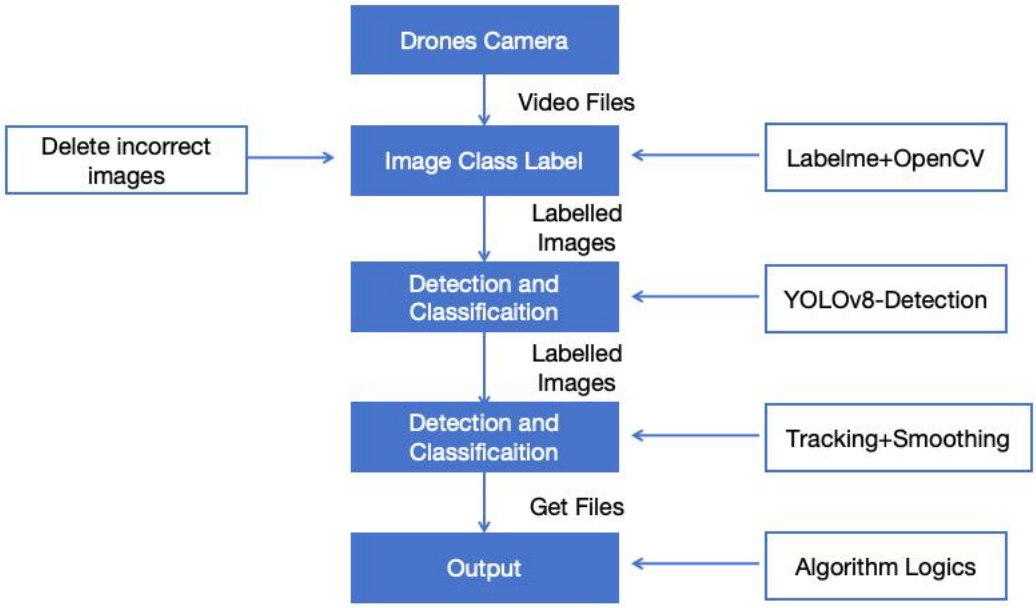



Figure 4.9. Whole procedure of data extraction from drones

The following table displays overall model performances of drone detection with flying height less than 100 meters in our tested scenarios. Generally speaking, detection accuracy is better for low drone height . If drone flies too high (> 150m), the object is too small to detect on the ground, the detection accuracy will be largely compromised.

Table 4.4. Overall model performances in drone detection in tested scenarios.

| Accuracy | Car | Bikes | Pedestrian |
|---|---|---|---|
| Detection | 99.2% | 96.8% | 95.3% |
| Classification | 98.9% | 95.7% | 94.6% |
| Tracking | 98.6% | 94.9% | 93.5% |

This study also compares different model performances in both detection and tracking procedures.

Table 4.5. Comparison of detection algorithms

| Model | Algorithms | Pros and Cons |
|---|---|---|
| YOLO-v8 | 1) YOLO does not show the process of obtaining region proposals;<br>2) YOLO is unified as a regression problem | High Accuracy,<br>Fast Speed |
| U-Net | Used for semantic segmentation, not for detection purpose | Slow Speed |
| Faster-RCNN | Although RPN and Fast R-CNN share convolutional layers in Faster R-CNN, it is necessary to repeatedly train the RPN network and Fast R-CNN network during model training. | High Accuracy,<br>Low Speed |
| SSD | Unlike YOLO which uses a fully connected layer at the end, SSD directly uses convolution to extract detection results from different feature maps. | Fast Speed,<br>Accuracy not good |

Table 4.6. Comparison of tracking algorithms

| Model | Algorithm Logic | Pros. And Cons. |
|---|---|---|
| YOLO-v8 | one-stage model, combine detection and re-ID into the same process. | Fast Speed,<br>High Accuracy |

| | | |
|---|---|---|
| Fairmot | 1) Multiple tracks execute Kalman filtering in parallel, which is faster than deepsort's Kalman filtering.<br>2) Only one feature vector is saved, and exponential sliding average is used to fuse multiple feature vectors to speed up calculation.<br>3) Anchor Free, accurate positioning | High Accuracy, Medium Speed |
| Deepsort | two-stage network, detection and re-ID are separated | High Accuracy, Low Speed |
| SDE | Detection and Embedding are divided into two independent models, with high performance but poor real-time performance. | High Accuracy but Low Speed |
| Kalman Filtering | Conventional tracking algorithm, not very useful in deep learning | Low Accuracy, Fast Speed |

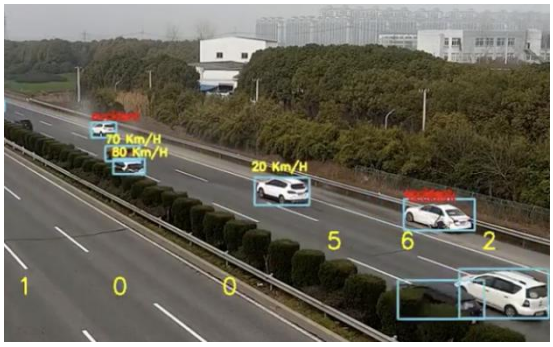
## 4.6 Results Analysis of Video Analytics

### 4.6.1 Speed Detection Accuracy

Due to the dearth of publicly available labeled traffic cameras as the ground truth source for speed evaluation, a custom dataset with traffic footages labeled by LiDAR was established for model evaluation in this study. The validation dataset is composed of a total of two-hours videos with 15 minutes for each freeway section (with a coverage of 200m), six videos were taken at daytime (two front angles, four side angles), two videos (both are side angles) were taken at nighttime. The traffic scenes are displayed as follows in Figure 4.10.



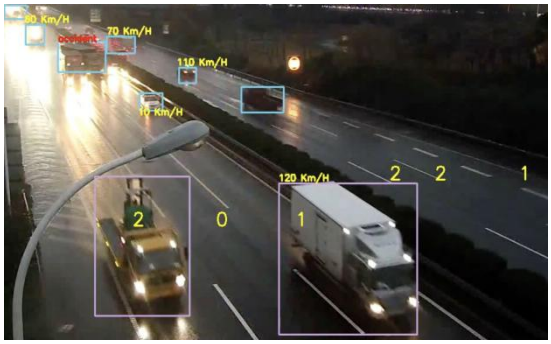

Frontal view: Gantry Camera Daytime



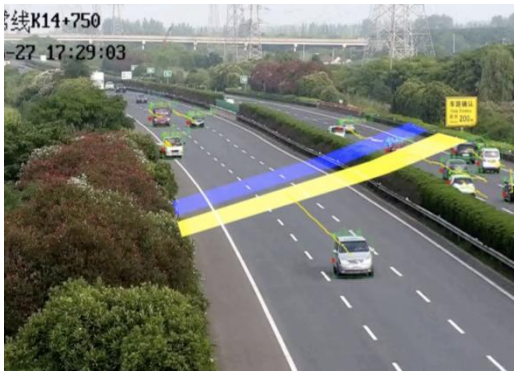

Side view: Roadside Camera Daytime



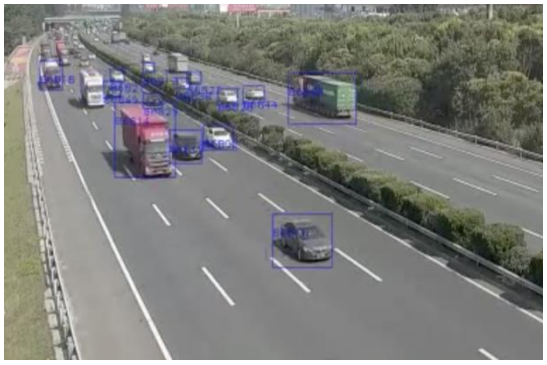
Side view: Roadside Camera Daytime




Side view: Roadside Camera Nighttime




Side view: Roadside Camera Daytime



Side view: Roadside Camera Daytime



Frontal view: Gantry Camera Daytime




Side view: Roadside Camera Nighttime

Figure 4.10. Representative scenarios used for speed detection

For an output of length M, a simple mean square error of the loss function J was incorporated for model evaluation as follows:

$$J(\theta_{output}) = \frac{1}{M}\sum_{i}^{M}(\theta_{output,i} - \theta_{groundtruth,i})^2 \quad (24)$$

False negatives during the object detection phase are treated as output speed 0. For ease of calculation and generalizability, the vehicle speed θ denotes the speed mean over a frame sequence of S instead of individual frames.

The dedicated validation dataset consists of footage captured from various traffic camera heights and angles to simulate a real-world application scenario. The dataset is categorized into groups based on the camera's respective view (e.g., parallel, diagonal, or perpendicular to the road's direction). Cameras installed with a perpendicular view to the road, although rare on existing freeways, were selected to assess how perspective view distance impacts the model's accuracy. Losses from detections across different distance ranges on the ground plane are separated to highlight the effects of detection distance on accuracy.

Detection accuracy is calculated as one minus the percentage of errors, which represents the proportion of difference between actual speed and estimated speed. This measure is less significant in footage with a perpendicular view since the forward motion of a vehicle is unaffected by projection transformation, thereby maintaining precision.

A notable challenge arises from the constant fluctuations in speed for vehicles near the vanishing point in parallel views. Theoretically, the magnitude of these fluctuations increases exponentially for vehicles closer to the vanishing point, as each pixel corresponds to a larger span in world space. These fluctuations can be reasonably mitigated using a Proportional Integral Derivative (PID) controller, with the kernel function σ mentioned earlier, which helps to reduce sporadic spikes of false acceleration or deceleration (Czado et al., 2009). The PID function, initially developed for industrial process control, is effective for noise reduction and signal filtering.

While integrating a filtering kernel significantly reduces fluctuating noise, its effectiveness diminishes after approximately 50 meters in footage obtained from standardized traffic cameras positioned at an elevation of 12 meters. It's important to note that the distance referenced in Table 4.7 is measured along the horizontal plane, without accounting for the camera's elevation.

Table 4.7. Speed Detection Accuracy on Different Perspective Settings

| Distance (meter) | Side View | Right Frontal View |
|---|---|---|
| ≤20 | 96% (daytime) / 92% (nighttime) | 98% (daytime) / 94% (nighttime) |
| ≤50 | 91%(daytime) / 84%(nighttime) | 95% (daytime) / 88% (nighttime) |
| > 50 | 75%(daytime) / 70%(nighttime) | 85% (daytime) / 80% (nighttime) |

As noticed from Table 4.7, the estimated speed is quite precise within 50m in daytime with respect to the frontal view. For nighttime, the estimation is badly influenced by miss detection as the available sight distance is short.

### 4.6.2 Traffic Volume and Abnormal Scenarios Detection

The Modified Fairness Multi-Object Tracking (mFairMOT) models, combined with various specific detection logic, were employed to extract traffic operation parameters and emergency events from roadside video recordings. These parameters include vehicle speed, traffic flow by lane, vehicle types, individual vehicle trajectories, accidents, abnormal parking, pedestrians on the road, unexpected objects, traffic congestion, vehicle fires, and more. Two distinct mFairMOT tracking models were trained: one for vehicle tracking (mFairMOT-vehicle) and another for tracking individuals (mFairMOT-person).

1) Abnormal Parking

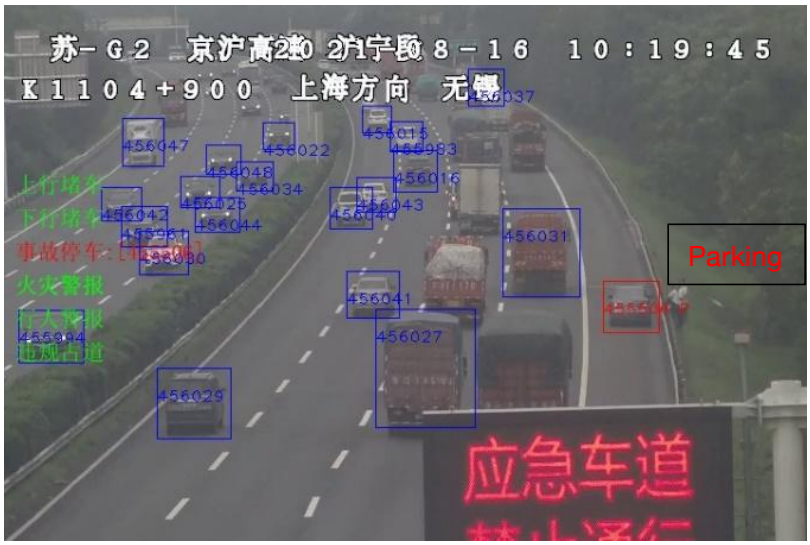


Figure 4.11. Abnormal Parking Detection

The Modified Fairness Multi-Object Tracking (mFairMOT) neural network model was trained to assign a unique ID to each vehicle. Even if a vehicle is temporarily obscured or shadowed, it retains the same ID when it reappears, provided that its features are correctly extracted and remain consistent over a short time span. The system triggers an alarm if the same ID is detected after one minute on screen, given that there is no 'traffic congestion' and no 'pedestrian on the road.' Figure 4.11 illustrates the detection of an abnormal parking scenario.

2) People on the road



Figure 4.12. Person on Freeway Detection

The mFairMOT pedestrian tracking neural network model was trained to assign a unique ID to each detected person. Even if the same person disappears temporarily, their ID remains the same when they reappear. The system triggers an alarm if it detects a pedestrian walking on the freeway for five consecutive frames, as illustrated in Figure 4.12.

3) Traffic Congestion

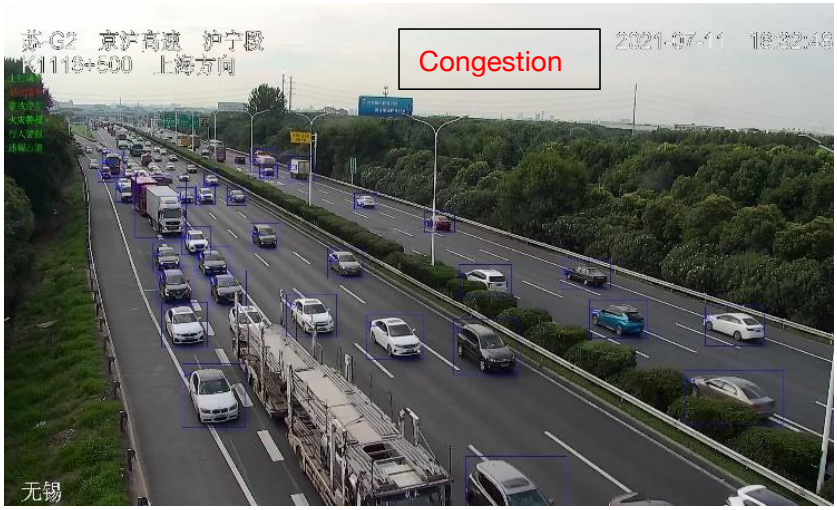



Figure 4.13. Traffic Congestion Detection

The mFairMOT-vehicle tracking model calculates the number of vehicles on the screen. If the Intersection over Union (IoU) (Area of overlap/Area of union) exceeds 0.5 (a value that can be adjusted for specific scenarios), and this condition is met consistently over ten consecutive frames, the system triggers an alarm and reports the traffic congestion status to the relevant control centre. The threshold is set as a tunable parameter to minimize false positive alerts in various traffic scenarios. Figure 4.13 illustrates the detection of congestion.

4) Vehicle fires




Figure 4.14. Detection of vehicles fires

The mFairMOT network is utilised to detect smoke and fire simultaneously over three consecutive frames. If either fire or smoke is detected, no alarm is triggered specifically for the fire. Both the Fire and Smoke classes have been pre-trained and stored in the mFairMOT backend database. Figure 4.14 shows the detection of vehicle fires.

In summary, detection accuracy on different perspective settings is displayed in Table 4.8.

Table 4.8. Detection Accuracy on Different Perspective Settings

| Item | Accuracy | False Positive Reason | Solutions |
|---|---|---|---|
| Traffic Flow | 96% | Influenced by articulated vehicle | Label more data for special vehicles |
| Parking | 90% | recognise road side signs as car, especially at night | Labeling more data that cater to specific scenarios |
| Pedestrian Walking | 95% | recognise road side tree as person occasionally | Labeling more data for specific scenarios |
| Vehicle Fires | 97% | Sometimes when the intensity of the fire is low, the algorithm does not make any alarm. | |

| | | | |
|---|---|---|---|
| Traffic Congestion | 92% | Affected by tracking models. Same ID may assign twice. | Improve tracking model stability by changing its structure |

Automatic crash detection and traffic flow analysis are crucial for proactive traffic safety management. Current traffic crash prediction models often rely on sensor data and external hardware, such as radar, which can lead to substantial implementation and maintenance costs (Tian et al., 2019; Yao et al., 2019). Moreover, many existing roadway cameras lack integration with advanced traffic analysis systems, resulting in a dependence on manual monitoring. To tackle these challenges and make use of pre-existing roadside cameras, this study developed a real-time system for analysing multi-vehicle motion parameters using standard surveillance cameras.

The speed predictions demonstrated reasonable accuracy when compared to ground-truth data obtained from LiDAR. A PID filter was effective in reducing noise for vehicles close to the camera, but its effectiveness diminished beyond approximately 50 meters, leading to a 27% average reduction in object tracking accuracy. This variability was mainly attributed to discrete predictions across frames, which caused inconsistencies in the bounding box shapes of vehicles. While this had a minor impact on position predictions, it significantly affected speed accuracy at greater distances, where noise suppression was less effective.

Estimation accuracy varied notably between day and night due to differing lighting conditions. Compared to radar or LiDAR, computer vision techniques provide a cost-effective alternative for speed estimation, offering additional information such as vehicle types and traffic flow. The modified FairMOT model, which replaces the original ResNet34 backbone with CSPDarknet53, enhances detection and re-identification capabilities in traffic scenarios through deeper feature extraction and lightweight architecture.

Nonetheless, the model has its limitations, particularly in detecting distant vehicles, as accuracy declines with increased distance from the camera due to low-resolution footage. The

effectiveness of the PID suppression also wanes beyond 50 meters, complicating reliable speed predictions at longer ranges.

For crash prediction models, incorporating dynamic traffic features as input variables results in significantly higher accuracy compared to models that rely solely on historical crash data, weather conditions, and holiday effects. This indicates a close relationship between crash characteristics and dynamic traffic parameterss, suggesting that future studies could benefit from video processing techniques to analyse pre-crash scenarios.

## 4.7 Future Development of Computer Vision Techniques

Future developments in this study will focus on estimating the probability of traffic crashes by utilising the vehicle speed data collected. The goal is to create a crash prediction framework aimed at proactively preventing traffic accidents. Furthermore, the study will explore the integration of computer vision techniques with crash prediction to improve the accuracy and effectiveness of these models. This integration seeks to leverage advanced image processing and statistical machine learning algorithms to analyse real-time traffic data and identify potential risk factors for crashes. Such an approach has the potential to enhance overall traffic safety by facilitating the development of early warning systems and proactive management strategies to mitigate collisions. Key points include:

- Lane Detection Integration: The model could incorporate lane detection methods, allowing for the inclusion of detailed dynamic traffic parameterss such as lane changing times and speed variations, thereby improving the accuracy of real-time crash predictions.

- Causal Analysis: The study will analyse the causal relationships between crash occurrences and dynamic traffic parameterss.

- Deep Learning Techniques: Advanced deep learning computer vision techniques will be employed to extract traffic parameterss related to pre-crash scenarios, examining the influence of independent variables on crash occurrences.

This thesis has introduced a deep learning video processing method capable of estimating highly disaggregated traffic characteristics from video data. The novel features and contributions of the proposed methodology include:

- Calibration-Free Approach: Unlike existing techniques that require prior measurements, this method does not necessitate calibration, making it a more generic solution.

- Estimation of Advanced Parameters: The approach allows for the estimation of critical parameters previously unattainable through conventional camera-based video processing methods, including lane change behaviour, speed variance, fire detection, and vehicle trajectories.

- Enhanced Accuracy: The technique promises improved accuracy, particularly in estimating individual vehicle speeds. It can be applied to real-time videos and existing footage, regardless of camera angles or positions.

- Optimized FairMOT Network: The study enhances the Fairness Multi-object Tracking (FairMOT) network by incorporating the CSPDarknet53 structure, which improves its ability to detect and track vehicles. This optimization involves using an Encoder-Decoder network to refine bounding box predictions and maintains the DLA structure to fuse features effectively, allowing for accurate vehicle association across frames.

- Noise Suppression: A Proportional Integral Derivative (PID) controller has been integrated to suppress sporadic noise in speed estimates due to low-resolution limitations.

- World Space Speed Calculation: The study achieves accurate world-space speed

estimation by transforming image-space offsets using a projection matrix based on pre-labeled road markings, facilitating precise calculations across varying angles and distances.

Results from the study demonstrate:

- Minimal speed estimation differences within 5% per vehicle over distances up to 50 meters in parallel views during freeway analysis.
- Effective noise reduction by 36.62% through the PID implementation.

- Real-Time Traffic Alarming System: The developed deep learning technique, coupled with decision-making logic, enables the creation of a real-time abnormal traffic condition alarm system. This system detects incidents like speed anomalies, lane congestion, vehicle types, trajectories, accidents, and unexpected objects, demanding sufficient GPU computing power and internet connectivity for real-time data processing. It is suitable for integration into freeway management control centres to monitor traffic conditions and deploy preemptive measures for emergency incidents.

- Future Directions: The chapter concludes by discussing future research directions, such as exploring direct speed estimation using deep learning methods and addressing challenges in real-world applications where video quality or environmental conditions may affect accuracy. Additionally, the integration of more advanced computer vision techniques beyond traditional transportation engineering applications is highlighted, suggesting potential advancements in traffic management and safety systems.

Overall, this chapter provides a comprehensive overview of the applied computer vision techniques, their technical implementations, and their implications for traffic parameters extraction and real-time traffic management.

## 4.8 Summary

Building on the groundwork laid in Chapter 2 regarding computer vision techniques and sensor introduction, this chapter focuses more on introducing specific technical routes and deep learning models used in this study to extract traffic parameterss in different scenarios. In order to extract dynamic traffic parameterss from video processing, mathematical logic and equations are designed to calculate speed, driving angle, acceleration, and traffic volume. Once the world coordinates are known, deriving those traffic dynamic data will be straightforward to calculate. Therefore, a key question arises: how to measure world coordinates from image pixels. This chapter discusses a method to convert image coordinates to world coordinates using spatial matrix derived from object projection, incorporating camera parameters such as focal length f, camera length l, and some prespecified lane width and camera height. Nevertheless, if the camera is positioned at the top of the road, conversion from image coordinate space to world space is simplified. It only requires lane width in meters to find the corresponding lane width in pixels to get the transformation equation. With this conversion equation established, all other traffic parameterss can be calculated accordingly with logical methods.

This chapter also includes results analysis and findings discussion on the application of computer vision techniques in different scenarios. Real world applications are typically more challenging than research settings because environments are various and some are very complicated. Therefore some necessary adjustments need to be made to the proposed technical route. For instance, calibration-free methods may not perform well with extremely distorted videos, necessitating preliminary measurements. Futhermore, if high precision is needed, it is advisable to restrict analysis to the closest zone, disregarding distant areas that could introduce errors.

This chapter already goes deeper into computer vision techniques which is beyond traditional transportation engineering. Currently, some researchers try to calculate speed directly by using deep learning instead of conventional computer vision. However, the effectiveness of

these newly put forwarded methods have not been validated through empirical studies.

In summary, this chapter offers a comprehensive exploration of the technical methodologies and challenges involved in extracting traffic parameterss (speed, acceleration, traffic volumes, etc) from video data using computer vision. It emphasizes the need for adaptable approaches capable of accommodating real-world complexities. Additionally, it suggests future research endeavors to improve the effectiveness of deep learning methods for traffic crash prediction, accident analysis, and proactive traffic management.

# Chapter 5 Development of Traffic Crash For Prediction Models

The concept of real-time crash prediction is interpreted as predicting crash occurrences on a specific road segment within a very short time window by using instantaneous traffic dynamics (Hossain et al., 2019). short-term crash prediction plays a more and more important role in promoting overall traffic safety level, managing proactive roadway safety, and preventing potential traffic incidents from occurring (Zheng and Sayed, 2020). Lee et al. (2003) put forwards a probabilistic Bayesian model to predict crash risk and stated that crash potential must be estimated on a real-time basis by monitoring short-term traffic conditions. Cai et al. (2022) used computer vision methods to utilise roadside surveillance cameras to extract dynamic traffic features for crash prediction and found that crash characteristics are largely related to dynamic traffic operation data.

Although proactive traffic safety management systems have been a well-studied problem over the past decade, several challenges endure for short-term crash prediction. Different from making prediction on traffic conflicts of the ego and preceding vehicles, the likelihood of an actual traffic crash occurring is extremely low. Collecting sufficient historical crash data takes several years to obtain. Furthermore, historical crash data is severely imbalanced which is amplified for data segmented in short time windows. Many studies focus on real-time traffic conflicts prediction by using sensors equipped on ego vehicle, but few consider short-term prediction in roadway base analysis. Huang et al. (2020) studied the sensitivity of the time window on the crash prediction accuracy for 1-minute, 5-minutes and 10-minutes intervals and concluded that it is more difficult to predict accurately 10-minutes prior the crash. The challenge is magnified during 30-minute intervals, but it provides a suitable time frame for traffic control centres and freeway operational teams to implement effective safety measures without causing significant disruption to traffic conditions.

The growing accessibility of various sensor and image recognition technologies that can be

used for collecting roadway traffic safety data, combined with recent advancements in modern data-driven methods, especially in Time Series Modelling, Machine Learning, and Deep Learning, has led to a surge of interest in data-driven road safety research in recent years (Sohail et al., 2022). Road crashes stem from a complex interplay of factors, such as road infrastructure (e.g., roadway geometric design), road user behaviour (e.g., driver behaviours), traffic conditions (e.g., congestion), and environmental conditions (e.g. snowy and rainy) (Sohail et al., 2022). Analysing risk factors is crucial for developing relevant actions and interventions to prevent unsafe traffic conditions and enhance roadway safety (Touahmia, 2018).

Crash prediction is a retrospective study based on historical data to form the relationship between traffic parameterss and crash occurrences. An effective crash prediction model can investigate the association of contributory factors affecting traffic crashes. Pertinent intervention and prevention strategies can then be devised to promote traffic safety level and decrease crash risk, which builds the foundation of proactive safety management and predictive safety approaches. This thesis focuses on utilising data-driven approaches including time series modelling, statistical machine learning, and deep learning models to predict the likelihood of traffic crashes or conflicts occurring at a specific location and time to devise proactive interventions to promote traffic safety. The datasets used in this study were collected in freeways and urban junctions in China and the UK to model unsafe traffic conditions and identify crash influencing factors. Various traffic information was included in the datasets such as historical crash data, vehicle speed, speed variances by lanes, traffic volumes, vehicle types, roadway geometry, weather conditions, occupancy, truck to car ratio, and the forth, which were extracted from roadside surveillance cameras through image processing and various sensors (e.g. LiDar, Radar, ILDs).

Based on data-driven traffic crash prediction modelling, this chapter introduces different types of crash prediction models from both conventional time series forecasting approach and

spatio-temporal deep learning neural network approaches in hourly and semi-hourly crash prediction respectively. This chapter also provides mathematical properties of the model to measure the goodness of fit in order to penalise for complexity through LASSO regularisation methods. In addition, it discusses the suitability of crash prediction models in different contexts and compares the advantages and disadvantages of the proposed models in different use cases.

## 5.1 Zero-inflated log count data time series intervened seasonal model (ZILT)

Early traffic crash prediction models typically utilised various regression techniques, such as multiple linear regression, Poisson regression, and Negative Binomial regression (Ma and Kockelman, 2006; Park and Lord, 2019; Ma et al., 2008; Rakha et al., 2008; Montella et al., 2008). Traffic crashes are generally perceived as random events, and the continuous occurrence of crashes within a specific geographic area over a short time frame is relatively rare. As a result, traffic crash count data often features a significant number of zeros, especially in hourly observations. To address the overdispersion caused by these excessive zeros, zero-inflated models (including Zero-Inflated Poisson and Zero-Inflated Negative Binomial) and Hurdle models have been introduced (Abdulhafedh, 2017; Lord and Mannering, 2014). While these models perform well in scenarios with many zeros in the dependent variables—common in traffic crash data—they often struggle to capture the temporal and spatial structures inherent in the data.

The rise of machine learning and deep learning, alongside regression-based models that utilise neural networks or ensemble learning structures, has transformed the analysis of aggregated time series data, particularly when both spatial and temporal components are present. These approaches often outperform conventional time series models in terms of accuracy. The introduction of generalised Autoregressive Conditional Heteroscedasticity (GARCH) models by Bollerslev offers an alternative for modeling time series data without assuming a normal distribution (Bollerslev,

1986). For count time series data—characterized by integer values—Integer-Valued generalised Autoregressive Conditional Heteroscedasticity (INGARCH) models have gained popularity (Liboschik et al., 2017). Given that traffic crash data consists of nonnegative integer counts, applying INGARCH initially seems appropriate. However, INGARCH struggles when the response variable contains excessive zeros.

While recent developments in time series truncated data methods have emerged, they often fail to accommodate zero-inflated or hurdle structures, which are essential for handling truncated data (Liboschik et al., 2017). Although state space models can address spatio-temporal correlated time series count data, their complexity can make them less practical, and they also do not adequately manage the problem of excess zeros (Liboschik et al., 2017; Czado et al., 2009). Similarly, regression models like zero-inflated Poisson (ZIP) models have been employed in other contexts, such as analysing air pollution impacts on emergency room visits (Hassan et al., 2012) or forecasting daily phone call volumes (Wang et al., 2001), but none have been effectively applied to real-time traffic crash data (Lord et al., 2017). Moreover, many of these methods overlook the integration of seasonality and intervention effects in forecasting.

In order to deal with such common issues of excessive zeros, zero-inflated models such as ZIP and ZINB are adopted by some researchers. Yet, Lord et al. highlights their limitations in capturing the complex nature of traffic crash data, which is influenced by various interactions and spatio-temporal structures (Algawbaa and Diawarab, 2021). Although traffic crash data is characterized by a preponderance of zeros, the occurrence of traffic crash is a combination of complex interactions between various variables including the temporal spatial structure within the variable. Even though ZIP and hurdle models can manage zero inflation by combining logistic/probit regression with count data models, they fall short in incorporating the temporal and spatial dynamics inherent in traffic crash occurrences (Lord et al., 2017). Traffic crashes frequently exhibit strong spatio-temporal autoregressive characteristics. The data is highly skewed, displaying an excess of zeros along with a heteroscedastic structure. The central research question in our study is how to effectively forecast segment-based traffic crashes over short time spans that exhibit excessive zeros while accommodating a strong

autocorrelated heteroscedastic structure. Consequently, many regression-based models in traffic crash prediction struggle to effectively address both the time series structure and the issue of excessive zeros.

Therefore, a composite model designed to address the challenges of excessive zeros and the skewed distribution of crash data, while also capturing seasonality and periodicity by specifying time order as tuning parameters and considering the serially autocorrelated variance of the error term should be proposed to address the above mentioned limitations of existing models.

To predict near-future crash characteristics, this model must: (i) effectively address the excessive zeros present in the hourly crash count, unlike traditional regression models; (ii) manage spatio-temporal correlations in traffic crash counts, a capability that conventional zero-inflated and Hurdle models lack.

By tackling these issues, the proposed model could have broad applications in various fields that deal with excessive zeros and strong temporal structures in dependent variables.

The variable "hour" is categorical, representing the 24 hours of a day, to capture the influence of the temporal distribution of daily commutes. Crashes are random, rare events, and hourly crash patterns typically show excessive zeros. ZIP and Hurdle models are frequently employed in count data analysis to manage these excessive zeros in crash prediction, based on Poisson or Negative Binomial assumptions. These models serve as foundational methods in the proposed ZILT model, which builds on the count data process for traffic crash data to address the structure of excessive zeros. Specifically, ZIP employs a dual-state system for handling zero and non-zero crash time spans, while Hurdle models utilise a two-component mixture model to address different zero patterns. Other count data models were not considered in this study due to their inability to manage the excess zeros in crash data.

However, neither ZIP nor Hurdle models are well-equipped to handle the autoregressive

conditional heteroskedasticity present in serially autocorrelated temporal data. Thus, this study proposes an integrated ZIP or Hurdle model with an Integer-GARCH structure, incorporating mechanisms for addressing seasonality and intervention. Compared to existing models, ZILT expands beyond the strict normal distribution assumed by ARIMA, adopting generalised linear regression assumptions (such as Poisson and Negative Binomial) with a logarithmic link. The ZILT model also introduces a GARCH structure to address heteroskedasticity where the variance of the error term is serially autocorrelated, following an autoregressive moving average process. Additionally, it effectively handles the common problem of excessive zeros found in traffic crash analysis through a dual-state zero-inflated system. ZILT can be viewed as a composite and integrated statistical learning approach for managing autocorrelated temporal data with excessive zero issues.

The primary objective of this study is to develop a statistical model that can simultaneously control for both excessive zeros and serial autocorrelation in time-series crash counts. Our approach begins with zero-inflated and Hurdle models as the foundation, then incorporates requirements for temporal dependencies, seasonality, and intervention into crash counts, resulting in a combined model known as the zero-inflated log count data time series Intervened Seasonal INGARCH (ZILT) Model. The introduction of the models used in this research is as follows:

**Hurdle model**

The Hurdle model was first developed by Cragg in 1971 to predict the demand for durable goods (Cragg et al., 1971). Due to its outstanding ability to handle excessive zeros in the dependent variable, it has been widely used in various domains to resolve the excessive zeros issues. In contrast to ZIP's dual-state system, Hurdle models are considered as a two-component mixture model (Feng, 2021). The first component predicts the probability of being zero ( $p_i$ ), followed by the second component consisting of the regular count data prediction.

Let $Y_i$ be the dependent variable of the $i^{th}$ observation. The basic structure of a Hurdle model is written as follows:

$$p(Y_i = n_i) \begin{cases} p_i & n_i = 0, \\ (1 - p_i) \frac{p(y_i; \mu_i)}{1 - p(y_i = 0; \mu_i)} & n_i > 0 \end{cases} \quad (25)$$

where $p(y_i; \mu_i)$ refers to the probability mass function (PMF) for a regular count distribution. The typical probability mass function in the second component includes Poisson and negative binomial distribution. To be consistent with ZIP and our ZILT, we adopt Poisson regression in the second component for the Hurdle model in our experiment.

**Zero-Inflated model**

Zero-inflated model was first proposed by Diane Lambert to predict a random event with excessive zero-count data and was later introduced into crash prediction due to its ability to overcome the overdispersion issue caused by excessive zeros in traffic crash data (Lambert, 1992). Zero Inflated model consists of a degenerate distribution at zero and untruncated count distribution for non-zeros. The general structure of a zero inflated model is given as follows:

$$\Pr(n_i = 0) = p_i + (1 - p_i) R_i(0) \quad (26)$$

$$\Pr(n_i > 0) = (1 - p_i) R_i(n_i) \quad (27)$$

where $n_i$ refers to the response variable; $R_i(n_i)$ refers to the untruncated count distribution.

Zero-inflated Poisson Model (ZIP)

One of the most widely used distributions in the untruncated count distribution process is the Poisson distribution, which is referred as a Zero-inflated Poisson (ZIP) model. For ZIP, the count distribution process is predicted by the standard Poisson model, which can be written as:

$$R_i(n_i) = \frac{e^{-\mu_i} \mu_i^{n_i}}{n_i!} \quad (28)$$

Therefore, the general structure of ZIP can be formulated as the following:

$$Pr(Y_i = n_i) \begin{cases} p_i + (1 - p_i)e^{-\mu_i} & n_i = 0, \\ (1 - p_i)\frac{e^{-\mu_i}\mu_i^{n_i}}{n_i!} & n_i > 0 \end{cases} \quad (29)$$

The two parts of the zero-inflated model are: (i) a binary model, usually a logit or probit model to model which of the two processes the zero outcome is associated with and (ii) a count model, e.g. Poisson in our case, to model the count process. Maximum likelihood estimate is used to estimate the parameters for the ZIP model.

**Zero-Inflated Logarithmic link for count Time-series (ZILT) Model**

The overall structure of our ZILT is based on the structure of a general ZI model, which is showed in previous section. $R_i$ ($n_i$) in ZILT refers to the untruncated count time series Poisson distribution and is predicted by log linear version of count data time series model INGARCH, which is described here:

Let $\{Y_t : t \in N\}$ be a count time series and $\{X_t : t \in N\}$ be a time-varying r-dimensional covariate vector, where $X_t = \{X_{t,1}, \ldots, X_{t,1}\}^T$. The general form of the count data time series model can be written as:

$$g(\lambda_t) = \beta_0 + \sum_{k=1}^{p} \beta_k \tilde{g}(Y_{t-i_k}) + \sum_{l=1}^{q} \alpha_l (g(\lambda_{t-j_l})) + \eta^T X_t \quad (30)$$

where

$$g : \mathbb{R}^+ \to \mathbb{R} \quad (31)$$

is the link function and

$$\tilde{g} : \mathbb{N}_0 \to \mathbb{R} \quad (32)$$

is the transformation function. The parameter $\eta$ refers to the effects of covariates and $\{Y_{t-i_1}, Y_{t-i_2}, \ldots, Y_{t-i_p}\}$ are the lagged observations that the model regresses on, and $\{\lambda_{t-j_1}, \lambda_{t-j_2}, \ldots, \lambda_{t-j_q}\}$ are the lagged conditional means. Specification of P = {1, 2, ..., p}

and Q = {1, 2, ..., q}, or in other words, model order parameters for autocorrelation functions of the observed data is similar to the order selection process for ARMA models (Liboschik et al., 2017). In this study, to capture the seasonality and autocorrelation in hourly crash data, we chose P = {1, 24} and Q = {24}.

The log linear model of count data time series which allows for negative covariate effects can be written as:

$$\nu_t = log\,(\lambda_t) = \beta_0 + \sum_{k=1}^{p} \beta_k log\,(Y_{t-k} + 1) + \sum_{l=1}^{q} \alpha_l \nu_{t-l} \quad (33)$$

Combining the Poisson assumption, $Y_t = y|\mathcal{F}_t - 1 \sim Poisson\,(\lambda_t)$, with the general form of count data time series model implies that

$$P\,(Y_t = y|\mathcal{F}_t - 1) = \frac{\lambda_t^y exp\,(-\lambda_t)}{y!},\ y = 0,1,\ldots. (27)$$

with the assumption $var\,(Y_t|\mathcal{F}_t - 1) = E\,(Y_t|\mathcal{F}_t - 1) = \lambda_t$ (34).

The quasi maximum likelihood approach is employed for parameters $\Theta$ estimation under mixed Poisson assumptions, where

$$\Theta = \{\vartheta \in R^{p+q+r+1}: \beta_0 > 0, \beta_1, \ldots, \beta_p, \alpha_1, \ldots, \alpha_p, \eta_1, \ldots, \eta_r \geq 0,\ \sum_{k=1}^{p} \beta_k \sum_{k=1}^{p} \alpha_\iota < 1\}$$

(25)

and

$$\vartheta = (\beta_0, \beta_1, \ldots, \beta_p, \alpha_0, \ldots, \alpha_q, \eta_1, \ldots, \eta_r)^T \quad (36)$$

For a log linear model with covariates where the parameters can be negative, the parameter space is taken to be

$$\Theta = \{\vartheta \in R^{p+q+r+1}: \beta_0 > 0, |\beta_1|, \ldots, |\beta_p|, |\alpha_1|, \ldots, |\alpha_p|,\ |\sum_{k=1}^{p} \beta_k + \sum_{k=1}^{p} \alpha_\iota| < 1\} \quad (37)$$

Under the Negative Binomial distribution, the quasi-maximum estimation for the dispersion parameter φ given regression parameter $\Theta$ expects to iterate until convergence (Liboschik et al., 2017).

For a given vector of observations y= $\{y_1, \ldots, y_n\}^T$ , the conditional quasi log likelihood function, up to a constant, expresses as

$$P(\vartheta) = \sum_{t=1}^{n} \log p_t(y_t; \vartheta) = \sum_{t=1}^{n} (y_t \ln(\lambda_t(\vartheta)) - \lambda_t(\vartheta)) \quad (38)$$

where $p_t(y_t; \theta)$ refers to the probability density function and $\lambda_t(\theta)$ refers to the conditional mean.

Back to the ZIP equation, when $n_i > 0$, the equation formula for $Pr(Y_i = n_i)$ is changed to $P(Y_t = y|\mathcal{F}_t - 1) = \frac{\lambda_t^y exp(-\lambda_t)}{y!}, y = 0, 1, \ldots$ that introduces the conditional mean of $F_{t-1}$.

**Zero-Inflated Logarithmic link for count Time-series (ZILT) Model via penalised maximum likelihood LASSO regularisation (Penalised ZILT model)**

To avoid overfitting issue and conduct variable selection, a penalised maximum likelihood Least Absolute Shrinkage and Selection Operator (LASSO) regularisation method can be applied to negative binomial regression. Expectation-Maximization (EM) algorithm is used to estimate parameters (Wang et al., 2017). A parsimonious model can therefore be obtained through penalised regression with penalty function or variable selection procedures to offer sufficient interpolation. The penalised ZILT model can handle with additional overdispersion and conduct variable selection procedure simultaneously since some variable coefficients are shrunken to be zero to obtain parsimonious model.

The log-likelihood function of zero inflated negative binomial model is given by

$$l(\varphi) = \sum_{y_i=0} log[p_i + (1 - p_i)(\frac{\theta}{\mu_i + \theta})^\theta] + \sum_{y_i>0} log[(1 - p_i)\frac{\Gamma(\theta + y_i)}{\Gamma(y_i + 1)\Gamma(\theta)}(\frac{\mu_i}{\mu_i + \theta})^{y_i}(\frac{\theta}{\mu_i + \theta})^\theta]$$

(39)

where $\mu_i = \exp(x_i^T\beta)$ and $p_i = \frac{\exp(v_i^T\delta)}{1+\exp(v_i^T\delta)}$ , and $\log(\mu_i) = x_i^T\beta$, and $\log(\frac{p_i}{1-p_i}) = v_i^T\delta$, $\beta$=

$(\beta_0 , \beta_1 , \beta_2 , \beta_{q1})$ and $\delta=(\delta_0 , \delta_1 , \delta_2 , \delta_{q2})$, vector $x_i$ is with length q1, $\mu_i$ is with length q2.

The penalised Zero inflated model is

$Pl(\varphi) = l(\varphi) - p(\beta, \delta)$ (40)

And the nonnegative penalty function is given by

$p(\beta, \delta) = n\sum_{j=1}^{q1} p(\lambda_{NB};|\beta_j|) + n\sum_{k=1}^{q2} p(\lambda_{BI};|\delta_k|),$ (41)

Where $\lambda_{NB}$ and $\lambda_{BI}$ are determined by data-driven methods. In this study, the LASSO penalty for $\lambda \geqq 0$, $p(\lambda; |\S|)=\lambda|\S|$ is investigated (Tibshirani, 1996).

**Expectation-Maximization Method for penalised ZILT model**

Let $z=(z_1, \ldots, z_n)^T$ is the observable state series with $z_i=1$ if $Y_i$ is from the zero state and $z_i=0$ if $Y_i$ is from the NB state. The complete data penalised log-likelihood function of zero inflated negative binomial regression is :

$$pl_c(\phi) = \sum_{i=1}^{n} \{(z_i v_i \delta - \log(1 + \exp(v_i\delta)) + (1 - z_i)\log(f(y_i; \beta, \theta))\} - p(\beta,\delta) \quad (42)$$

The EM method computes the expectation of the complete-data log-likelihood that is linear in z. Specifically, E-step updates the conditional expectation of z at iteration m given the observed data and past parameter estimates:

When $y_i = 0$, $E(z_i^{(m)}) = (1 + \exp(-v_i\hat{\delta}^{(m)})^{-1})[\frac{\hat{\theta}^{(m)}}{\exp(x_i\hat{\beta}^{(m)})+\hat{\theta}^{(m)}}])^{-1}$

When $y_i > 0$, $E(z_i^{(m)}) = 0$

The expectation of the complete-data log-likelihood is calculated as:

$$Q(\phi|\hat{\phi}^{(m)}) = E(pl_c(\phi | y, z)|y, \hat{\phi}^{(m)}) = Q_1(\beta,\theta | \hat{\phi}^{(m)} + Q_2(\delta|\hat{\phi}^{(m)}) \quad (43)$$

Where $Q_1(\beta,\theta | \hat{\phi}^{(m)})=\sum_{i=1}^{n} (1 - \hat{z}_i^{(m)})\log f(y_i, \beta,\theta) - n\sum_{j=1}^{q1} p(\lambda_{NB}; |\delta_k|)$

$Q_2(\beta,\theta | \hat{\phi}^{(m)})=\sum_{i=1}^{n} (1 - \hat{z}_i^{(m)})\log f(y_i, \beta,\theta) - n\sum_{k=1}^{q2} p(\lambda_{BI}; |\delta_k|)$

EM method updates the estimates by maximizing $Q_1(\beta,\theta \mid \hat{\varphi}^{(m)})$ and $Q_2(\beta,\theta \mid \hat{\varphi}^{(m)})$, where $Q_1(\beta,\theta \mid \hat{\varphi}^{(m)})$ is a weighted penalised negative binomial log-likelihood function and $Q_2(\beta,\theta \mid \hat{\varphi}^{(m)})$ is a penalised logistic log-likelihood function. The EM method iterations are repeated for both E-step and M-step until convergency (Wang et al., 2017).

## 5.2 Time-Series based Models for semi-hourly crash prediction

Short-term crash prediction has garnered significant attention in modern traffic analysis, with the goal of improving proactive road safety. The key hypothesis is that the probability of a crash occurring is related to the dynamic traffic data of that specific period (Zheng and Sayed, 2020). However, due to the inherently low frequency of crashes, crash risk, and traffic conflicts are often used as surrogates for actual crash occurrences. For instance, Hossain and Muromachi (2011) developed a Bayesian-based network to predict real-time crash risk, rather than predicting actual crash counts. Similarly, Zheng & Sayed (2020) utilised traffic conflicts derived from detailed vehicle trajectories as an intermediate step for crash prediction. Machiani and Abbas (2016) proposed a real-time safety surrogate measure for evaluating safety at intersections based on traffic conflicts. The use of actual crash data for real-time, short-term crash prediction is challenging due to the highly imbalanced dataset. Moreover, although autoregressive integrated moving average (ARIMA) models are commonly used for forecasting, ARIMA is not suitable for short-term crash prediction due to the non-negative integer nature of crash data, which is highly skewed and violates the normal distribution assumption of residuals (Quddus, 2008; Cai et al., 2024).

Hossain et al. (2019) categorized real-time crash prediction methods into two broad types: statistical methods and data-driven methods. Common statistical approaches include logit and probit models, along with mixed generalised linear models. In contrast, data-driven methods such as machine learning classification models and Bayesian networks are increasingly popular. Basso et al. (2018) developed a model using raw, imbalanced crash data without generating synthetic data. They initially employed a random forest method to identify

significant variables, followed by a real-time crash prediction (RTCP) model using logistic regression and SVM, achieving an accuracy of 67.89% with a false positive rate of 20.94%.

Theofilatos et al. (2019) compared various machine learning and deep learning techniques for crash prediction, concluding that deep neural networks outperformed random forest, decision trees, logistic regression, SVM, and shallow neural networks. Yang et al. (2022) introduced a reinforcement learning tree method, which surpassed the deep neural network model by detecting 96% of crashes with a false alarm rate of just 10%.

Convolutional Neural Networks (CNN), first introduced by Yann LeCun in the 1980s, are a type of artificial neural network that employs convolutional mathematical operators, primarily for image processing. Over time, CNNs have been extended to a variety of applications, including crash prediction. Basso et al. (2021) used a multiple input CNN with a deep convolutional generative adversarial network (GAN) and found this oversampling method yielded the best results. Rahim and Hassan (2021) also applied a CNN model with a custom F1-loss function, transforming crash data into images using a nonlinear dimensionality reduction technique (t-SNE) and a convex hull algorithm.

Given that crash data is inherently imbalanced due to the rarity of crashes, oversampling techniques are frequently used. Popular methods for creating synthetic data include Synthetic Minority Over-sampling Technique (SMOTE), Adaptive Boosting, and Generative Adversarial Networks (GANs). Man et al. (2022) demonstrated the effective use of GANs for synthetic data generation, showing that their model performed well with transfer learning on other motorways. To address the zero-inflation issue, some models are specifically designed to handle such data. Pew et al. (2020) argue that zero-inflated models are particularly useful for such scenarios and outperform other state-of-the-art approaches. Their research concludes that zero-inflated binomial regression models yield better results. For example, Song et al. (2021) applied a zero-inflated binomial regression model to study freeway bridges. CNNs are also effective at dealing with imbalanced datasets, as they can recognise specific features in the data. Yu et al. (2020) proposed a focal loss function to enhance CNN's ability to

accurately predict crashes with imbalanced data.

What happens just before a crash is very significant to predict the crash itself, therefore considering time dependencies is important for RTCP. Many studies have used time-series methods to attempt to solve this challenge. Sun and Sun (2015) developed a dynamic Bayesian network (DBN) model with time sequence traffic data and compared it with a static Bayesian network demonstrating that the time consideration is valuable both in terms of accuracy and transferability. Hassouna & Al-Sahili (2020) have used an autoregressive integrated moving average (ARIMA) method to study the impact of the crash dataset's size in years on the prediction's accuracy. Yuan et al. (2019) have proposed a long-short-term memory recurrent neural network (LSTM-RNN). Many papers focus on real-time traffic conflict prediction methods, however, few papers tackle real-time short-term crash prediction. This is important because the leeway enables proactive safety management to be put in place.

Both method types considering spatial and temporal features have been previously combined in several studies. For instance, Li et al. (2020) have developed a LSTM-CNN crash prediction model. The LSTM has the ability to capture temporal dependencies while the CNN can detect time-invariant attributes. An improved method has been proposed using the same model combination but with the addition of an attention layer to the LSTM (Deva Hema & Ashok Kumar, 2022; Li & Abdel-Aty, 2022). They have shown that the attention layer significantly improves the model as it captures time-series data, thus demonstrating the importance of time-series for crash prediction.

While LSTM models excel at capturing temporal aspects of data, they have limitations, particularly when applied to traffic and crash data. One key limitation is their inability to model seasonality or calendar effects. Additionally, the gated structure of LSTMs does not explicitly handle time in the same way traditional time-series methods do, such as through partial autocorrelation. To address these limitations, Martínez et al. (2022) proposes using a time-series generalised regression neural network. This model better captures time-series

patterns and is also more interpretable. It incorporates a flexible lag approach, allowing the model to select the number of time steps it considers, which can be predefined or fine-tuned during training. Additionally, the model utilises a weighted sum approach at each layer to emphasize the most significant training patterns. The use of a radial basis function (RBF) in this approach leads to more efficient training, as RBF-based models have single-pass learning, require only one parameter, and produce deterministic results (Martínez et al., 2022). This makes the time-series generalised regression neural network particularly well-suited for predicting short-term traffic states in real-time.

In this thesis, all of the available models will be used to detect crash events and also classify non-crash events by updating crash and traffic data every period of 30 minutes to validate their superiority on the MIDAS dataset which is stored in a database operated by Mott McDonald containing microscopic traffic data collected by loop detectors every minute from the M1 for 2019 in UK motorway. Candidate models for evaluation prediction accuracy in short-term crash occurrences include: Joint model of Time-series generalised Regression Neural Network and Weighted CNN (TGRCN), multilayer perceptron (MLP), time series artificial neural network, long short-term memory network (LSTM), spatio-temporal graph convolutional neural network (STGCN), GARCH (generalised AutoRegressive Conditional Heteroskedasticity), and ARIMA (Autoregressive Integrated Moving Average).

Short-term crash data is highly dispersed. Extremely imbalanced datasets make it difficult to capture pro-crash traffic dynamics and make reliable crash prediction. Temporal and spatial characteristics of dynamic traffic variables are significant factors contributing to crash occurrence. The model proposed in the thesis has two components: (i) a time series generalised regression and (ii) a weighted convolutional neural network. The model structure is comprehensive, it not only tackles temporal characteristics including autocorrelation and seasonality but also considers spatial correlation and imbalanced sample problems by capturing crash features in the projected chronogram image. Figure 19 presents the functional architecture of the joint model. First, a time-series generalised regression neural network (TSGRNN) is employed to predict the future traffic state $X_{t+1}$ from the series of past until

current traffic state $X_{t-k,\ldots,t}$. The traffic state is characterised by five variables: speed, speed variance, flow, occupancy, and headway. The output is then fed into a weighted sequential convolutional neural network (WCNN) to predict the crash probability $\hat{Y}_{t+1}$ in the future 30-minute interval. Predicting the crash probability is not sufficient for a traffic control centre to introduce any intervention without knowing what factors may be attributed to the collision risk. To tackle this challenge, a forensic analysis was conducted on the results of the predictive model to enable targeted actions aiming to prevent the crash. The two components of the model are briefly discussed below.

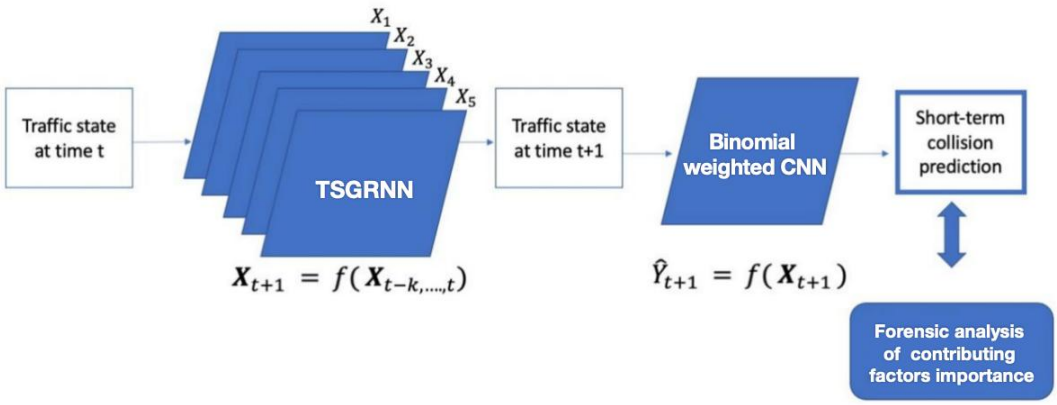



Figure 5.1. Functional architecture of the joint model

### 5.2.1 Time-series generalised regression neural network (TSGRNN)

generalised regression neural network (GRNN) is a generalised version of artificial neural network (ANN) which performs better than ANN in many domains (Martinez, et al., 2022). Contrast with the commonly used back propagation in ANN, it uses memory-based radial basis function (RBF) network as hidden layer to estimate continuous variables with convergence to linear or non-linear regression surface (Specht, 1991). It can be used for sparse data in multidimensional measurement space for both classification and regression purposes that linearity is not justified (Specht, 1991). However, conventional GRNN does not

consider time series structure such as autocorrelation, seasonality, and moving average that plays an important role in temporal related use cases. Therefore, an RBF neural network is introduced to project non-linear data onto a hyperplane and include temporal parameters to capture time features in the following ways: 1) it uses a single-pass learning; 2) set smoothing parameters to tune weighted average in output; 3) produce deterministic results after smoothing parameter chosen (Martinez, et al., 2022). The resulting model is termed as the time-series generalised regression neural network (TSGRNN) model.

The model and its application can be represented as follows:

$$x_{t+1} = f(X_{t-k,\ldots,t}) \tag{44}$$

with X a vector of the traffic characteristics, f is the time-series GRNN model and k the lag values. GRNN is composed of three layers: input layer, hidden layer of RBF neurons, and output layer. The radial basis function is the multivariate Gaussian function:

$$G(x, x_i) = \exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right) \tag{45}$$

where $x_i$ represents centre parameter, $\sigma^2$ represents smoothing parameter, x is the input variable vector (24). The structure of GRNN can be displayed as follows.

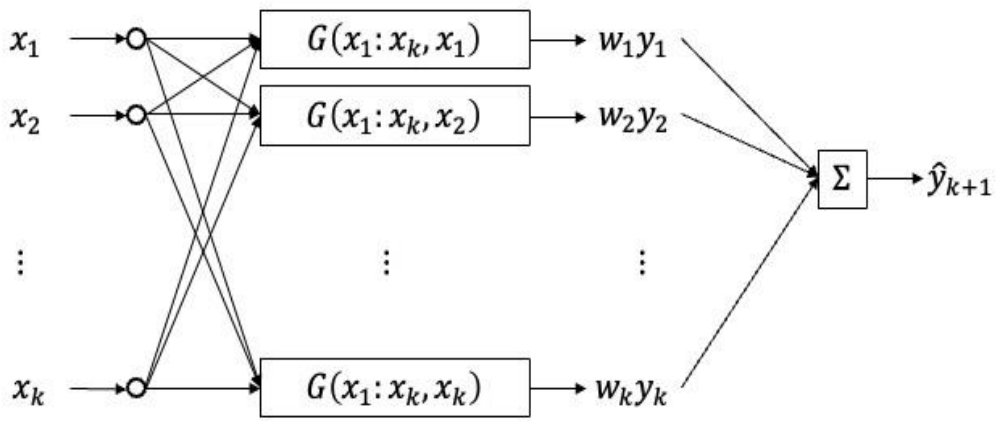



Figure 5.2. TSGRNN Structure (adapted from Martinez et al., 2022)

Each data point in the time series inputs is assigned a weight proportional to its proximity to the prediction time, thus emphasising the importance of closer values over those further away. The values are then aggregated in a weighted sum as presented in Equation 35:

$$\hat{y}=\sum_{i=1}^{n} w_i y_i, \quad w_i = \frac{\exp(-\frac{\|y-y_i\|^2}{2\sigma^2})}{\sum_{j=1}^{n} \exp(-\frac{\|y-y_j\|^2}{2\sigma^2})} \tag{46}$$

The weights sum to one and the smoothing parameter influences the number of variables that play a significant role in the outcome (Martinez, et al., 2022). When the smoothing parameter $\sigma$ is large, weights are small and similar, the output is close to the targets average. If the smoothing parameter $\sigma$ is small, only the closest targets have significant weights to influence prediction (Martinez, et al., 2022).

The accuracy and robustness of GRNN is subject to the optimum value of the smoothing parameter $\sigma$. Mean square error (MSE) is used to measure the performance of GRNN as loss function:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{i=n}[(Y_{GRNN})_i - (Y_{exp})_i)]^2 \tag{47}$$

where n is the number of data points, $Y_{GRNN}$ is the GRNN prediction, and $(Y_{exp})_i$ is the experimentally measured data (Ding et al., 2019). Therefore, train and test sets should be built to find the optimum $\sigma$ by minimizing MSE with consideration of bias and variance trade off.

In the meantime, the selection of proper lag values is also important to consider seasonality. Autocorrelation (ACF), Partial Autocorrelation (PACF), and time differencing methods that are proposed in ARIMA model can also be applied to decide lag values. Generally speaking, if apparent seasonal period is indicated, lags should be chosen according to seasonal patterns, weekly, monthly, or quarterly. The significant lag values will then be selected to build training patterns for linear relationship test (Martinez, et al., 2022).

### 5.2.2 Weighted convolutional neural network (WCNN)

Convolutional neural network is typically used in image recognition, pattern recognition and signal processing for having the ability of learning translation invariant patterns that have spatial hierarchies (Chollet, 2018). As a strong classifier in feature extraction and spatial correlation analysis, CNN has been applied to various anomaly detection in highly imbalanced dataset. CNN projects sequential data onto chromagram image and use convolution neurons to extract spatial features for classification. To handle extremely imbalanced data, CNN initiates different weights to different classes. The less representative class usually receives a higher weight that forces CNN to adjust weights following gradient descent direction during the training process (Han and Jeong, 2020). the thesis initiates a weighted CNN to capture overdispersion characteristics in traffic crash data, assigning dynamic weights inversely proportional to class frequency to every training step in fitting CNN model by tuning parameters in the direction of increasing the probability of classifying traffic crash from non-crash events. CNN model proposed in this study is a sequential base structure with three convolutional layers and two densely connected to form formidable learner and dropout to reduce overfit. A rectified linear unit function was set as the activation function. In total, 20,898 parameters were tuned through a back-propagation process. The architecture of this deep learning neural network consists of 30 epochs with 100 steps each, each epoch trained to tune the parameters. The structure is as follows.

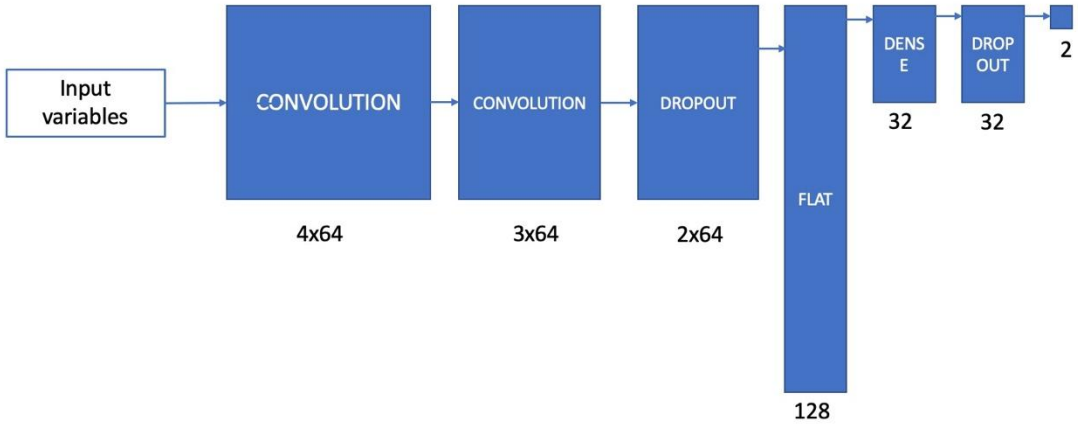



Figure 5.3. Sequential Convolution Neural Network Structure

Synthetic Minority Over-sampling Technique (SMOTE) is a commonly used oversampling technique to generate data for underrepresented samples. Using K-Nearest Neighbour methods, synthetic samples are generated between a randomly selected sample and its randomly selected neighbour to get reasonable samples close in feature space to the existing samples (Marchesi et al., 2022). Generative Adversarial Networks (GANs) are advanced generative models that produce entirely new data samples across various domains through deep neural networks and adversarial training (Marchesi et al., 2022). Compared to GAN, the SMOTE technique is easier to apply and targets to generate underrepresented samples through interpolation of existing data points. Although for high dimensional datasets, SMOTE may decrease data variability and have correlation between samples (Marchesi et al., 2022), for low dimensional and insufficient datasets, SMOTE can outperform GAN since GAN is a deep neural network based model that demands lots of training data.

In this study, SMOTE is used to generate crash data for training the CNN model, which makes learners stabilize its gradients and tuning parameters with sufficient crash data. However, the model was tested on the original dataset to assess its accuracy in real-world scenario, thus validating it for industry applications.

In order to prevent overfitting and improve CNN generalisation, regularisation term can be added to the loss function to penalize large weights and complex model architectures. L1 normalization (LASSO) and L2 normalization (Ridge) can both be applied to CNN to penalize weights (Ismoilov and Jang, 2018). L1 norm adds the sum of absolute values of the weights to the loss function such as MSE used in this case. L2 norm adds the sum of squared weights to the loss function to promote shrank but non-zero weights. Besides, dropout regularisation technique is also used. The dropout technique randomly drops out a subset of neurons by setting their outputs to zero with a certain probability, such as 0.2 in this case during training procedure to avoid overfitting and improve generalisation ability. The dropout technique forces CNN or other types of networks to learn more robust and independent features rather than specific neurons. However, the dropout value should not be too high or

the training procedure may not be convergent. L1, L2, and dropout regularisation methods have already been built in libraries such as Keras and Tensorflow and are easy to call from the backend in programming.

### 5.2.3 Combined methods TGRCN for semi-hourly crash prediction

Conventional spatio-temporal model conducts prediction of time t+1 from time t-k to t. It captures the autocorrelated temporal structure and employs one step lagged spatial characteristics. However, traffic crashes are more spatially correlated with dynamic traffic data occurring in the same time dimension rather than the previous time window. Therefore, initiating a joint model to predict traffic crashes with dynamic traffic data by transferring series to the same time dimension is a true innovation in crash prediction analysis. The joint model termed as Time-series Generalised regression Convolutional Neural network (TGRCN) developed in this study employs the TSGRNN model to obtain the predicted values of the covariates at time t+1 and inputs them in the WCNN (weighted CNN) model to forecast the probability of a crash event in the same time dimension. This structure has the advantage of capturing spatial hierarchies and analysing spatial features rather than finding autocorrelation in temporal series. In the meantime, the use of weights that are inversely proportional to class frequency empowers CNN with strong classifying ability in detecting under representative class with attention on studying the minority class. Therefore, the TSGRNN model is only applied to obtain the predicted values of dynamic traffic variables at time t+1 and feed the predicted variables as input of CNN to form the chronogram image in the same time stamp. TSGRNN learns temporal features and the weighted CNN extracts spatial correlation features in the same time dimension. The combination of both methods decomposes crash characteristics and maximizes prediction ability of TSGRNN and CNN by compensating their respective inherent limitations.

The structure of TGRCN model is displayed as follows.

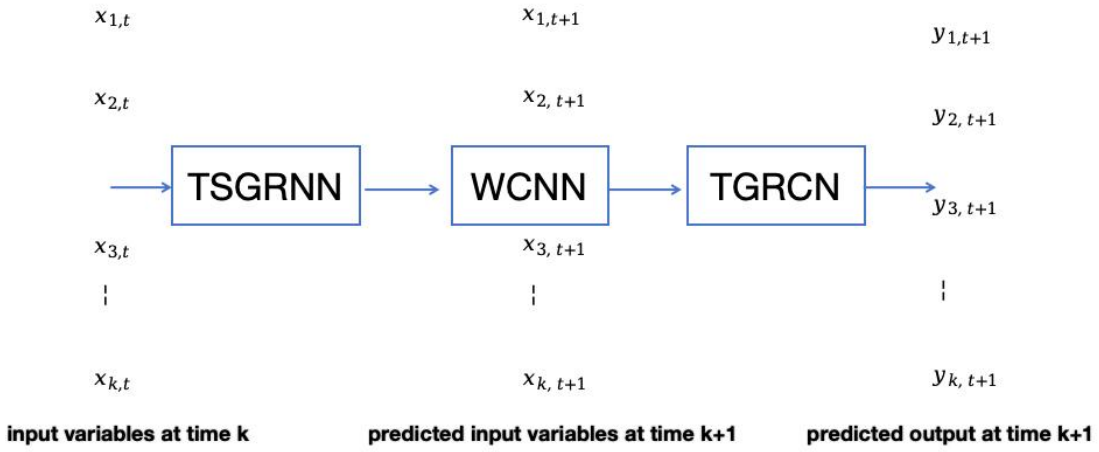



Figure 5.4. Structure of TGRCN model

## 5.3 Model Interpretability

Understanding the causes of traffic crashes is essential for preventing motor vehicle collisions. Roilson et al. (2018) assessed law enforcement perspectives, opinions from ordinary drivers, and road accident records to identify the main factors contributing to traffic crashes. Athiappan et al. (2022) used the Spearman ranking frequency index to rank influential factors leading to traffic accidents, revealing that human factors ranked highest, followed by vehicle and geometric factors. Elyassami et al. (2020) applied gradient boosting trees to predict traffic crashes and identified key contributors such as disregarded traffic signals, road design issues, poor visibility, and adverse weather conditions.

Deep learning methods are often considered "black boxes" due to the challenges in interpreting the relationships between classification results and their underlying classifiers. As models become more complex, understanding the contributing factors behind predictions becomes increasingly difficult. Traditional machine learning interpretation methods, such as random forests and gradient boosting, are not suitable for feature selection and analysis in deep neural networks. Therefore, this study employs the recently introduced Local Interpretable Model-agnostic Explanations (LIME) method to analyse the contributing factors

and variable importance for short-term crash incidents within a CNN model.

LIME explains the predictions of any classifier by locally approximating it with an interpretable model (Ribeiro et al., 2016). This model-agnostic explanation approach learns a potentially interpretable model, where the explanation acts as a gradient vector that captures locality intuition on the predictions of the original model (Ribeiro et al., 2016). LIME is commonly used to elucidate classifier importance in image classification and ensemble learning methods. In this study, it is applied to investigate factors associated with crashes in CNN classifications.

Feature importance selection algorithms and model-based interpretations represent advanced forms of association analysis and correlation. These methods extend beyond traditional intervention analysis and counterfactual reasoning (Dablander, 2020). While association, intervention, and counterfactual reasoning provide visual diagrams to clarify statistical dependencies between independent variables and outcomes, causal effect analyses utilise do-calculus to examine how X influences changes in Y (Cartwright, 2023).

Deep learning models are often seen as "black boxes" due to their complex network structures and lack of explainability. Visualizing and interpreting CNN models is particularly challenging because of the sequential and densely connected convolutional layers (convnets). Intermediate Convnet Activations Visualization (ICAV) is one of the most widely used methods for understanding how input layers are transformed through successive convolutional layers, allowing for the interpretation of individual convnet filters (Chollet and Allaire, 2018). Feature map visualizations consist of three dimensions: width, height, and depth (channels). Each channel encodes relatively independent features, and 2D images of each channel are displayed as feature maps to illustrate what each CNN layer has learned (Chollet and Allaire, 2018). LIME is applied to CNN feature maps under the assumption that the CNN model behaves linearly on a local scale, thus mimicking the performance of the global model within that locality (Ribeiro et al., 2016). The algorithm follows this logic (Ribeiro et al., 2016):

Permute observations to create replicated feature data with slight randomness.

Compute a similarity measure between the original observation and the permuted observations.

At each iteration:

Fit a CNN to a subset of variables from the permuted dataset.

Evaluate feature importance by testing model accuracy on another permuted dataset, weighted by its similarity to the original observation.

Repeat the previous two steps by adding or removing a feature at each iteration to compare feature importance based on the prediction accuracy achieved.

Use the resulting feature weights to explain local behaviour, reflecting the importance of individual features.

By employing this joint method of ICAV-LIME, variable importance can be effectively inferred.

## 5.4 Summary

This chapter serves as the core of methodology development within this thesis, covering various scenarios including freeway segment analysis, urban city infrastructure junction analysis, and vehicle-based analysis. Different models are tailored for specific applications.

The chapter begins by introducing the Zero-inflated log count data time series intervened seasonal INGARCH (ZILT) Model, a novel approach proposed in this study for extracting crash features and making predictions based on time series data. Derived from conventional zero-inflated models, ZILT is equipped to handle datasets with inherent excessive zeros. Its integration of INGARCH's time series structure and seasonal intervention enhances its ability to capture temporal characteristics of crashes. However, ZILT is more suited for predicting traffic crashes over longer time intervals, given that real-time traffic dynamic parameters are only considered as model covariates.

Next, the chapter introduces the Time Series generalised Regression Neural Network (TSGRNN) and the Weighted Convolutional Neural Network (WCNN) model (TGRCN). It compares the performance of these models with other deep learning methods such as Graph Neural Network, Transformer, Multilayer Perceptron, and Long Short-Term Memory Model (LSTM). TSGRNN is designed as a neural network specifically for time series data, focusing on capturing temporal crash characteristics. On the other hand, WCNN leverages the principles of CNNs, where crash data is projected akin to an image and classified using computer vision techniques to detect crashes.

Finally, the chapter evaluates and assesses the advantages and drawbacks of each method within the specified scenarios. It provides a comprehensive analysis of how each model performs under different conditions, offering insights into their applicability and effectiveness in crash prediction tasks.

This approach ensures that the methodology developed in this thesis addresses the complexities of traffic analysis across varied contexts, aiming to enhance prediction accuracy and model robustness in real-world applications.

# Chapter 6 Development of Traffic Conflict Prediction Models

The rarity of crash data and inaccurate and delayed records also bring question to its suitability of being the best indicator of safety during a short observation period (Zheng et al., 2021). In response to the challenge posed by the scarcity of collision data, the concept of traffic conflicts has emerged as a valuable tool for evaluating traffic safety. According to (Amundsen and Hyden, 1977), traffic conflict is defined as "an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged". According to the original definition, traffic conflict is a crash surrogate that include proximity, evasive actions, and other critical events with multiple road users (Zheng et al., 2021).

Theoretical frameworks, including extreme value theory and crash probability analysis, have been employed to validate the relationship between traffic conflicts and collisions (Cai et al., 2024). Studies have shown that strong correlations exist between crashes and traffic conflicts (Amundsen and Larsen, 1977; Xie et al., 2016; Charly and Mathew, 2019), indicating that traffic conflicts can be treated as a precursor of traffic crashes. Being crash surrogates, traffic conflicts and crashes share the same failure mechanism in the driving process, environmental influence, and surrounding vehicle interactions (Zheng et al., 2021). In emerging era of vast amounts of real-time vehicle data from autonomous and connected vehicles, traffic conflicts as crash surrogates play a more and more important role in traffic safety analysis and proactive safety management (Zheng et al., 2021).

To promote traffic safety levels and reduce crash occurrences, a complete and immediate paradigm shift should be built from reactive study to proactive management theories and lead to a predictive approach. Traffic crash prediction as we introduced in the last chapter builds the foundation of reactive analysis. Traffic conflict, however, is the key component of crash

proactive management theory and provides the foundation of predictive approaches. Traffic conflict prediction provides the technical routes to transfer passive safety protection to proactive crash prevention utilising various kinds of surrogate safety measures to derive active/proactive in-vehicle safety systems. Research shows that although SSMs are correlated with traffic crashes, a single crash indicator may not mimic crash occurrence pattern precisely. The combination of SSMs captures conflict characteristics in different aspects, giving insights into establishing the relationship between vehicle kinematics, traffic dynamic parameters, and crash risk. The gained knowledge can be exploited to inform active safety warning systems, to efficiently support drivers and to prevent more crashes (Papazikou et al., 2019).

In contrast with conventional modelling procedure that uses one statistical or machine learning model to make conflict prediction, this chapter puts forward a new stacked ensemble modelling procedure by integrating several predicting methods into one strong classifier to make robust predictionss and calculate individual variables contributing importance, so as to get more accurate prediction result and receive real-time feedback of finding the most influential crash indicators.

## 6.1 Stacked Ensemble Learning Methods

The stacked ensemble learning approach integrates predictions from several machine learning models into a single meta-learner model to make robust predictionss and improve the overall model's generalisability (Kalule et al., 2023). The robustness achieved in stacked ensemble models is the accumulation of performances from several estimators enables them to capture the nonlinearities in the dataset (Kalule et al., 2023). However, only a few research applied stacked ensemble models to make traffic conflict prediction. In some related studies, Bokaba (2022) used ensemble models for predicting traffic congestion. It compared prediction accuracy with different combinations of stacking models and found that the combination of AdaBoost with decision trees exhibited the best performance (Bokaba et al., 2022). Ahmad et

al. (2023) used heterogeneous ensemble learning for enhanced crash forecasting. The stacking model applied by Ahmad et al. (2023) is the integration of decision tree, random forest, negative binomial, Poisson regression, and gradient boosting as the base-learner, random forest with grid search optimization as meta learner. The study showed that the performance of the stacking model outperforms the individual machine learning model as well as the count data model (Ahmad et al., 2023). Tang (2019) put forward a two layer stacking framework with random forest, AdaBoost, and Gradient Boosting Decision Tree as the first layer. A simple Logistic Regression model was set as the second layer to make predictions on traffic crashes. Results showed that the stacking model achieves superior performance in comparison to other typical machine learning models (Tang et al., 2019). Additionally, Xiao (2019) used support vector machine and KNN ensemble learning for traffic incident detection and found that stacking model achieved good performance in small likelihood incidents and maintain model robustness as well (Xiao, 2019). Zhang (2022) applied the stacking model integrated with random forest, support vector machine, long short-term memory network, an attention mechanism as first layer model, and bidirectional LSTM as meta learner to make prediction for the recognition of the pedestrian crossing intention. It said that the proposed stacked model shows greater advantages in recognition accuracy with 95.36% when the model is recognised at 0.5s before crossing the zebra crossing (Zhang et al., 2022).

The effectiveness of stacked ensemble model is subject to the sub-models within it. Therefore, suitability and appropriateness of different level models should also be investigated. The procedure of building stacked ensemble model can be described briefly as follow.

- Multiple different machine learning models are trained on the same dataset to find base models.
- A new model, known as the meta-model, is trained on the predictions made by the base models.
- The meta-model learns how to best combine the predictions from the base models to

produce the final output.

- Cross-validation is applied to avoid overfitting.

### 6.1.1 Random Forest

Random forest (RF) is a classical and widely used strong classifier that combines multiple decision trees to obtain classification results through a voting mechanism. Random forest outperforms decision trees by handling well with overfitting problem in which each decision tree will not grow deep and different trees are trained to learn different features. Decision tree is a greedy method, which uses a greedy algorithm to choose which variable to split on with minimized error (Berk, 2016). Therefore, even with bagging, the decision trees can have a lot of structural similarities and in turn high correlation in their predictions (Berk, 2016). Random Forest is an improvement over bagged decision trees that combines predictions from multiple models in ensembles and performs the best if the predictions from the sub-models are uncorrelated or weakly correlated (Berk, 2016). Random Forest changes the bagging algorithm for the way that the subtrees are learned so that the resulting predictions from all of the subtrees have less correlation.

RF acts as the advanced version of the bagging method to enhance the performance and predictive power of the ensemble decision trees. For each bootstrap sample taken from the training data, there will be samples left behind that were not included. These samples are called Out-of-Bag samples or OOB. The performance of each model of RF on its left out samples when averaged can provide an estimated accuracy of the bagged models. This estimated performance is often called the OOB estimate of performance (Berk, 2016). The classification algorithm of RF is as follows (Berk, 2016).

1. Take b bootstrapped samples from the original dataset.
2. Build a decision tree for each bootstrapped sample. When building the tree, each time a split is considered, only a random sample of m predictors is considered as split candidates from the full set of p predictors. The value of m is usually set to be the square root of p.
3. Average the predictions of each tree to come up with a final model.

RF is also used for model interpretability by analysing the contributing importance of each independent variable (Hastie et al., 2001).

The predicted value for a RF model can be shown as follows:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} f_b(x') \qquad (48)$$

Where B is the bagging time, $f_b(x')$ is the prediction of individual regression trees on the sample of $x'$ in the regression problem (Hastie et al., 2001).

For the classification problem, it randomly selects observations, builds a decision tree, and takes the average result through majority votes (Hastie et al., 2001).

If a predictor is important, then assigning other values for that predictor randomly but 'realistically' for example, permuting this predictor's values over dataset), should have a negative influence on prediction, for example, using the same model to predict from data that is the same except for the one variable, should give worse prediction. Therefore, a predictive measure, for instance, Mean Square Error (MSE) can be taken with the original dataset and then with the 'permuted' dataset, and then make a comparison between them. Random Forest, while not having a single "loss function" in the traditional sense, uses criteria like Gini impurity or entropy for classification and mean squared error (MSE) or mean absolute error (MAE) for regression to guide the splitting of nodes in its constituent decision trees.

For regression based:

Three typically used predictive measures are MSE, Root Mean Square Error (RMSE), and MAE (Mean Absolute Error).

MSE = $\sqrt{E((\hat{\theta} - \theta)^2)}$ (49)

RMSE is also known as RMSD, is an estimator $\hat{\theta}$ with respect to an estimated parameter $\theta$, which is the square root of the mean squared error:

$$\mathrm{RMSE}(\hat{\theta}) = \sqrt{\mathrm{MSE}(\hat{\theta})} = \sqrt{\mathrm{E}((\hat{\theta} - \theta)^2)} \quad (50)$$

MAE is the average of the absolute values of the errors.

$$\mathrm{MAE} = |\hat{\theta} - \theta| \quad (51)$$

For classification based:

For a dataset with *C* classes, the Gini impurity *G* is calculated as:

$$G=1-\sum_{i=1}^{c} p_i^2$$

Where $p_i$ is the probability of an element belonging to class *i*.

Gini impurity is widely used in classification tasks, such as spam detection, sentiment analysis, and traffic event classification, to build decision trees that effectively split data into homogeneous groups. The thesis applies random forest to predict real time traffic conflict with Gini impurity as the loss function since it can be treated as classification problem.

Another widely used loss function is cross-entropy loss, which measures the difference between the true distribution *y* (ground truth) and the predicted distribution $\hat{y}$. The cross-entropy loss *L* is defined as:

$$L(y, \hat{y})=-\sum_{i=1}^{c} yi \log(\hat{y}i)$$

where:

$y_i$ is the true probability of the i-th class (usually one-hot encoded, e.g., $y_i$=1 for conflict events and $y_i$= 0 for others).

$\hat{y}_i$ is the predicted probability of the i-th class.

**Regularisation in Random Forest - Guided Random Forest in feature selection**

The guided regularised random forest (GRRF) leverages importance scores derived from a random forest (RF) model trained on the full dataset to enhance the information gain at each local node (Deng and Runger, 2013). However, Deng (2013) pointed out that the trees in

GRRF can still be highly correlated and GRRF cannot be built in parallel. Therefore, an optimised Guided Random Forest (GRF) was built by utilising importance scores derived from a random forest (RF) to guide its process, with each tree in GRF being constructed independently (Deng, 2013).

Let gain ($X_i$) represent the Gini information gain obtained by using feature Xi to split a tree node. The core concept of GRF is to adjust gain ($X_i$) by weighting it with the importance scores derived from a random forest (RF).

$gain_G(X_i) = \lambda_{i\ gain}(X_i)$, where $\lambda_i = 1-\Upsilon+\Upsilon\frac{Imp_i}{Imp^*}$ (52)

where $Imp_i$ is the importance score of $X_i$ calculated by random forest, and $Imp^*$ is the maximum importance score, $\frac{Imp_i}{Imp^*}$ is the normalized importance score, and $\Upsilon$ is within (0,1) controlling the weight of the importance scores from random forest. Features with lower importance scores are penalized more heavily in GRF, and this penalty intensifies as the regularisation parameter ($\Upsilon$) increases. When $\Upsilon$ is set to 0, GRF essentially becomes equivalent to a standard random forest (RF). When $\Upsilon$ is set to 1, $gainG(X_i)$ is gain $(X_i)\frac{Imp_i}{Imp^*}$.

GRF improves RF and GRRF generalisation ability and reduce the risk of overfitting by building trees independently and can make the trees to be implemented in parallel. Deng (2013) also showed that GRF achieves significantly higher accuracy and better interpretability than both GRRF and ordinary RF in terms of classification, feature selection, and generalisation.

## 6.1.2 Gradient Boosting Machine (GBM)

Gradient Boosting Machine (GBM) is an ensemble method sequentially combining the predictions of multiple weak learners and decision trees. Contrast with random forests that relies on simple averaging of multiple models to make predictions. Boosting methods use a different approach for forming ensembles (Natekin and Knoll, 2013). Boosting involves

adding new models to the ensemble sequentially. At each iteration, a new weak base learner is trained to address the errors made by the ensemble up to that point (Natekin and Knoll, 2013). GBM builds models sequentially and the subsequent models reduce the errors of the previous model through minimizing the loss function with optimal gradient descent in each iteration step. Similar to Random Forest, the basic prediction model used for GBM is decision trees (Hastie et al., 2009).

The algorithm of GBM is as follows.

1. Initialize $f_0(x)$ so that the constant $\kappa$ minimizes the loss function: $f_0(x) = \arg\min_\kappa \sum_{i=1}^{N} L(y_i, \kappa)$.[9]
2. For $m$ in $1, \ldots, M$, do steps a–e.
   (a) For $i = 1, 2, \ldots, N$ compute the negative gradient approximation as the working response

$$r_{im} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f=f_{m-1}}.$$

   (b) Randomly select without replacement $W$ cases from the dataset, where $W$ is less than the total number of observations. This is a simple random sample, not a bootstrap sample, which seems to improve performance. How large $W$ should be is discussed shortly.
   (c) Using the randomly selected observations, each with their own $r_{im}$, fit a regression tree with $J_m$ terminal nodes to the $r_{im}$, giving regions $R_{jm}$ for each terminal node $j = 1, 2, \ldots, J_m$.
   (d) For $j = 1, 2, \ldots, J_m$, compute the optimal terminal node prediction as

$$\gamma_{jm} = \arg\min_{\gamma} \sum_{x_i \in R_{jm}} L(y_i, f_{m-1}(x_i) + \gamma),$$

   where region $R_{jm}$ denotes the set of $x$-values that define the terminal node $j$ for iteration $m$.
   (e) Drop all of the cases down the tree grown from the sample, and update $f_m(x)$ as

$$f_m(x) = f_{m-1}(x) + \nu \cdot \sum_{j=1}^{J_m} \gamma_{jm} I(x \in R_{jm}),$$

   where $\nu$ is a "shrinkage" parameter that determines the learning rate. The importance of $\nu$ is discussed shortly.
3. Output $\hat{f}(x) = f_M(x)$.

Figure 6.1. Algorithm of GBM (Berk, 2016)

GBM aims to improve overall predictive performance by optimizing the model's weights

based on the errors of previous iterations, gradually reducing prediction errors and enhancing the model's accuracy based on the loss function minimization in classification problem (Mason et al., 1999). The loss function of GBM for classification is as follows:

$$\text{Loss Function} = -\sum_{i=1}^{n} y_i \log(p) + (1-p)\log(1-p) \quad (53)$$

In this function, $y_i$ is the observed values and $p$ is the predicted probability.

In gradient boosting machines (GBMs), the learning process involves sequentially fitting new models to improve the accuracy of the response variable estimate. GBM algorithm creates new base learners that are highly correlated with the negative gradient of the loss function, which reflects the errors of the entire ensemble (Natekin and Knoll, 2013). For the loss function of GBM for regression, the typical choice is mean squared error (MSE) which results in consecutive error-fitting in the learning process.(Natekin and Knoll, 2013). However, other loss functions can also be chosen for different purposes as a matter of trial and error. For binary classification problem, the typical loss function used is binomial deviance. Regularization via shrinkage (learning_rate < 1.0) improves performance considerably. In combination with shrinkage, stochastic gradient boosting (subsample < 1.0) can produce more accurate models by reducing the variance via bagging. Subsampling without shrinkage usually does poorly. Another strategy to reduce the variance is by subsampling the features analogous to the random splits in Random Forests (via the max_features parameter) (Hastie et al., 2009).

### 6.1.3 Support Vector Machines

Support Vector Machine (SVM) is a supervised machine learning algorithm primarily used for classifying data into distinct categories (Berk, 2016). Unlike many other algorithms, SVM utilises a hyperplane, which serves as a decision boundary to separate different classes of data (Berk, 2016). One of the key advantages of SVM is its versatility; it can be applied to both

classification and regression problems. Typically, SVM is used for classification tasks, while Support Vector Regression (SVR) is employed for regression problems.

SVM can also handle non-linear data classification by leveraging the kernel trick. The kernel trick involves transforming the data into a higher-dimensional space where a clear boundary exists between classes, making it easier to separate them. Kernel functions allow for the transformation of non-linear data into linear ones, simplifying the task of drawing a hyperplane to distinguish between the classes (HofmDNN et al., 2008; Thurnhofer-Hemsi et al., 2020). This technique makes it possible to solve complex non-linear classification problems by identifying a suitable hyperplane in this higher-dimensional space.

SVMs come with a variety of built-in kernel functions, including Gaussian, Linear, Radial, and Polynomial kernels. These kernels help to address complex optimization and classification problems by applying linear estimation methods in a higher-dimensional feature space using functional analysis (HofmDNN et al., 2008; Thurnhofer-Hemsi et al., 2020). Radial Basis Function (RBF) SVM is commonly used for both classification and regression tasks.

The radial basis kernel function (RBF) for SVM is with expression as:

$$K(x, x_i) = \exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right) \quad (54)$$

It is the multivariate Gaussian function, where $x_i$ represents centre parameter, $\sigma$ represents smoothing parameter, x is the input variable vector. RBF kernels are the most generalised form of kernelization and are among the most commonly used kernel functions because of their resemblance to the Gaussian distribution. RBF kernels are usually used for classifying non-linear patterns and are robust in making out of sample prediction.

Other kernel function expressions are as follow, where the parameter b represents the offset or

distance of the hyperplane from the origin along the normal vector w.

The linear kernel function expression is: $K(w, b) = w^T x + b$ (55)

The Polynomial kernel function expression is: $K(w, x) = \gamma \omega^T x + b$ (56)

The Sigmoid kernel function expression is: $K(x_i, x_j) = \tanh(\alpha x_i^T x_j + b)$ (57)

SVM searches the optimal hyper-plane that has a maximum margin between the nearest positive and negative samples with the expression as:

$$\arg\min \frac{1}{2}||w||^2, \text{ s.t. } y_i(w^T \phi(x) + b) \geq 1 \quad (58)$$

Where $\phi(.)$ is the feature-space transformation function, and

$b$ is the linear classification bias.

The closest data points to the hyperplane are known as support vectors. The hyperplane is drawn based on these support vectors and an optimum hyperplane will have a maximum distance from each of the support vectors. The distance between the hyperplane and the support vectors is known as the margin. An optimal hyperplane is defined as the distance between the hyperplane and the support vectors is maximum (Berk, 2016).

The regularization parameter (lambda) plays a critical role in Support Vector Machines (SVM), and determining the model's tolerance for misclassification. SVM solves a quadratic optimization problem aimed at maximizing the margin between two classes while minimizing misclassification. However, for non-separable problems, the misclassification constraint must be relaxed to find a solution, which is achieved by setting the regularization parameter. Intuitively, as lambda increases, the model's tolerance for misclassification decreases. When lambda approaches infinity, the solution tends toward a hard margin (allowing no misclassification). Conversely, when lambda approaches zero, the model allows more misclassification. There is a clear trade-off between these two, and typically, choosing a smaller lambda value enables the model to achieve better generalization performance.

### 6.1.4 Stacked Ensemble Model

Stacking typically involves utilising diverse base learners, training them concurrently, and then integrating their predictions through a meta-learner. This meta-learner takes these predictions as input features and the actual target values from the input dataset. Its goal is to optimize how these input predictions are combined to produce a more accurate final prediction. A common choice of meta-learner is the logistic regression. A generalisation is to replace the logistic regression model with other classification models. The selection of suitable models as components of stacked ensemble model is through global test of all possible candidate models with various combinations in two or three stacked layers. For example, one possible combination could be the first layer: SVM, GBM, Decision Tree, and the second layer: RF. It could also be the first layer: SVM, RF, GBM, the second layer: DNN and KNN, and the third layer: Logistic Regression. Although this selection procedure is exhaustive searching, it can ensure the stacked model combination has the best performances in terms of prediction accuracy for a particular chosen scenario. Empirically, the number of layers is typically limited to three at most and models in one layer is limited to four to be maximum. After testing various model combinations and making comparisons, the selected models are:

First Layer: SVM-RBF, Three hidden layer-DNN, RF

Second Layer: Stochastic GBM

The setup and training procedure are described as follows:

1. Specify Base Algorithms (L base algorithms) for first level modelling:

Choose a set of diverse base learning algorithms, each with specific parameters. In our study, we select:

- Random Forest
- Support Vector Machine with kernel='rbf'
- Deep Neural Network with three hidden layers.

- L Algorithm

L algorithm is a linear computational complexity graph searching algorithm for path planning (Niewola and Podsedkowski, 2018). L algorithm uses bidirectional sublists to ensure the linear computational complexity and maintain the optimality (Niewola and Podsedkowski, 2018). L algorithm is faster than many other algorithms in various path planning scenarios. L algorithm is applied to optimize stacked ensemble model by training parameter space.

RBF kernel is applied for its advantage in dealing with non-linear classification problems and similarity with Gaussian distribution. However, all kernel functions are tested with SVM to check model performances. Results show that RBF kernel achieves best prediction accuracy compared to other kernel methods.

2. Specify Meta learning Algorithm for second level modelling:

- Select a meta learning algorithm that will combine predictions from the base learners. In our case, we use:

- Gradient Boosting Machine (second-level) with learning_rate=0.01, n_estimators=100

3. Train the Ensemble:

- Train each of the L base algorithms on the training set using their respective parameters.

- Perform k-fold cross-validation (CV) on each base learner to obtain cross-validated predicted values. In our case, we use 10 fold cross validation on each base learner.

4. Create Level-One Data:

- Collect the cross-validated predictions from each of the L base algorithms. This results in an N x L matrix (where N is the number of samples in the training set and L is the number of base algorithms).

- Combine this matrix with the original response vector (target values). This combined dataset is termed the "level-one" data.

5. Train the Meta learner:

Train the meta learning algorithm (e.g., Gradient Boosting Machine, Random Forest) on the level-one data. The meta learner takes the cross-validated predictions from the base learners as input features and learns how to best combine them to predict the target variable.

6. Generate Ensemble Predictions:

To predict on new data:

Firstly, generate predictions from each of the L base learners using their trained models.

Secondly, use these predictions as input to the trained meta learner to generate the final ensemble prediction.

Stacking involves training multiple base learners on the training data, using cross-validation to obtain predictions, and then using a meta learner to combine these predictions into a final ensemble prediction. This approach can often improve prediction accuracy by leveraging the strengths of different algorithms and mitigating their individual weaknesses. The following graph depicts the stacked ensemble learning model structure. The meta-model is trained using predictions generated by base models on out-of-sample data, and these predictions, together with the actual outputs, form the input-output pairs for training the meta-model.

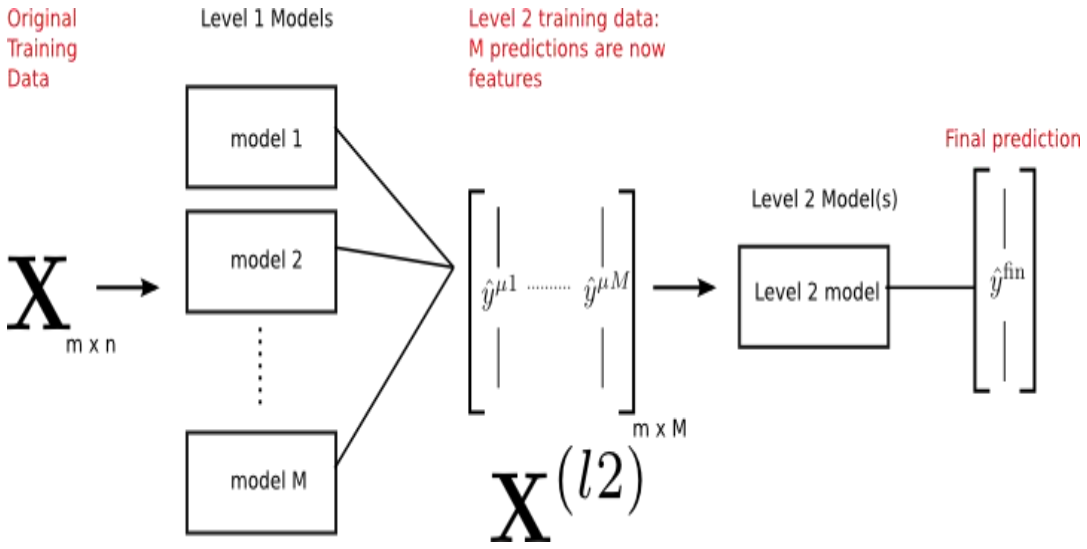



Figure 6.2. Training of Meta-model.

In our study, the predictive model to predict traffic conflicts is a stacked ensemble learning model composed of two layers and presented in Equation 43 and Figure 6.2. In the first layer, three models run in parallel: (i) Random Forest (RF), (ii) Support Vector Machine Radial

(SVM-R), and (iii) deep neural network comprising of three hidden layers. The results generated by these three models serve as inputs to the second layer which is a Gradient Boosting Machine (GBM) model whose output is the final binary prediction detecting the presence or absence of a conflict.

$$y_{pred} = GBM(RF(X), SVMR(X), DNN(X)) \quad (59)$$

In our analysis, thirteen commonly used SSMs involve time-based, distance-based and deceleration-based measuring metrics are selected. Time-based metrics include Time-To-Collision (TTC), modified TTC (MTTC), Post-Encroachment Time (PET), Time integrated TTC (TIT), Time Exposed TTC (TET), Headway (H) and Gap Time (GT). Selected distance-based metrics are headway, Proportional Stopping Distance (PSD) and Difference of Stopping distance and Safety distance (DSS). Deceleration-based metrics employed are Deceleration Rate to Avoid a Crash (DRAC), Potential Index for Collision with Urgent Deceleration (PIUCD) and Crash Index (CAI). In addition to SSMs, dynamic traffic parameterss such as speed, speed variances, lane change, acceleration, traffic flow, are also involved into analysis.

The stacked ensemble model structure is RF, DNN, SVM-RBF to be base learner, and GBM to be meta learner. These four models and this architecture were selected for their highest performance among 60 combinations of 25 machine learning models through exhaustive global testing of all candidates. Each model in the first layer is independently trained on the dataset. The models' outputs create a new training set to train the GBM forming the second layer. Various hyper-parameter fine-tuning techniques were applied across different models. With consideration of appropriateness, effectiveness, and model accuracy, the Adam optimizer was utilised for the DNN, while the Grid Search method was implemented for SVM, RF, and GBM.

Adam optimizer is an optimization algorithm designed for first-order gradient-based optimization of stochastic objective functions (Kingma and Ba, 2015). It operates by

adaptively estimating lower-order moments, making it straightforward to implement and computationally efficient (Kingma and Ba, 2015). Adam requires minimal memory, remains invariant to diagonal rescaling of gradients, and is particularly well-suited for problems with large datasets or parameters (Kingma and Ba, 2015). It excels in scenarios involving non-stationary objectives and challenges like very noisy or sparse gradients (Kingma and Ba, 2015).

Grid search is an intuitive and heuristic optimization technique where the design space is divided into a finite number of mutually exclusive partitions of equal size (Myung et al., 2013). Each partition is evaluated exhaustively one at a time, and the partition yielding the highest global utility value is selected as the optimal design (Myung et al., 2013). The global utility function is assessed numerically through a Monte Carlo procedure to estimate its value across the partitions (Myung et al., 2013).

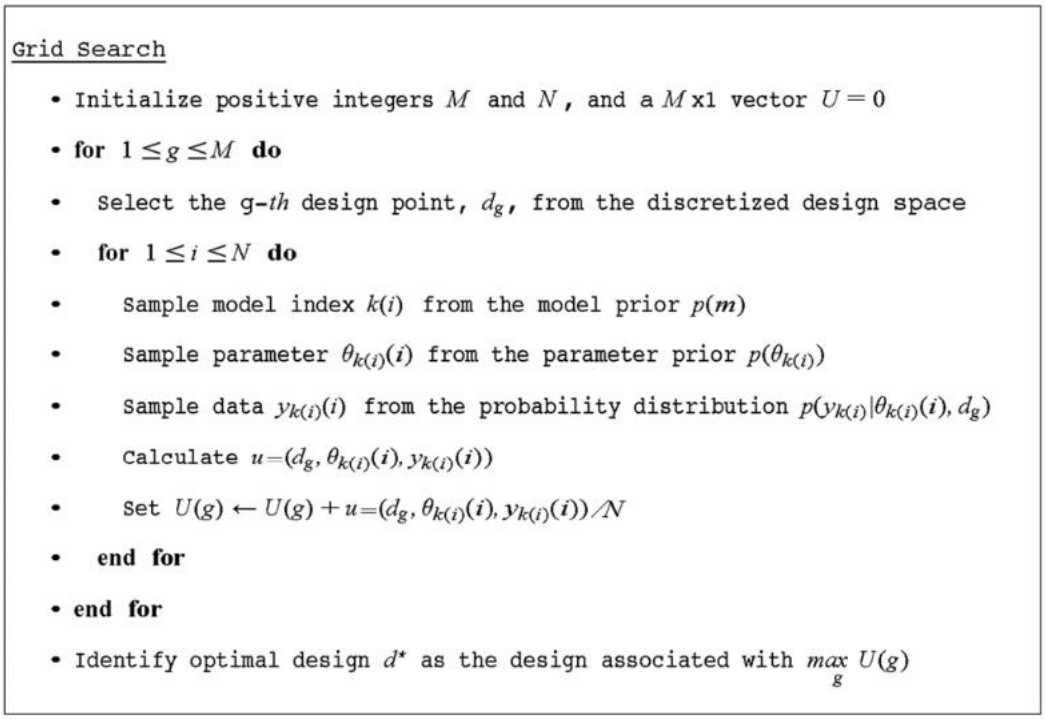



Figure 6.3 Grid Search Algorithm of Utility Function (Myung et al., 2013)

To mitigate overfitting, an early stop mechanism was employed. Furthermore, the dataset was divided into training and test sets in a 7:3 ratio. Early stop mechanism used in model selection

is to calculate the performance of the model on the validation set during training. When the performance of the model on the validation set begins to decline, stop training, so as to avoid the problem of overfitting caused by continued training. The main steps are as follows:

1. Divide the original training data set into training set and validation set
2. Train only on the training set, and calculate the error of the model on the validation set every cycle, for example, every 15 epochs (a cycle in mini batch training)
3. Stop training when the error of the model on the validation set is worse than the last training result
4. Use the parameters in the last iteration result as the final parameters of the model

How to avoid overfitting and the parameter settings of each model, the default settings are the default parameter settings

The following figure presents the architecture of the proposed stacked ensemble learning model.

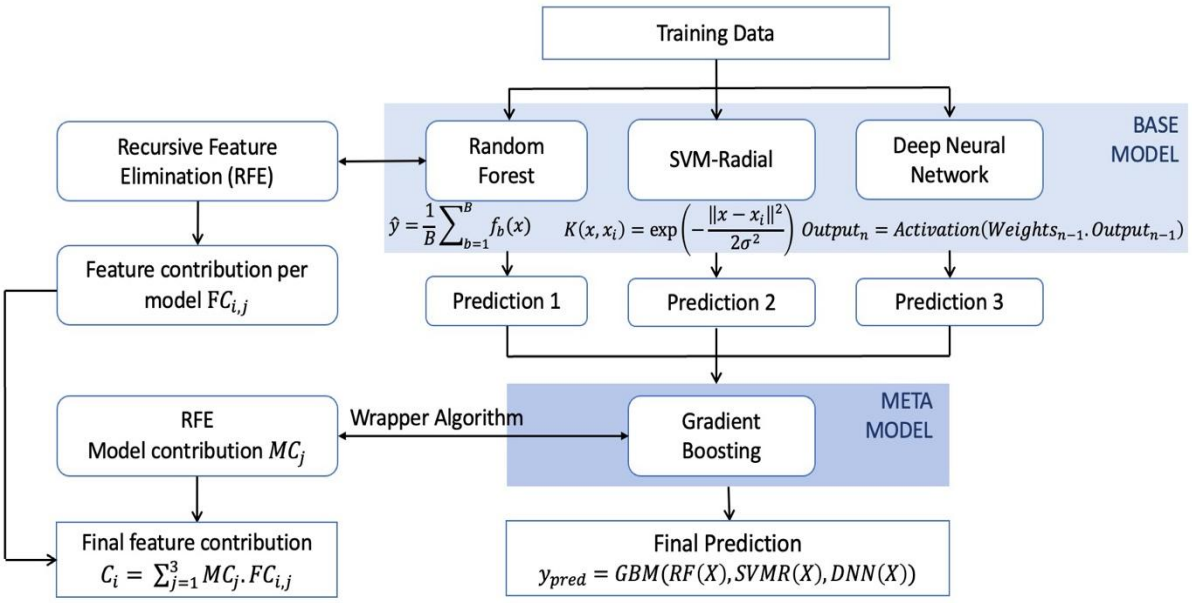



Figure 6.4. Stacked ensemble learning model and variable contribution assessment architecture

The stacked ensemble learning approach integrates predictions from several machine learning

models into a single meta-learner model to make robust predictions and improve the overall model's generalizability (Kalule et al., 2023). The robustness achieved in stacked ensemble models results from leveraging the strengths of different machine learning algorithm as each individual model may excel at capturing different aspects of the dataset (Kalule et al., 2023). The next section introduces each individual model employed.

The advantages of the proposed stacked ensemble learning model are listed as follows.

1) From leveraging the strengths of different machine learning algorithms as each individual model to form stacked ensemble model may excel each individual element model at capturing different aspects of the dataset (Kalule et al., 2023).

2) The stacking ensemble learning model combines predictions from multiple machine learning models into a single meta-learner model, and uses different optimization strategies to find optimal hyper-parameters by scanning over a wide hyperparameter space, enhancing prediction speed and improving the overall generalisation of the model (Kalule et al., 2023).

3) The stacked ensemble model integrates different learners to form comprehensive ensemble classifier, avoiding the difficulty of model selection and producing a more robust predictive performance than individual model or average ensembles.

Compared to LSTM and CNN, the primary distinction lies in their suitability for different types of data: the stacked ensemble model is more suitable for general classification tasks involving independent data points, whereas LSTM and CNN are better suited for sequential and spatial data, respectively. LSTM specializes in capturing long-term dependencies in time-series data, while CNN is designed to detect patterns in images by utilising local connectivity and shared weights across the data structure (Srivatsav and Nanthini, 2024). To be more specific, the strengths and weaknesses of the stacked ensemble model are listed as follows.

Stacked ensemble model:

Strengths:

a) It is an interpretable model primarily used for classification tasks involving weakly related data points (Berk, 2016).

b) SEM (Stacked Ensemble Model) performs well with small datasets due to its ensemble structure and non-parametric nature, which avoids making strong assumptions about the underlying data distribution (Berk, 2016).

c) SEM can handle missing data through surrogate splits, where alternative features approximate the splits that would have been made using the missing feature. Additionally, ensemble tree-based models can impute missing values by using the most frequent category for categorical features or the median/mean for numerical features, a technique widely adopted in literature (Stekhoven, 2022; Berk, 2016; Srivatsav and Nanthini, 2024).

d) It is robust to noise and outliers in datasets. By aggregating the results of all trees, the overall model reduces the influence of noise and missing data, producing reliable predictions (Berk, 2016; Srivatsav and Nanthini, 2024).

e) Ensemble learning models are easy to interpret and perform well on diverse datasets, enabling effective feature importance analysis (Berk, 2016; Srivatsav and Nanthini, 2024).

f) Stacked ensemble learning models combine predictions from multiple heterogeneous models, improving accuracy, robustness, scalability, and flexibility. This approach is particularly powerful for capturing complex relationships through hierarchical learning when no single model can fully represent the data's intricacies (Natekin and Knoll, 2013; Srivatsav and Nanthini, 2024).

Weaknesses:

a) SEM may struggle with sequential data, especially when complex relationships are present (Srivatsav and Nanthini, 2024).

b) It is prone to overfitting when applied to large, intricate datasets (Srivatsav and Nanthini, 2024).

Compared to stacked ensemble learning models, LSTM (Long Short-Term Memory) models are effective for time series forecasting, as they excel at capturing long-term dependencies

and complex patterns within sequential data. However, they require large amounts of data to train effectively, can be computationally expensive, and may not perform well in tasks that lack strong temporal relationships (Mishara, et al., 2024; Liu and Zhang, 2021; Srivatsav and Nanthini, 2024). In this use case, the traffic conflict dataset is small and is not time sequential data. Therefore, even though LSTM is good at dealing with time series data, applying LSTM to capture traffic conflict features is not effective due to lack of long-term dependencies within sequential temporal data and should not be used in this specific application.

On the other hand, CNN (Convolutional Neural Network) models are particularly powerful for image recognition and analysis, as they are designed to identify spatial patterns in data such as images or signals. Despite their strengths, CNNs are less suitable for tasks without spatial structure and often require substantial amounts of data to achieve optimal performance. (Begum et al., 2022; Srivatsav and Nanthini, 2024). For this specific use case, even though CNN works well for classification tasks, our dataset is not image based, and applying CNN may be faced with an overfitting issue and DNN that is used as one of the based models has already captured spatial patterns existing in the dataset.

However, one obvious drawback of stacked ensemble model is that stacking brings additional added complexity, which makes the final model difficult to interpret. Therefore, adopting proper feature selection methods to explain variable importance and its contribution to final prediction is necessary for implementation of stacked ensemble model for prediction and results interpretation.

## 6.2 Effective Feature Selection: Recursive Feature Elimination

The Recursive Feature Elimination (RFE) algorithm is employed to identify the most influential SSMs for conflict prediction in each scenario. Feature importance evaluation has been performed throughout the stacked model using the Recursive Feature Elimination (RFE) method. Recursive feature elimination is a process where predictors are systematically

removed from a full set based on their importance scores, which are calculated through cross-validation (Guyon et al., 2002). RFE is a wrapper algorithm that uses the same machine learning model as the base learner or meta learner to select the most relevant features for the intrusion detection problem (Awad and Fraihat, 2023). RFE is applied with cross-validation to identify the optimal number of features to enhance the classification accuracy and calculate individual variable importance (Kuhn and Johnson, 2013). RFE proceeds backward selection algorithm to progressively eliminate features based on their significance and contribution to model accuracy, ultimately identifying the most effective features with important scores (Awad and Fraihat, 2023).

In our study, RFE-Cross Validation is firstly applied to the three base models (e.g. RF, SVM, DNN) in the first layer to calculate the outputs feature contribution $FC_{i,j}$ for each feature i and model j. Secondly, each model contribution $MC_j$ is computed by applying RFE on the GBM model in the second layer as the input features are the prediction from each model of the first layer. The final contribution $C_i$ of each feature i is computed with a weighted sum as presented as follows.

$$C_i = \sum_{j=1}^{3} MC_j . FC_{i,j} \quad (60)$$

The recursive feature elimination procedure is integrated with the stacked ensemble learning model. Therefore, once the result is calculated from the stacked ensemble model, variable importance is returned simultaneously. Integration of prediction and feature selection model provide users the convenience of achieving conflict prediction results and also knowing which variables significantly contribute to conflict occurrences. Therefore, tasks of model prediction and interpretability are achieved by building one integrated model.

## 6.3 Summary

This chapter encompasses both traffic conflict prediction and model interpretation, leveraging influencing factors (causal factors). It introduces a novel stacked ensemble learning approach for real-time traffic conflict prediction, integrating machine learning and deep learning models to create a robust classifier for conflict classification. The stacked ensemble model consists of two layers: Support Vector Machine (SVM), Random Forest (RF), and Deep Neural Network (DNN) in the first layer; and Gradient Boosting Method (GBM) in the second layer. Ensemble learning models excel in feature extraction from imbalanced datasets and detecting underrepresented phenomena.

Barely seen from prediction outputs, the stacked Ensemble Model in traffic conflict prediction achieves the highest prediction accuracy. It is probably due to the representation of conflicts are much more than that of the actual crashes. Actual crash datasets are extremely imbalanced datasets (e.g. less than 0.01% in semi-hourly crash datasets). Many prediction models fail to classify under representative samples. However, for the conflict dataset, because conflicts are identified by human perspectives, the representative of conflict is well reflected. Therefore, the performance of the conflict classification model seems much better than the others. Another possible reason is latent correlation existed between traffic conflict and SSMs which are independent variables in the model. Although in this study conflict is identified by human, many other studies use SSMs as criteria by setting thresholds to identify conflicts.

Additionally, this chapter delves into model interpretation to examine variable importance in explaining the factors contributing to crash occurrences. It compares different factors influencing traffic conflicts, analysing their importance across various scenarios. Model interpretation and contributory factor analysis are crucial for traffic conflict prediction models. Unlike traditional statistical regression, machine learning and deep learning models are often considered "black boxes," making interpretation of their outputs challenging. Different algorithms existed for calculating variable importance in machine learning models. This study employs Intermediate Convnet Activations Visualization (ICAV), Local Interpretable

Model-agnostic Explanations (LIME), and Recursive Feature Elimination for feature selection and variable importance ranking. Furthermore, it discusses algorithms for assigning weights to variables at different layers and aggregating these weights to obtain overall weighted scores for each variable in the stacked ensemble learning model.

# Chapter 7 Data Collection and Processing

This chapter introduces data collection procedures in this study. Crash and conflict data were conducted in both China and the United Kingdom. In China, crash data was collected in Sutong Bridge freeway and Guidu mountainous freeway. Conflict data was collected in Sutong Bridge freeway and Shanghai and Suzhou urban city junctions. Crash data from these locations were extracted by the author and sourced from local traffic police stations, freeway management companies, and roadside surveillance cameras. Crash data was also collected from UK freeways. Crash data of London M1 motorway were extracted from the UK national accident database. Contrast with crash data collection, conflict data were collected by the author using UAV flying object to record videos from the selected urban junctions in China. However, the collected data are raw data. Massive data cleaning and preprocessing work are needed to make it structured and able to be fit into the model.

Statistical machine learning models are built to make monthly, hourly, semi-hourly, and real-time traffic prediction using collected dataset in different roadway scenarios. Data from different sources ensures modeling diversity and increases model robustness. Modeling accuracy and transferability are cross validated and tested by using different data sources from roadway scenarios of various locations.

## 7.1 Data Collection at Sutong Bridge Freeway

The Sutong Yangtze River Bridge is a cable-stayed freeway bridge spanning the Yangtze River, connecting Nantong and Suzhou in China, with a total length of 32.4 kilometers (20.2 miles). It features three lanes in each direction, and the maximum speed limit is 80 km/h under ideal driving conditions. Although the cross-river section of the bridge measures only 8.2 kilometers (5.1 miles), frequent traffic crashes often lead to congestion, delaying the response times of traffic authorities and emergency services. To address this issue and support the development of an intelligent transportation management system, this study focuses on the cross-river section of the Sutong Yangtze River Bridge.

Data on hourly traffic crashes for each direction were collected from the Suzhou municipal traffic police station, serving as the dependent variable. To account for the impact of traffic conditions on crashes, daily average vehicle speed, traffic flow, and truck-to-car ratio were also gathered. Daily average speed data were sourced from Gaode Map, one of China's largest navigation apps, while traffic flow and truck-to-car ratio were obtained from radar systems. Additionally, to assess the effects of holidays on road crashes, holiday information was collected as a categorical variable based on China's statutory holidays.

The study utilised ten months of data from July 2020 to April 2021, comprising 7,296 hourly observations. Table 7.1 presents a description of all the variables used in this research.
During the modeling process, the dataset was divided into training and testing sets in a 0.75 to 0.25 ratio to optimize the model structure, fine-tune parameters, and evaluate the overall predictive performance.

Table 7.1 Description of the Variables

| Variable | Type | Description | Key Statistics |
|---|---|---|---|
| Crash | Discrete | The number of crashes happened in the hour | Zero: 95.2%<br>One: 4.1%<br>Two: 0.6%<br>Three: 0.1% |
| Traffic operation variables | | | |
| Traffic flow for Lane 1 | Continuous | Traffic volume of vehicles (veh/h) for Lane 1 | Mean: 635.43<br>Std: 403.43<br>Max:1656 |
| Traffic flow for Lane 2 | Continuous | Traffic volume of vehicles (veh/h) for Lane 2 | Mean: 561.5<br>Std:254.6<br>Max:1569 |
| Traffic flow for | Continuous | Traffic volume of vehicles (veh/h) for Lane | Mean: 602.03 |

| | | | |
|---|---|---|---|
| Lane 3 | | 3 | Std: 247.44<br>Max: 1713 |
| Average speed | Continuous | Daily average speed of vehicles (km/h) | Mean:69.73<br>Std:15.49<br>Max:104.63 |
| Truck to Car Ratio | Continuous | The ratio of number of trucks to the number of passenger vehicles | |
| Other variables | | | |
| Hour of day | Categorical | The hour in each day, which is from 0 to 23 | |
| Holiday | Dummy | 0: today is not a legal holiday in China<br>1: today is a legal holiday in China | |
| Weather | Categorical | 0: Sunny<br>1: Partially Cloudy<br>2: Cloudy<br>3: Drizzle<br>4: Rainy<br>5: Rainy (Heavy)<br>6: Stormy<br>7: Shower<br>8: Rainy - Shower<br>9: Drizzle - Rainy<br>10: Sleet<br>11: Snow | |
| Speed | Numerical | The average speed within an hour (km/h) | Mean: 69.32<br>Std: 15.49<br>Max: 104.63 |

As shown in Table 7.1, the distribution of traffic crashes on the Sutong Bridge is highly skewed, with zero crashes accounting for over 95% of the recorded incidents. Traffic flow across the three

lanes is balanced. The hourly speed variance is notably high, with a standard deviation of 15.49 km/h. The truck-to-car ratio is also provided, as a higher ratio may elevate the risk of accidents. Holidays are classified into two categories: whether they are official public holidays in China. The traffic patterns on working days differ from those on holidays. Weather conditions are categorized into ten types to encompass all possible scenarios, as weather is a potential factor influencing the occurrence of crashes. The following figure illustrates the layout of the Sutong Bridge Freeway.



Figure 7.1 The portrait of Sutong Yangtze Bridge

## 7.2 Data Collection at Guidu Mountainous Freeway

In order to validate the effectiveness of video processing system and the stability of forecasting algorithm in different scenarios, I am collecting traffic data from Guidu freeway with total length of 80 km, which is a mountainous freeway located in Guizhou province. Roadway geometric design features in Guidu is more complex than that of Sutong Bridge due to mountainous terrain. Crash rate in Guidu is the highest in its province and also much higher than Sutong freeway. Crash data is collected since 1st Jan. 2018 to now in Guidu freeway.

Due to the lost of video data storage, past speed and traffic flow data between 1st Jan 2018 and 31st Dec 2021 were collected from ETC, and others were collected through video processing. Holiday and weather condition data were provided by Guidu freeway control centre. I divide this 80 km long freeway into ten segments from two directions with consideration of police station, interchange, ramp, wrecker, service zone, and other factors that may influence the rescue in the situation when crash takes place. Therefore, the division is meaningful for practical application of prediction system in real situation.

Table 7.2. Guidu Freeway Segment Division Statistics

| Seq | Segment | Pile Number | Length | Direction |
|---|---|---|---|---|
| 1 | Duyun the south- Duyun West | K1311+000 ~ K1338+500 | 27.5km | Guiyang |
| | | | | Duyun |
| 2 | Duyun West-Changming | K1338+500 ~ K1365+000 | 26.5km | Guiyang |
| | | | | Duyun |
| 3 | Changming-Longli | K1365+000 ~ K1385+200 | 20.2km | Guiyang |
| | | | | Duyun |
| 4 | Longli-Guiyang East | K1385+200 ~ K1408+000 | 22.8km | Guiyang |
| | | | | Duyun |
| 5 | Guiyang East-Qinqi | K1408+000 ~ K1411+000 | 3km | Guiyang |
| | | | | Duyun |

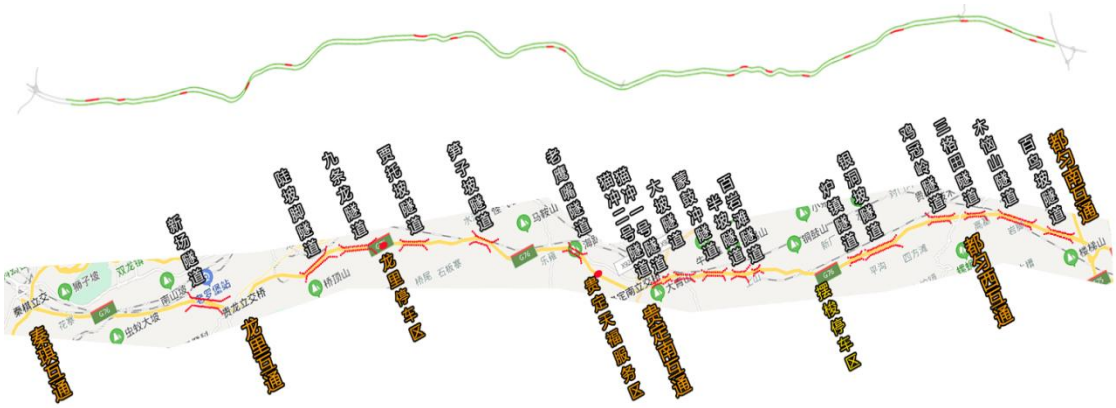


Figure 7.2 Portrait of Guidu Mountainous Freeway

## 7.3 Data Collection at Urban City Intersection

The most challenging aspect in traffic conflict studies is accurately detecting "actual" traffic conflicts from data captured by various sensors such as drones, roadside cameras, LiDAR, radar, etc. Data acquisition from roadside cameras, LiDAR, and radar presents more challenges compared to using UAV drones, which can collect data and apply computer vision methods to extract dynamic traffic parameterss in real-time. UAV drones provide an advantageous top-down view for video recording, ensuring more precise measurement of traffic data.

The infrastructure-based data was collected with an Unmanned Aerial Vehicle (UAV) flying over five typical junctions in Shanghai and Suzhou, China for the junction data and motorway segments on the Sutong Bridge in China for the motorway data.

Table 7.3 shows the selected junctions and road segment characteristics.

Table 7.3. Road information that collected by drones

| Location | Length and Width | City |
|---|---|---|

| | | |
|---|---|---|
| Jiangyue Road and Pinglong Road | Jiangyue Road the north: 12.7 meters<br>Pinglong Road East: 26 meters<br>Jiangyue Road the south: 12.5 meters<br>Pinglong Road West: 26 meters | Suzhou |
| Panjing Road and Yangnan Road | Panjing Road the south: 39 meters<br>Yangnan Road East: 27 meters<br>Panjing Road the north: 38.5 meters<br>Yangnan Road West: 26.5 meters | Shanghai |
| Wanrong Road and Lingshi Road | Wanrong Road the south: 27 meters<br>Lingshi Road East: 16 meters<br>Wanrong Road the north: 26.5 meters<br>Lingshi Road West: 20 meters | Shanghai |
| Wanrong Road and Yonghe Road | Wanrong Road the south: 25.5 meters<br>Yonghe Road West: 13.5 meters<br>Wanrong Road the north: 25 meters<br>Yonghe Road East: 13 meters | Shanghai |
| Sutong Bridge Freeway | Width: 3.75 meters wide | |

Our Study used Dajiang Mavic 3 Drones to collect videos.

Drones' Parameters are displayed in Table 7.4.

Table 7.4. Drones' Parameters

| Items | Description |
|---|---|
| Longest flight time (windless environment) | 46 minutes |

| | |
|---|---|
| Longest hovering time (windless environment) | 40 minutes |
| Maximum fly distance | 30 kilometers |
| Maximum wind speed | 12 m/s |
| Hovering accuracy | ± 0.1 meters (when visual positioning works normally) |
| | ± 0.5 meters (when GNSS works normally) |
| Horizontal | ± 0.3 meters (when visual positioning works normally) |
| | ± 0.5 meters (when high-precision positioning system works normally) |
| Image sensor | 4/3 CMOS, effective pixel 20 million; 1/2 inch CMOS |
| Video format | MP4/MOV (MPEG-4 AVC/H.264, HEVC/H.265 |
| Video encoding and resolution | H264/H.265<br>4K: 3840×2160@30fps<br>FHD: 1920×1080@30fp |

For junction scenes, data was collected on typical road scenarios, four representative junctions were picked: one-way street, waiting area junction, multi-directional junction, and ordinary junction. Drones were used to take aerial photography and record aerial video in the daytime with normal traffic conditions between 10am-12pm (off-peak hours) and 4pm – 6pm (peak hours) respectively. For the motorway segments on the Sutong Bridge, data was collected between 11am – 2pm. Four roadway segments were picked in dense area to record

videos. The following table shows the road characteristics of Sutong bridge freeway.

**Table 7.5**. Road types that collected by drones

| Road Type | Location | Number of Lanes | UAV Height |
|---|---|---|---|
| Normal Junction | Jiangyue Road and Pinglong Road | 4 Lanes in total (both directions) | 80 meters |
| Normal Junction | Wanrong Road and Lingshi Road, Shanghai | 4 Lanes in total (both directions) | 100 meters |
| Normal Junction | Panjing Road and Yangnan road | 5 Lanes in total (both directions) | 120 meters |
| Freeway Segment | Sutong Bridge Freeway | 6 Lanes in total (both directions) | 100 meters |



Figure 7.3. Intersection of Panjing Road and Yangnan Road



Figure 7.4. Intersection of Wanrong Road and Lingshi Road



Figure 7.5 Intersection of Jiangyue Road and Pinglong Road



Figure 7.6. Sutong Bridge Freeway Segment I



Figure 7.7. Sutong Bridge Freeway Segment II



Figure 7.8. Sutong Bridge Freeway Segment III

**Video processing and feature extraction**

The data was first processed using computer vision with YOLO (You Only Look Once) v8 to detect road users and identify the category: vehicle, HGV, cyclists or pedestrian. From the bounding box, the real-world position was obtained through spatial coordinates transformation from the image space to the physical space. For infrastructure-base datasets, the vehicles' length and width were also computed using the bounding boxes. Yolo-v8 has built-in multi-object tracking model and was employed to track the detections from frame to frame. Calibration was needed to account for noisy object detection where the bounding box moved slightly from one frame to another. This was performed by smoothing the positions over several frames and by finetuning the detection models to increase the accuracy and the precision of the detections. From the real-world positions and the time elapsed between each frame, the velocity and acceleration could be calculated which enabled the calculation of all selected SSM between two road users. For the vehicle-based motorway scenario, only the data extracted from the closest vehicle to the ego-vehicle is included in the final dataset.

The following figures depicts the recognition and detection of dynamic objects on the motorway.

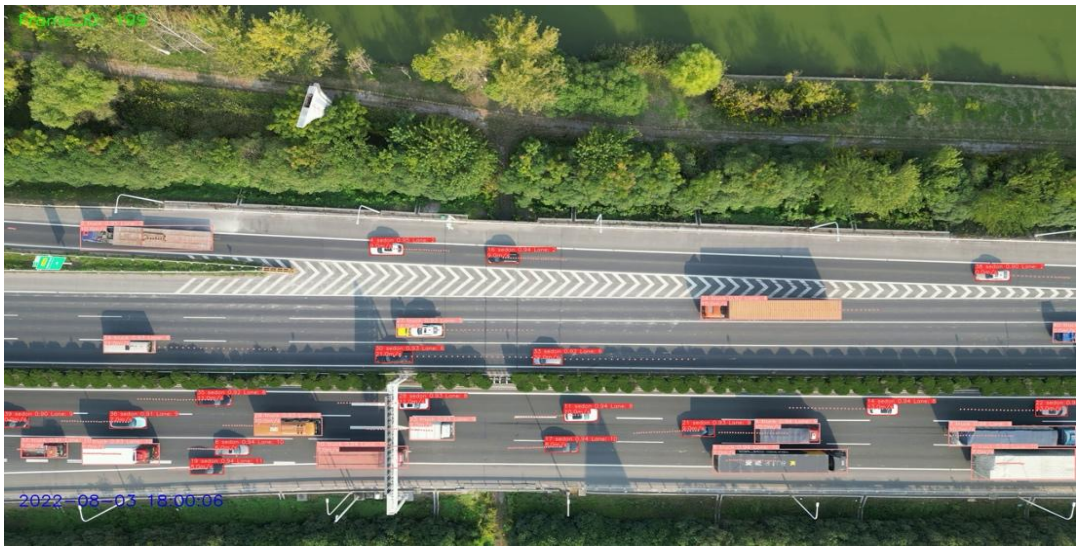



Figure 7.9. Collecting traffic dynamics data on motorway segment using a drone

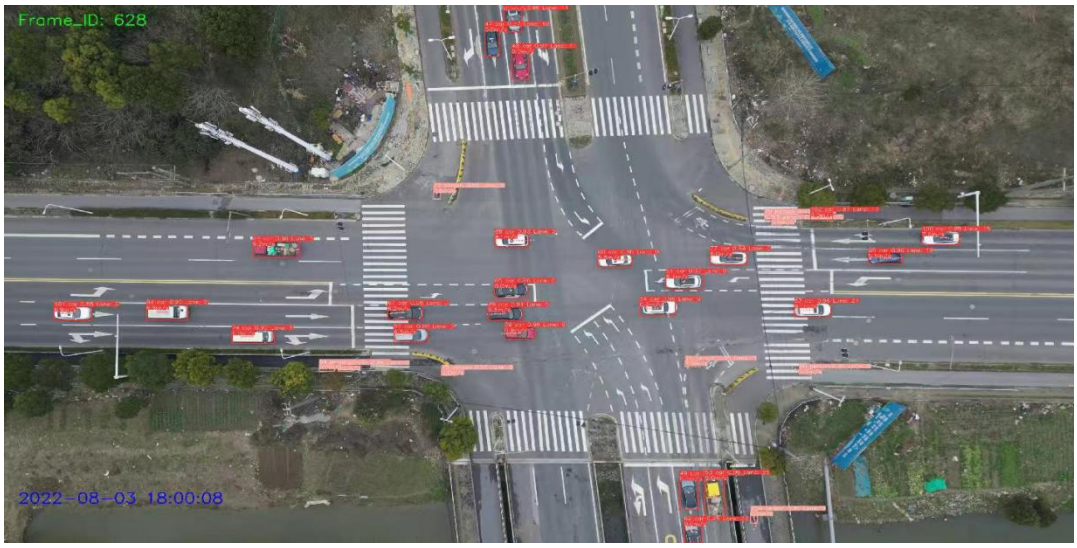



Figure 7.10. Collecting traffic data at junction of Panjing Road nad Yangnan Road




Figure 7.11. Collecting trafficdata at junction of Wanrong Road nad Lingshi Road

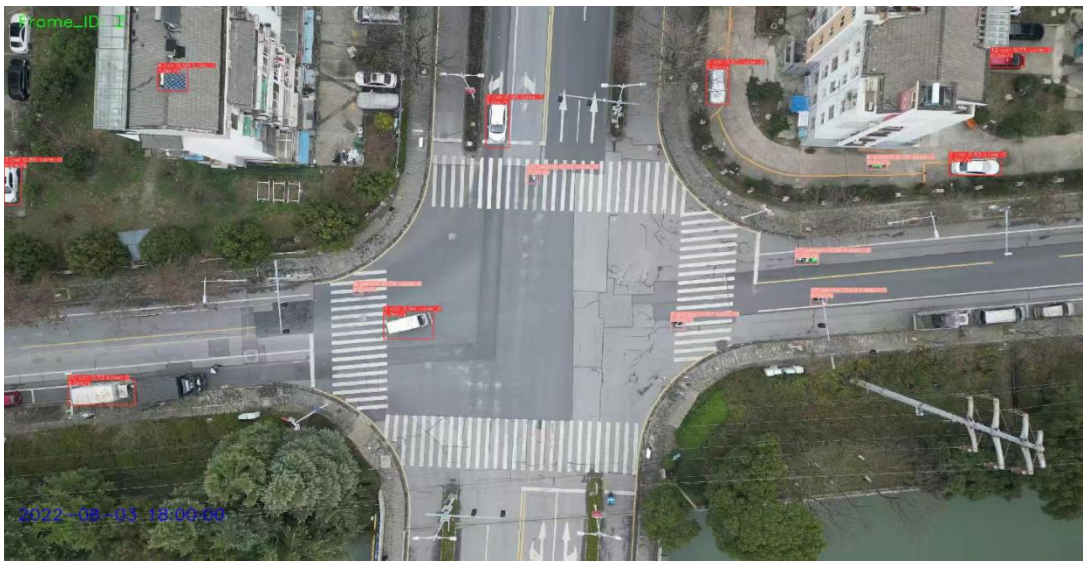


Figure 7.12. Collecting traffic conditions data at junction of Jiangyue Road nad Pinglong Road

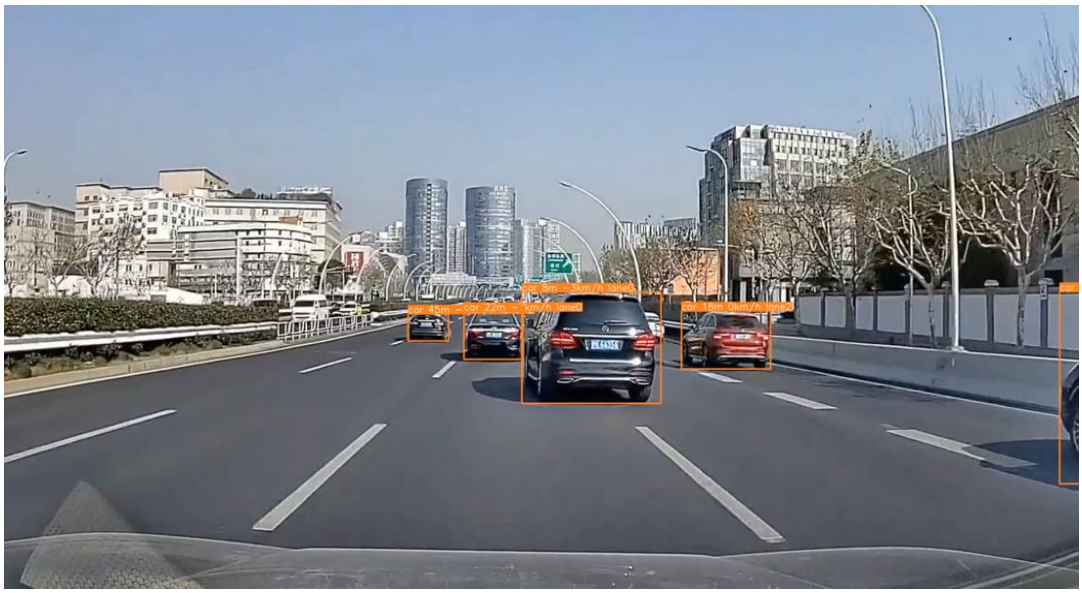


Figure 7.13. Collecting vehicle-based data using an instrumented vehicle

**Conflict identification**

Traffic conflicts were identified through human judgment for both infrastructure-based motorway and urban junction datasets collected by drone detection (Federal Highway Administration (FHWA), 1989). However, experts were trained to identify traffic conflicts with the identification of evasive maneuvers such as braking, swerving, and acceleration. During the training phase, the conflicts were cross validated by verifying that the associated TTC values were inferior to 3s. The TTC threshold used in previous studies has varied from 2

to 4 s (Berk, 2016; Yan and Shen, 2022). In order to include a greater number of conflict samples in this research, TTC* was set as 3 s at junction scenarios for the UAV data (Zhao et al., 2022). The reason why TTC was not used directly as a judgment standard is due to the potential correlation between conflicts and conflict affecting factors. If TTC was used directly to identify conflicts and TTC, MTTC, and other SSMs were used as independent variables to predict conflicts, the prediction accuracy would be very high but would have been meaningless because of the strong correlation is existed between the independent variables and the dependent variable.

Human observers' perception of traffic conflicts is an appropriate way to determine ground truth at junction scenarios (Wang et al., 2021). Human observers are recruited from experts in transportation, identifying evasive maneuvers on roadways. Many studies have proved this and suggest that human judgments are reliable and valid for detecting severity in traffic events (Natekin and Knoll, 2001). Hyden (1987) showed that with the right initial training, there is good agreement reached between observers in terms of identifying traffic conflicts (Hyden, 1987). Horst (1984) also showed that humans have an innate ability to assess the level of danger in a traffic situation especially when it is based on an actual observation (Horst, 1984).

For UAV data, an initial screening of video data was performed to identify potential traffic conflicts using continuously calculated TTC for all collected videos. A TTC value inferior to 5s triggered a manual check from a trained expert to determine whether the scene was a traffic conflict or not. A binary value (0, 1) was then assigned to every scene. The five second TTC threshold was selected conservatively because the majority of studies employed TTC thresholds comprised between 2 and 4 s (Mahmud et al., 2017, Li et al., 2014). The trained experts used the presence of an evasive maneuver such as braking, swerving, or accelerating to identify a conflict. Many studies have proved the validity of conflict identification by experts and suggest that human judgments are reliable and valid for detecting severity in traffic events (Diwakar et al., 2023).

For vehicle-based data, this study employs the method proposed by Formosa et al. (2020) to identify traffic conflicts. This automatic identification method relies on computer vision to detect several indicators found in the literature. Rear-end conflicts were identified when specific conditions—such as lateral distance below 1.75 meters, time headway under 3 seconds, and speed/braking dynamics between subject and leading vehicles—were met, alongside a braking threshold of ±2.943 m/s² (Naito et al., 2009; Angkititrakul et al., 2011). Similarly, conditions required for lane change conflicts included total time headway between two vehicles inferior to 3s, the lateral distance is comprised between 1.5m and 2.2m, and the longitudinal available space is less than 75mm. Formosa et al. (2020) validated the method through manual video reviews (Saunier et al., 2010).

The sample dataset is as follows.

| FrameID | Class | TrackID | X | Y | Width | Height | Speed km, | Accelerat | Angle | Location | acc_x | acc_y | North-South | West-East |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | car | 1 | 2073 | 978 | 461 | 158 | 0 | 0 | 0 | (2073, 978) | 0 | 0 | Green | Red |
| 2 | car | 2 | 1700 | 1241 | 192 | 146 | 0 | 0 | 0 | (1700, 1241) | 0 | 0 | Green | Red |
| 2 | car | 3 | 1691 | 131 | 122 | 262 | 0 | 0 | 0 | (1691, 131) | 0 | 0 | Green | Red |
| 2 | car | 4 | 3451 | 1120 | 218 | 94 | 0 | 0 | 0 | (3451, 1120) | 0 | 0 | Green | Red |
| 2 | car | 5 | 1098 | 1054 | 209 | 102 | 0 | 0 | 0 | (1098, 1054) | 0 | 0 | Green | Red |
| 2 | car | 6 | 2668 | 1199 | 205 | 96 | 0 | 0 | 0 | (2668, 1199) | 0 | 0 | Green | Red |
| 2 | car | 7 | 330 | 910 | 218 | 107 | 0 | 0 | 0 | (330, 910) | 0 | 0 | Green | Red |
| 2 | car | 8 | 146 | 744 | 202 | 106 | 0 | 0 | 0 | (146, 744) | 0 | 0 | Green | Red |
| 2 | car | 9 | 1011 | 870 | 454 | 178 | 0 | 0 | 0 | (1011, 870) | 0 | 0 | Green | Red |
| 2 | motor | 10 | 2746 | 941 | 66 | 34 | 0 | 0 | 0 | (2746, 941) | 0 | 0 | Green | Red |
| 2 | car | 12 | 3040 | 468 | 131 | 70 | 0 | 0 | 0 | (3040, 468) | 0 | 0 | Green | Red |
| 2 | motor | 13 | 1071 | 781 | 102 | 50 | 0 | 0 | 0 | (1071, 781) | 0 | 0 | Green | Red |
| 3 | car | 1 | 2067 | 977 | 461 | 158 | 22.77276 | 0 | 0 | (2067, 977) | 0 | 0 | Green | Red |
| 3 | car | 2 | 1703 | 1243 | 189 | 151 | 13.49853 | 0 | 0 | (1703, 1243) | 0 | 0 | Green | Red |
| 3 | car | 3 | 1691 | 131 | 120 | 262 | 0 | 0 | 0 | (1691, 131) | 0 | 0 | Green | Red |
| 3 | car | 4 | 3444 | 1119 | 218 | 93 | 26.4728 | 0 | 0 | (3444, 1119) | 0 | 0 | Green | Red |
| 3 | car | 5 | 1106 | 1057 | 205 | 101 | 31.98721 | 0 | 0 | (1106, 1057) | 0 | 0 | Green | Red |
| 3 | car | 6 | 2676 | 1199 | 212 | 95 | 29.95055 | 0 | 0 | (2676, 1199) | 0 | 0 | Green | Red |

Figure 7.14 Sample dataset of drones' collection

Columns includes: Frames ID, Vehicle types, TrackID, Lanes, X-coordinate in pixel, Y-coordinate in pixel, Vehicle length, Vehicle width, Speed, Acceleration, Drive angle, Traffic signal (the north-the south), Traffic signal (East-West), Speed in x-axis, Speed in y-axis, Acceleration in X-axis, Acceleration in Y-axis.

Frames ID, Vehicle types, Coordinates are returned by YOLOv8. Lanes means which lane is the vehicle at. To get this, lanes should be drawn ahead of time in the image. The default lane width is 3.5 meters for urban roadway, and 3.75 meters for freeways. It can be used as reference to convert pixel coordinates to world coordinates. Therefore, vehicle speed and acceleration in meters can be calculated. Driver angle is derived by calculating the angle between the horizontal line of vehicle forwarding direction with the default lane direction. Therefore, speed decomposition can also be derived.

Drone video processing can provide highly accurate estimations of traffic dynamic parameters. However, the accuracy of object detection is significantly influenced by the height of the drone. As the drone flies higher, ground objects become smaller and more challenging to recognise clearly. The choice of drone height is constrained by the need to cover a wider area of junctions or segments. Achieving a broader field of view requires flying the drone at a higher altitude, but this can compromise the accuracy of object detection.

Therefore, finding the optimal balance in drone detection research is crucial. Researchers must carefully weigh the trade-offs between altitude and detection accuracy to ensure effective data collection and analysis in traffic monitoring scenarios.

The following table depicts the detection accuracy for different drone's height in our research.

Table 7.6. Comparison of drone detection at different heights

| Height | Accuracy | Car | Bikes | Pedestrian |
|---|---|---|---|---|
| 40 meters | Detection | 99.6% | 98.8% | 97.3% |
| | Classification | 98.9% | 98.7% | 96.6% |
| | Tracking | 98.6% | 98.4% | 96.5% |

| | | | | |
|---|---|---|---|---|
| 70 meters | Detection | 99.1% | 98.8% | 96.5% |
| | Classification | 98.7% | 98.4% | 96.2% |
| | Tracking | 98.0% | 97.7% | 95.8% |
| 100 meters | Detection | 98.6% | 96.8% | 95.3% |
| | Classification | 98.3% | 96.3% | 94.6% |
| | Tracking | 97.6% | 96.0% | 94.2% |

Coverage of drones in different flying height is shown as following graph.




Figure 7.15 Map coverage of drones in different flying height

Figure 7.15 shows the relationship between drone's height and map coverage. The higher the drone is, the wider area can be covered by drones. This relationship is empirical based but is informative and can be referred when researchers are deciding flying height prior to on-site operations. In addition, the clearness of the recorded image often decreases alongside the increase in flight altitude of the UAV. The height is selected to capture the entire junction including zebra crossing and ensure that objects are sufficiently large to be detected. Another important parameter for height selection is to allow that the space is sufficient to calculate the

speed of the detected objects. Each junction and motorway segment had drone height varying from 40m to 100m.

In the study, different model performances in both detection and tracking procedures are also compared to decide the best model in object detection and tracking. Yolo-v8 outperforms others, which is reflected in Table 7.7 Comparison of detection algorithms and Table 7.8 Comparison of tracking algorithms.

Table 7.7. Comparison of detection algorithms

| Model | Algorithms | Pros and Cons |
|---|---|---|
| YOLO-v8 | 1) YOLO does not show the process of obtaining region proposals;<br>2) YOLO is unified as a regression problem | High Accuracy, Fast Speed |
| U-Net | Used for semantic segmentation, not for detection purpose | Slow Speed |
| Faster-RCNN | Although RPN and Fast R-CNN share convolutional layers in Faster R-CNN, it is necessary to repeatedly train the RPN network and Fast R-CNN network during model training. | High Accuracy, Low Speed |
| SSD | Unlike YOLO which uses a fully connected layer at the end, SSD directly uses convolution to extract detection results from different feature maps. | Fast Speed, Accuracy not good |

Table 7.8. Comparison of tracking algorithms

| Model | Algorithm Logic | Pros. And Cons. |
|---|---|---|
| YOLO-v8 | one-stage model, combine detection and re-ID into the same process. | Fast Speed,<br>High Accuracy |
| Fairmot | Multiple tracks execute Kalman filtering in parallel, which is faster than deepsort's Kalman filtering.<br>Only one feature vector is saved, and exponential sliding average is used to fuse multiple feature vectors to speed up calculation.<br>Anchor Free, accurate positioning | High Accuracy,<br>Medium Speed |
| Deepsort | two-stage network, detection and re-ID are separated | High Accuracy,<br>Low Speed |
| SDE | Detection and Embedding are divided into two independent models, with high performance but poor real-time performance. | High Accuracy but Low Speed |
| Kalman Filtering | Conventional tracking algorithm, not very useful in deep learning | Low Accuracy, Fast Speed |

In the majority of cases, detection accuracy is better for low drone height. If the drone flies too high (> 150m), the object on the ground is too small to be detected, resulting in compromised detection accuracy. Post-processing smoothing using the moving average technique and re-identification methods were also applied to YOLO-v8. Post-processing methods aims to smooth the tracking ID, particularly reducing the loss of object ID due to coverage and interference from trees, buildings, big trucks or buses, and ID jumps. These issues are often caused by occlusions such as vehicle and pedestrian passing through.

Innovations of this research are described as follows:

- This study obtained the empirical correlation between the drone shooting height and the intersection size, which can be used for typical scene selection;

- This study tracks objects based on target detection, obtains the transformation matrix between the spatial coordinate system and the video coordinate system, and obtains the real displacement distance through pixel displacement;

- In addition to detecting and tracking objects, the algorithm calculates pixel gradients without the help of sensors to obtain the actual vehicle running speed, acceleration and front angle in space, and finds conflict points by analysing trajectory characteristics to optimize the vehicle's assisted driving function.

## 7.4 Data Collection at London M1 Motorway

The MIDAS dataset is housed in a database managed by Mott McDonald, containing microscopic traffic data collected by loop detectors at one-minute intervals. This dataset includes five predictive variables: speed variance, speed, flow, occupancy, and headway. These variables are representative and effectively capture the dynamic state of traffic. By utilising the coordinates of junctions and loop detector locations, the loop detectors can be categorized into different road segments spanning from junction to junction, and are separated by the northbound and the southbound directions. By averaging the loop detector data across road segments, we can account for instances where certain detectors do not collect data at specific times. Traffic variables were averaged across all lanes over a 30-minute period, except for flow, which was summed during that time and then averaged across all lanes. Additionally, speed variance was calculated and included as a new variable. In total, our data encompasses junctions 1 to 12 and junctions 15 to 28 in both directions.

Crashes on the M1 motorway for 2019 were extracted from the database. A map-matching algorithm was applied to determine the exact coordinates of each crash location (Quddus,

2003). From these precise locations, crashes can be classified into the various road segments corresponding to the grouped loop detector traffic data. The direction of the vehicle immediately before the crash was used to identify its travel direction, with data separated for the northbound and the southbound traffic. When the direction was not available, it was randomly assigned. Since the traffic data is formatted in 30-minute intervals covering the entire year, crashes needed to be allocated to these intervals. This was accomplished by using the date and time of the crashes to convert them into the corresponding traffic data index. Once the time index was established, a new crash variable was added to the traffic data, marking 1s where crashes occurred and 0s otherwise. The below displays a plot of the crashes that occurred on the M1 in 2019.

The M1 motorway is one of the most crucial motorways in England, connecting London to Leeds and passing through several significant cities, including Milton Keynes, the northampton, Leicester, Nottingham, and Sheffield. It was the first inter-urban motorway built in the UK. The dataset created for this study covers a substantial portion of the motorway, starting at junction 1 near London and ending at junction 25 near Nottingham. However, due to construction work related to the smart motorway project, junctions 13 to 15 were unavailable in 2019.




Figure 7.16 The crashes' locations on the studied M1 Motorway

The traffic variables are presented in Table 7.7 with descriptive statistics of the data for the whole year of 2019 for the junction 1 to 2 as an example.

Table 7.7 Descriptive Statistics for explanatory variables

| Variable | Label | Flow | Speed | Occupancy | Headway | Speed Variance |
|---|---|---|---|---|---|---|
| Unit | Crash:1<br>Non-crash:0 | Vehicles/30 min per lane | Km/h | Vehicles/m | m | Km/h |
| Mean | 0 | 131.47 | 81.78 | 5.06 | 84.22 | 62.00 |
| | 1 | 133.75 | 87.82 | 2.97 | 96.43 | 60.67 |
| Standard Deviation | 0 | 4.56 | 14.20 | 9.78 | 20.91 | 29.62 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 19.04 | 1.96 | 0.58 | 6.71 | 21.88 |
| Max | 0 | 0.00 | 6.70 | 0.00 | 0.00 | 0.00 |
| | 1 | 112.25 | 85.56 | 2.34 | 92.08 | 35.84 |
| Min | 0 | 441.0 | 99.00 | 73.38 | 139.63 | 481.00 |
| | 1 | 148.5 | 88.98 | 3.48 | 104.16 | 77.10 |

## 7.5 Summary

This chapter details the comprehensive data collection process conducted in both China and the United Kingdom. In China, data collection encompassed several key locations: Sutong Bridge freeway, Guidu mountainous freeway, and urban city intersections in Shanghai and Suzhou. Crash data from these locations were sourced from local traffic police stations and freeway management companies.

For the UK, crash data specifically from London M1 motorway were extracted from the UK national accident database. The data collected from these locations were utilised differently based on their suitability for various prediction models.

Hourly crash prediction models were developed using data from Sutong Bridge freeway in China, while validation of model robustness was conducted using data from Guidu mountainous freeway.

Semi-hourly crash prediction models, which are more challenging due to the high requirements for specific crash records, were built and validated using data from London M1 motorway in the UK. These records are often lacking in detailed time and location information, posing common challenges for data analysis.

Traffic conflict data from freeways and urban junctions in Shanghai and Suzhou were gathered using UAV drones, with human eyes identifying conflicts. Conversely, traffic operation data from London M1 motorway was collected using inducted loop detectors. In other environments, operational data was extracted through computer vision techniques from UAV drones and roadside surveillance cameras.

Overall, the data collection procedure was intensive and spanned nearly three years to complete. This thorough approach ensured the acquisition of diverse datasets essential for developing and validating effective models for crash prediction and traffic conflict analysis in different geographic and operational contexts.

# Chapter 8 Findings: Crash and Conflict Prediction Models

Two different types of models are introduced in Chapter 5 and Chapter 6 respectively: near future crash prediction models of ZILT and TGRCN; real-time traffic conflict prediction model of the two layers stacked ensemble model. To evaluate model performances in a real application, crash data was collected at Sutong Bridge Freeway in China and London M1 Motorway in the UK, and traffic conflict data was collected at both Sutong Bridge Freeway and Shanghai urban city junctions. Hourly crash prediction performance was validated at Sutong Bridge Freeway and semi-hourly crash prediction performance was validated at London M1 Motorway. real-time traffic conflict prediction was validated at both Sutong Bridge Freeway and Shanghai urban city junctions. Modelling results, research findings, and model interpretation are discussed respectively in this chapter for both crash prediction and conflict classification. Feature importance selection algorithm is used for analysing influencing contributing factors (causal factors) affecting unsafe traffic conditions. This chapter also presents the findings on model transferrability by cross validation of applying different models in different scenarios: TGRCN model in freeway crash prediction in both London M1 Motorway and Sutong Bridge; Stacked ensemble model in freeway conflict prediction and urban junction prediction. Model improvements are also discussed in the summary part.

## 8.1 Sutong Bridge Next Hour Crash Prediction

Traffic crashes typically exhibit strong spatio-temporal correlation structures. Unlike other types of time-series data, traffic crash data is highly skewed, with most observations being zero. As a result, traditional models that rely on strict normality and homogeneity assumptions, such as ARIMA-GARCH, may not be suitable for analysing traffic data. Instead, Poisson or Negative Binomial distributions can better capture the skewed nature of traffic crash data. However, conventional Poisson or Negative Binomial count data models lack mechanisms to handle an excess of zeros. This study aims to develop a new

model—ZILT—that accommodates the temporal structure inherent in hourly crash data and addresses the issue of excessive zeros in crash counts.

ZILT is based on the zero-inflated model, featuring a degenerate distribution at zero and an untruncated count distribution for non-zeros. The model incorporates a log-linear framework based on Poisson or Negative Binomial assumptions, including a seasonal/periodicity term for the untruncated count process. It employs an Integer-valued generalised Autoregressive Conditional Heteroscedasticity (GARCH) approach, assuming that the error distribution follows Poisson or Negative Binomial to address inherent heteroscedasticity, rather than the typical Gaussian distribution associated with white noise. This innovative approach not only considers the skewness and excess zeros of traffic crash data but also integrates a time series GARCH model structure with a generalised linear regression and log-linear extension. Furthermore, it allows for the inclusion of intervention effects and state space transformations within the ZILT model.

The proposed ZILT model requires selecting either a Poisson or Negative Binomial distribution for the error term. An overdispersion test is conducted to determine if the overdispersion parameter is significant. If significant, it indicates that the mean does not equal the variance, suggesting that the Poisson distribution assumption is violated. In this case, the overdispersion test results indicated that the overdispersion parameter was statistically insignificant, meaning there is no issue with overdispersion in the data, thus favoring the Poisson regression model. The subsequent figures illustrate the procedures for the overdispersion test.

Diagnostic plots, including the autocorrelation function (ACF), Probability Integral Transform (PIT) plot, and goodness-of-fit criteria, were used to compare the fit of a Poisson conditional distribution with that of a Negative Binomial conditional distribution, as shown in Figure 8.1.

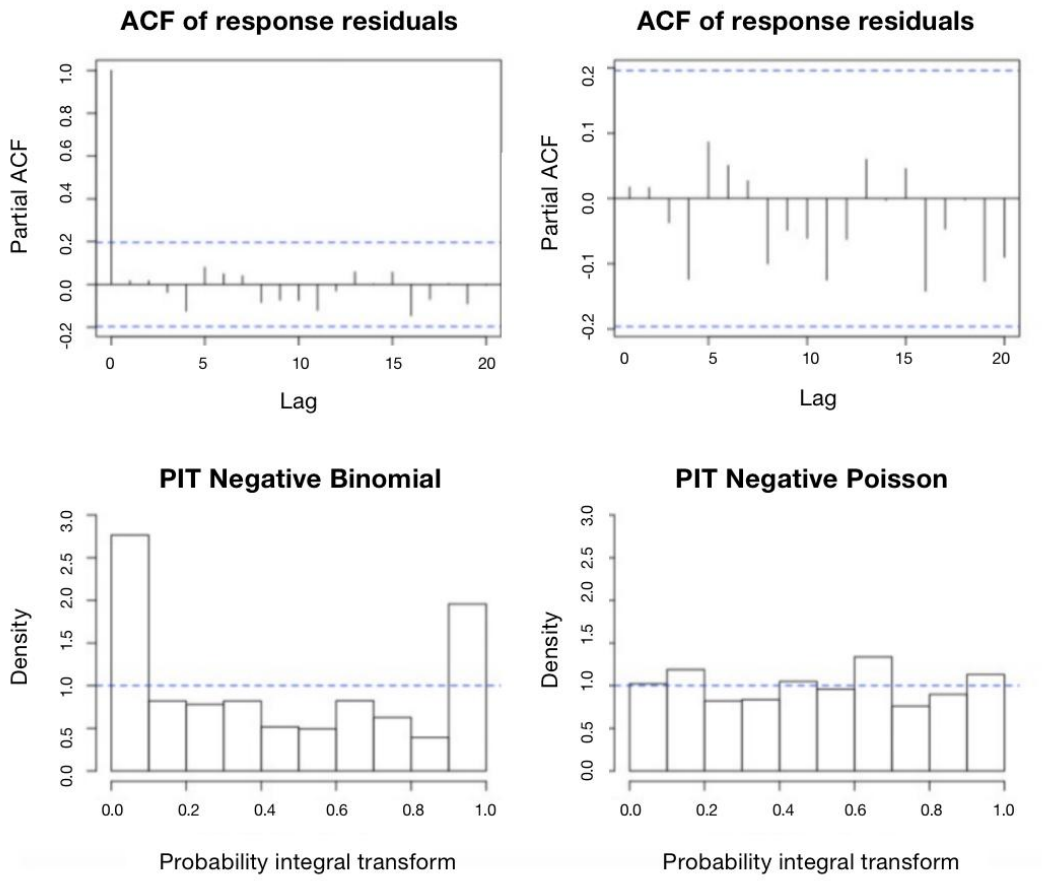



Figure 8.1 Diagnostic plots after model fitting to the traffic crash data

The ACF plot shows no signs of serial correlation or seasonality for both regression assumptions. Czado et al. (2009) proposed using a Probability Integral Transform (PIT) histogram as an effective diagnostic tool to assess dispersion. A U-shaped histogram indicates underdispersion in the predictive distribution, while a hump or inverse U-shape suggests overdispersion (Czado et al., 2009). A uniform PIT distribution shape indicates that the distributional assumptions are appropriate, while skewed histograms result from biased central tendencies (Czado et al., 2009). In the case of the PIT plot for the Negative Binomial distribution, a U-shaped histogram indicates that the Poisson distribution is better suited for model fitting, as the Negative Binomial distribution appears more uniform. Additionally, various statistical measures—such as mean logarithmic, quadratic, spherical, ranked probability, Dawid–Sebastiani, and squared error scores—were compared to determine the appropriate model dispersion level between Poisson and Negative Binomial. The model with

the lower score is favored (Czado et al., 2009). Table 8.1 indicates that the Poisson regression assumption is preferred over the Negative Binomial model.

Table 8.1 Summary Statistics for Comparison between Negative Binomial Assumption versus Poisson Assumption

| | logarithmic score | quadratic score | spherical score | ranked probability | Dawid-Sebasian i score | Squared error score |
|---|---|---|---|---|---|---|
| Negative Binomial | 2.952 | -0.072 | -0.279 | 2.099 | 4.484 | 13.85 |
| Poisson | **2.471** | **-0.106** | **-0.321** | **1.949** | **3.497** | **13.85** |

Validated by different overdispersion check tests, the Poisson assumption for the count data time series model is adopted because of the insignificant overdispersion issue within our data and the log extension of count data time series is employed to accommodate the negative effects of covariates.

Therefore, the ZILT-Poisson model was built for crash prediction. Table 8.2 shows the summary statistics for ZILT-Poisson model in each direction.

Table 8.2 Summary Statistics for Count Data Time Series in Suzhou and Nantong Direction

| Variable | Direction | Coefficient Estimates | Standard Error | Significance at 95% level |
|---|---|---|---|---|
| Intercept | Suzhou | -0.3950 | 0.1984 | |
| | Nantong | -0.7140 | 0.2573 | |
| Autoregressive order that correlated with Y(t-1)- $\beta_1$ | Suzhou | 0.6128 | 0.0739 | |
| | Nantong | 0.7527 | 0.0758 | |

| | | | | |
|---|---|---|---|---|
| Periodical autoregressive order that correlated with Y(t-24)- $\beta_{24}$ | Suzhou | 0.4994 | 0.1107 | |
| | Nantong | 0.4914 | 0.1007 | |
| Conditional Mean over the last 24 hours- $\alpha_{24}$ | Suzhou | -0.1724 | 0.0399 | |
| | Nantong | -0.2965 | 0.0367 | |
| Laneflow1 | Suzhou | 0.0004 | 0.0002 | |
| | Nantong | 0.0053 | 0.0004 | |
| Laneflow2 | Suzhou | 0.0021 | 0.0004 | |
| | Nantong | -0.0050 | 0.0005 | |
| Laneflow3 | Suzhou | -0.0028 | 0.0004 | |
| | Nantong | -0.0028 | 0.0004 | |
| Speed | Suzhou | -0.0519 | 0.0018 | |
| | Nantong | -0.0490 | 0.0018 | |
| Truck to Car ratio | Suzhou | 0.3686 | 0.0766 | |
| | Nantong | 1.1082 | 0.1114 | |
| Holiday | Suzhou | 0.0796 | 0.0860 | |
| | Nantong | 0.2749 | 0.0914 | |

$\beta_1$ , and $\beta_{24}$ refers to the previous observation from the last hour and the previous observation from the 24 hours ago, which is treated as a seasonal effect captured by the twenty-fourth order autocorrelation coefficient. $\alpha_{24}$ refers to the values of the conditional mean 24 hour back in time to accommodate the daily periodicity. Both the lagged observations and the conditional mean used in the model are statistically significant, indicating that periodicity and sequential time structure are present in crash prediction models. Furthermore, most covariates are also statistically significant, demonstrating that the current traffic conditions significantly influence the occurrence and frequency of traffic crashes.

Specifically, traffic flow is related to crash incidents, but the nature of this relationship varies across different lanes in a freeway's horizontal layout. In the inner lane, which is closer to the median, traffic flow is negatively associated with crash occurrences. In contrast, in the outer lane near the shoulder, traffic flow shows a positive correlation with crashes. This difference may be due to varying speed patterns between the inner and outer lanes and the increased interactions among vehicles in the outer lane, such as merging and exiting. Additionally, speed is negatively related to traffic crashes. The Sutong Bridge often experiences congestion, especially during crashes. High travel speeds indicate smooth traffic flow, while congestion increases the likelihood of crashes.

The truck-to-car ratio is positively correlated with hourly crash frequency; a higher ratio indicates a greater likelihood of crashes. This ratio is more strongly associated with traffic crashes in the Suzhou direction than in the Nantong direction. The holiday effect significantly influences crash rates in the Nantong direction but not in Suzhou. Weather effects were not found to be significant and were therefore excluded from the final model, likely because weather data is recorded daily, while the prediction model relies on hourly observations.

The prediction model is rolling-based, and the following displays show the daily aggregated actual and predicted crash numbers for both directions.

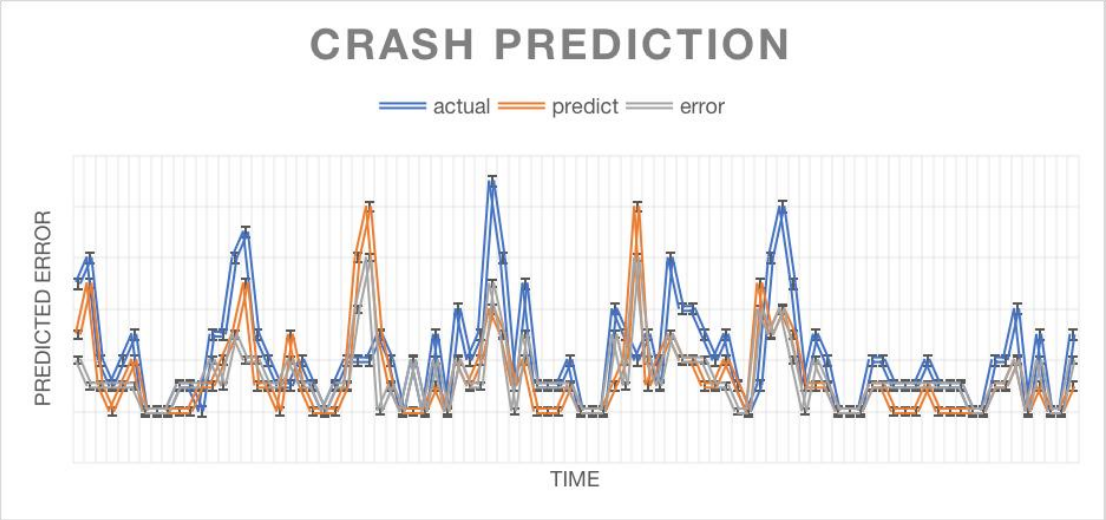



Figure 8.2 Actual traffic crash data vs. Predicted values

Comparison of Performances: ZIP, Hurdle models and ZILT

Overall performances of ZIP, hurdle model, and the ZILT are evaluated by goodness-of-fit statistics: RMSE and MAE. Threshold values for the logistic regression part in the developed ZILT are selected based on the ideology that maximizes both RMSE and MAE. The formula and details of RMSE and MAE are described in Chapter 6 (section 6.1.1). The performance metrics for each model are calculated based on the test dataset and presented in Table 8.3.

Table 8.3. Model Performance Evaluation

| Directions | Model | MAE | RMSE | MAPE | MASE | Pseudo-R-square |
|---|---|---|---|---|---|---|
| **Suzhou** | Hurdle | 0.285 | 0.793 | 1.349 | 2.443 | 0.9% |
| | ZIP | 0.198 | 0.554 | 10.701 | 1.532 | 4.7% |
| | ZILT | **0.068** | **0.320** | **0.906** | **0.584** | **10.2%** |
| **Nantong** | Hurdle | 0.117 | 0.266 | 1.566 | 1.152 | 7.4% |
| | ZIP | 0.105 | 0.263 | 15.5603 | 1.039 | 9.3% |
| | ZILT | **0.058** | **0.279** | **0.904** | **0.572** | **12.5%** |

The MAEs calculated for test data in both directions using the ZILT model are significantly lower than those obtained with the ZIP and Hurdle models. Furthermore, for the hourly crash prediction model in the Suzhou direction, the ZILT model demonstrates a substantially lower RMSE compared to both the ZIP and Hurdle models. Since RMSE and MAE are indicators of prediction errors, the ZILT model clearly outperforms the ZIP and Hurdle models by achieving notably reduced prediction errors. This exceptional performance may stem from the ZILT model's ability to incorporate the temporal spatial structure present in the data, which the ZIP and Hurdle models do not adequately address. As indicated in the previous section, factors like prior observations and their conditional means are statistically significant in hourly traffic crash predictions, suggesting that these variables are crucial to the prediction process. Consequently, the ZIP and Hurdle models may be less suitable due to their limited

capacity to integrate important temporal spatial structures. Our experimental results further confirm that their inability to account for these structures results in higher prediction errors compared to the ZILT model.

Additionally, findings from the log-linear INGARCH model, which is part of the ZILT prediction framework, show that the number of past traffic crashes influences both the occurrence and frequency of future crashes. Therefore, incorporating such temporal autoregressive characteristics in traffic crash data is essential. The ZILT model not only addresses the problem of excessive zeros typically encountered by ZIP and Hurdle models but also captures seasonal patterns by defining time order as tuning parameters. Our analysis supports the expectation that ZILT achieves greater accuracy than both ZIP and Hurdle models. Moreover, covariates such as speed, vehicle types, and traffic volumes were included in the analysis, with their significance indicating a relationship between traffic parameterss and crash predictions.

The ZILT model is particularly useful for traffic crash prediction, especially in scenarios characterized by excessive zeros and heterogeneity that often arise in short time span predictions. While conventional time series methods like seasonal ARIMA and GARCH are applicable for long-term crash predictions, they are unsuitable for short-term predictions due to differing distributional assumptions. Additionally, the ZILT model can be adapted to other contexts such as signal processing and econometrics, where similar count data processes and excessive zeros occur, extending its applicability beyond traffic crash analysis. The ZILT model has been developed using R version 3.7 with packages such as tscount, pscl, zip, and ModelMetrics, and it can also be replicated in Python and Matlab.

However, there are limitations to our analysis. The traffic data examined in this study are confined to the Sutong Yangtze River Bridge in China. Expanding the dataset to include nearby geographical areas, such as intersections and ramps, could enhance the spatial considerations in crash analysis. Furthermore, while deep learning methods like Long Short-Term Memory (LSTM) are gaining popularity in traffic crash prediction, this thesis

does not include comparisons between these methods and ZILT. Future research could explore such comparisons.

Moreover, incorporating a state space structure into the ZILT model could provide an alternative approach to modeling count time series data, offering greater flexibility in the data generation process. Given that the newly developed ZILT model effectively addresses issues of excessive zeros while simultaneously incorporating time series structures, its application potential extends well beyond traffic crash prediction. There is significant promise for ZILT to be utilised in other fields, such as public health and medicine, to tackle excessive zeros in dependent variables while also integrating time series structures in the data.

## 8.2 Half-hourly Crash Prediction Model: M1 Motorway (England)

In data pre-processing, it was discovered that a fraction of approximately 0.5% of the traffic data was missing. To address this, the MissForest R package was utilised to fill in the missing data, considering the presence of mixed data types. MissForest employs an iterative non-parametric imputation technique based on random forest ensemble learning as described by Stekhove et al. (2012). The random forest method imputes missing values by taking the average over numerous unpruned classifications or regression trees, and employs the built-in out-of-bag error to estimate the imputation errors. To assess the suitability of applying random forest imputation for missing values in the dataset, 1% of the known values in the train set were intentionally generated as "NA" (missing). Subsequently, random forest was employed to impute the true values for the artificially generated missing values. The imputation accuracy is shown in Table 8.4.

Table 8.4 Imputation accuracy for missing values in validation

| Average | Flow | Speed | Speed Variance | Occupancy | Headway |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| Actual | 262.0 | 85.8 | 7.69 | 68.17 | 74.25 |
| Predicted | 259.3 | 83.8 | 6.59 | 70.21 | 76.55 |

As shown in Table 8.4, we observe that the average of the imputed values closely aligns with the average of the actual values in the training set. Based on this observation, it is reasonable to utilise random forest imputation techniques to address the missing values present in the test set, given that the proportion of missing values is relatively low.

Prior to building crash prediction model, spatial and temporal correlation analysis was conducted to segment based data. the south direction encompasses junctions 1 to 12 and the north direction encompasses junctions 15 to 28. There are 17520 observations of the number of crashes within 30 minutes, which is equivalent to 365 days in one year. The dataset is panel data, consisting of traffic data with observation at consecutive time stamps in different road segments. The distribution of traffic data among different segments represents their spatial correlation. The distribution of traffic data along time stamps all over the year represents its temporal correlation.

The following plots show the spatial correlation of different traffic parameterss among different segments in the north direction.

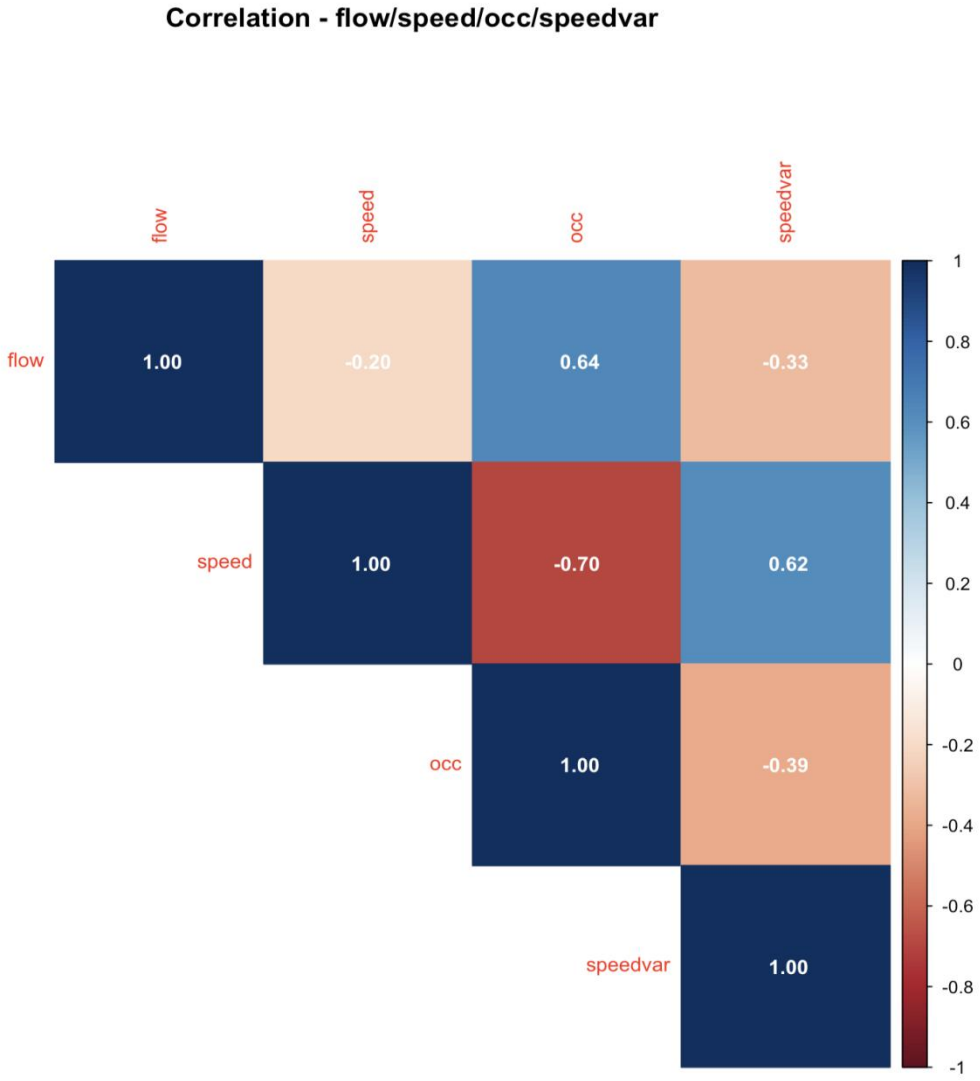



Figure 8.3. Correlation among different traffic operation parameters

It is can be seen from the pot that lane occupancy is highly correlated with traffic flow and speed variance is also correlated with speed.

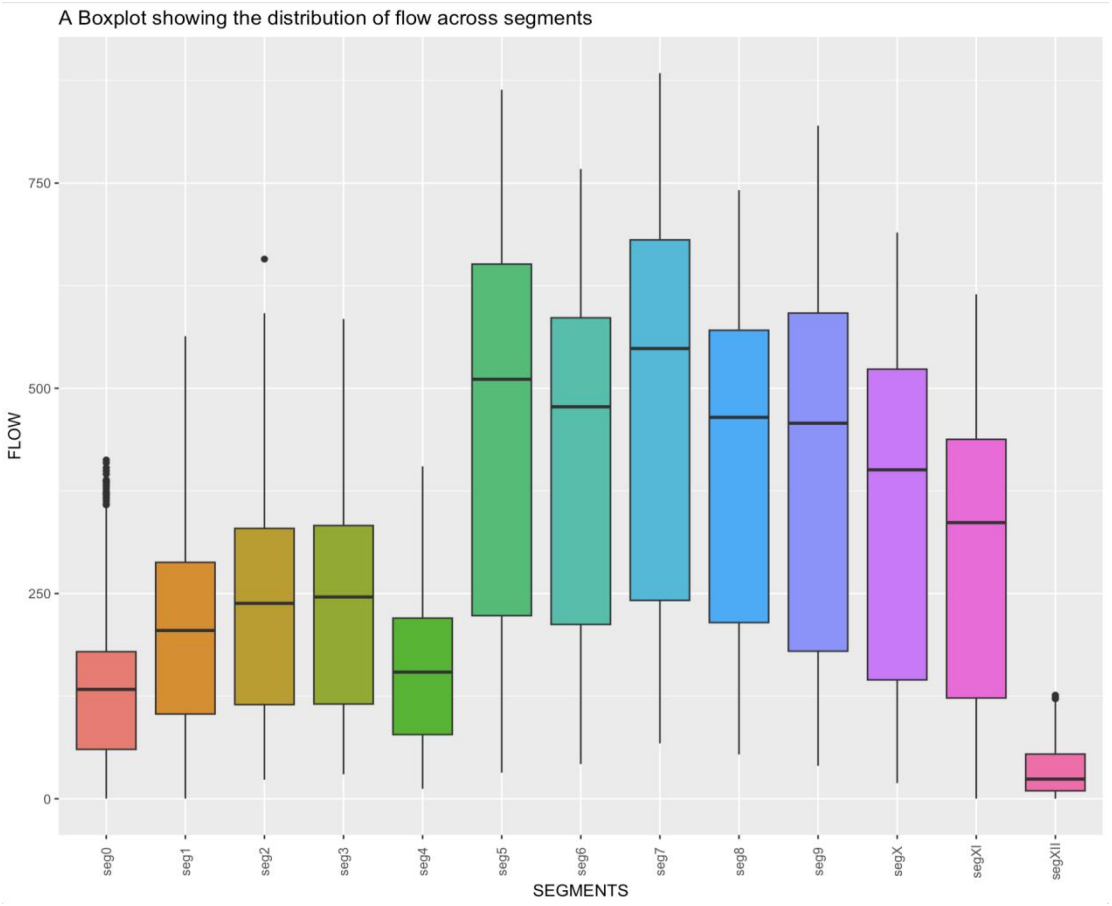



Figure 8.4. Boxplot showing the distribution of flow across segments

It can be seen that spatial correlation is significant among segment 0 to segment 4, and is also prominent among segment 5 to segment 11. However, no correlation is detected among road section of segment 0 to segment 4, road section of segment 5 to segment 11, and segment 12.

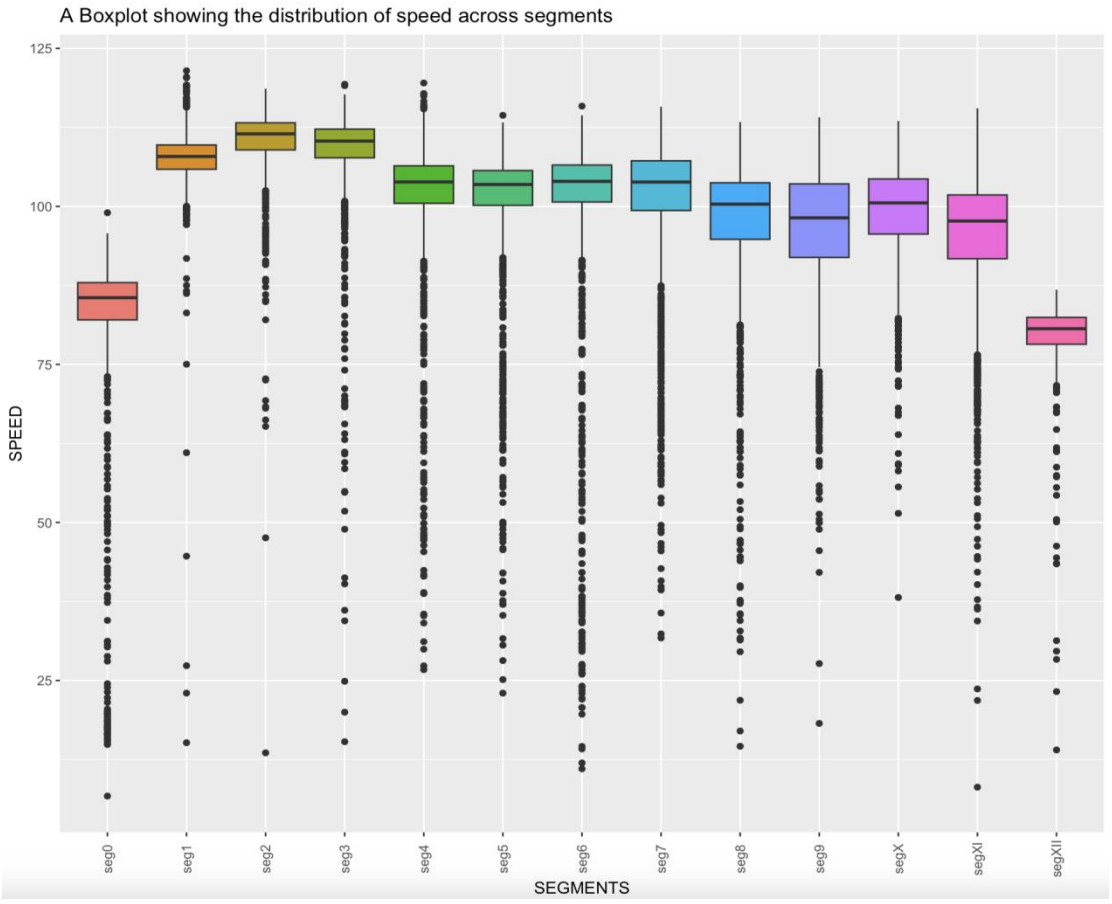



Figure 8.5. Boxplot showing the distribution of speed across segments

It can be seen that spatial correlation is significant among segment 1 to segment 3, and is also prominent among segment 4 to segment 11. However, no correlation is detected among segment 0, road section of segment 1 to segment 11, and segment 12.

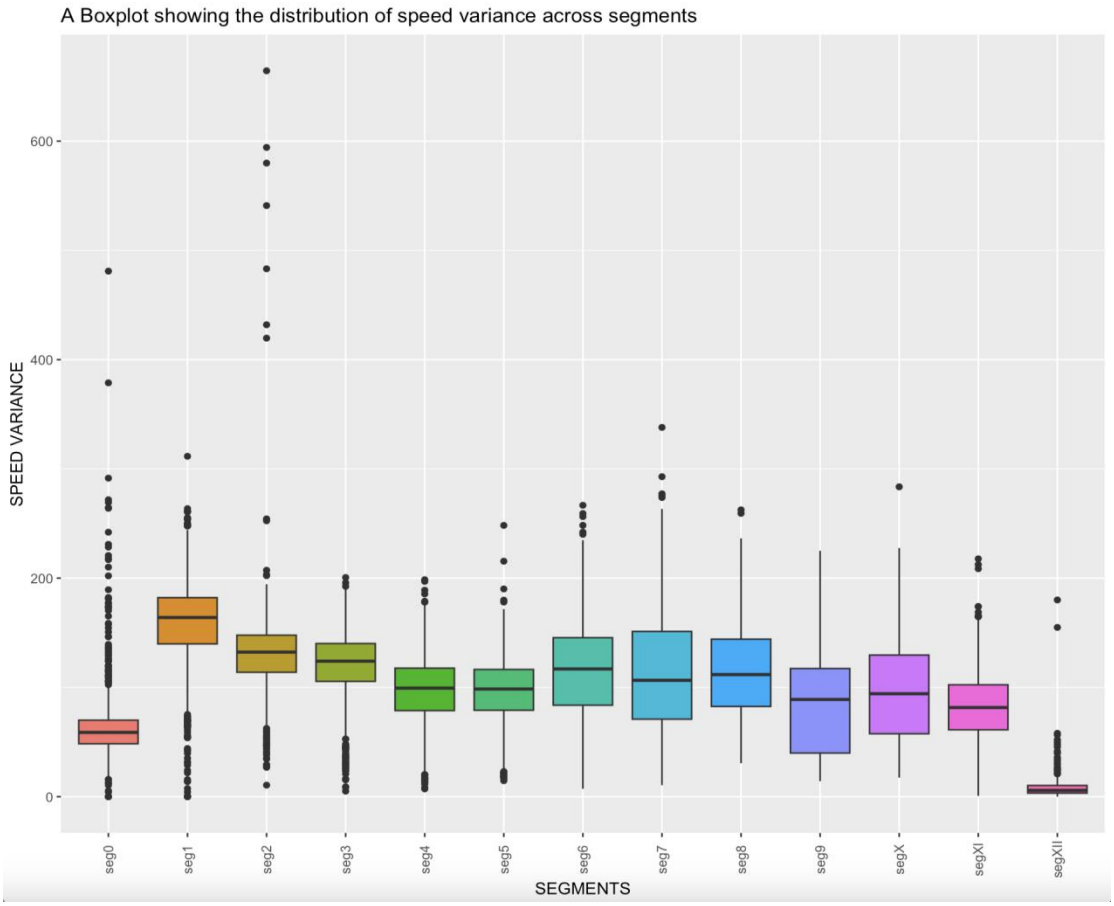



Figure 8.6. Boxplot showing the distribution of speed variance across segments

It can be seen that spatial correlation is significant between segment 2 to segment 11. However, no correlation is detected among road sections of segment 0, segment 1, road section of segment 2 to segment 11, and segment 12.

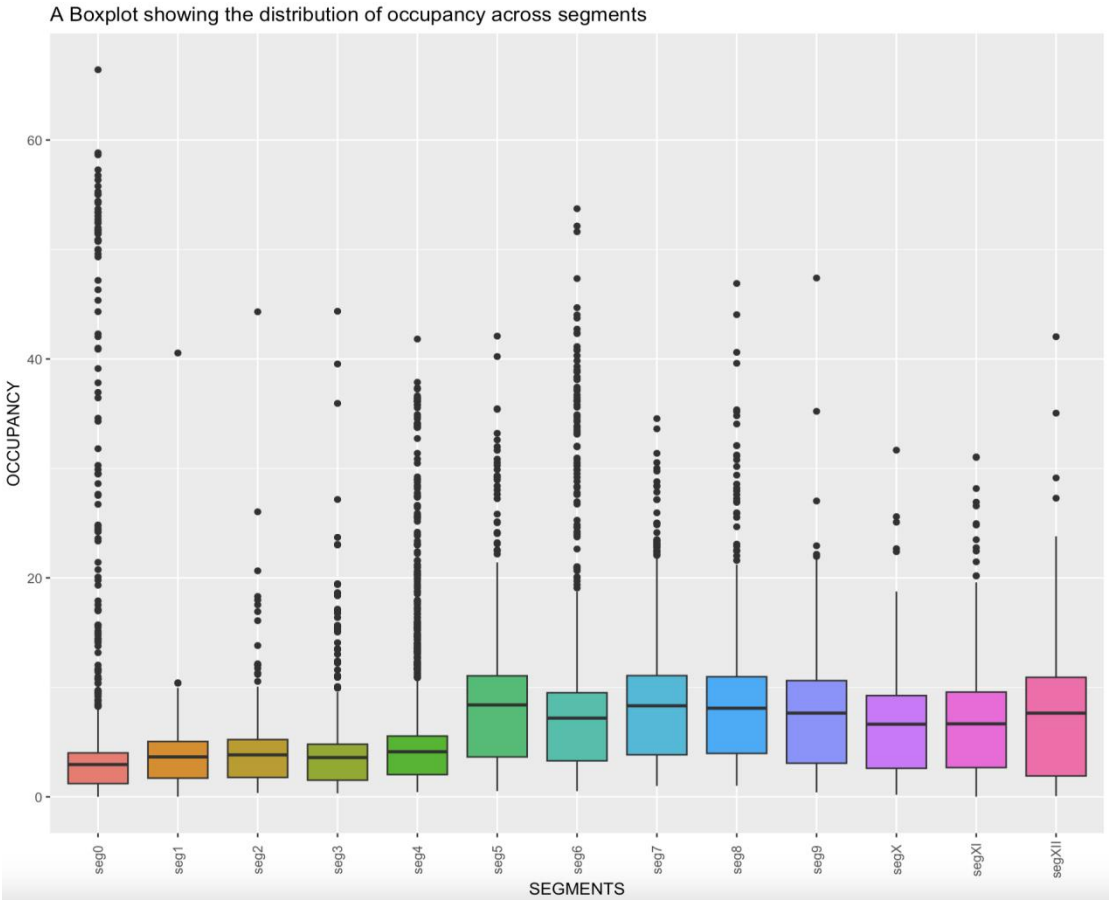



Figure 8.7. Boxplot showing the distribution of lane occupancy across segments

It can be seen that spatial correlation is significant among segment 1 to segment 3, and is also prominent among segment 4 to segment 11. However, no correlation is detected among segment 0, road section of segment 1 to segment 11, and segment 12.

The following plots show the spatial correlation of different traffic parameterss among different segments in the south direction.

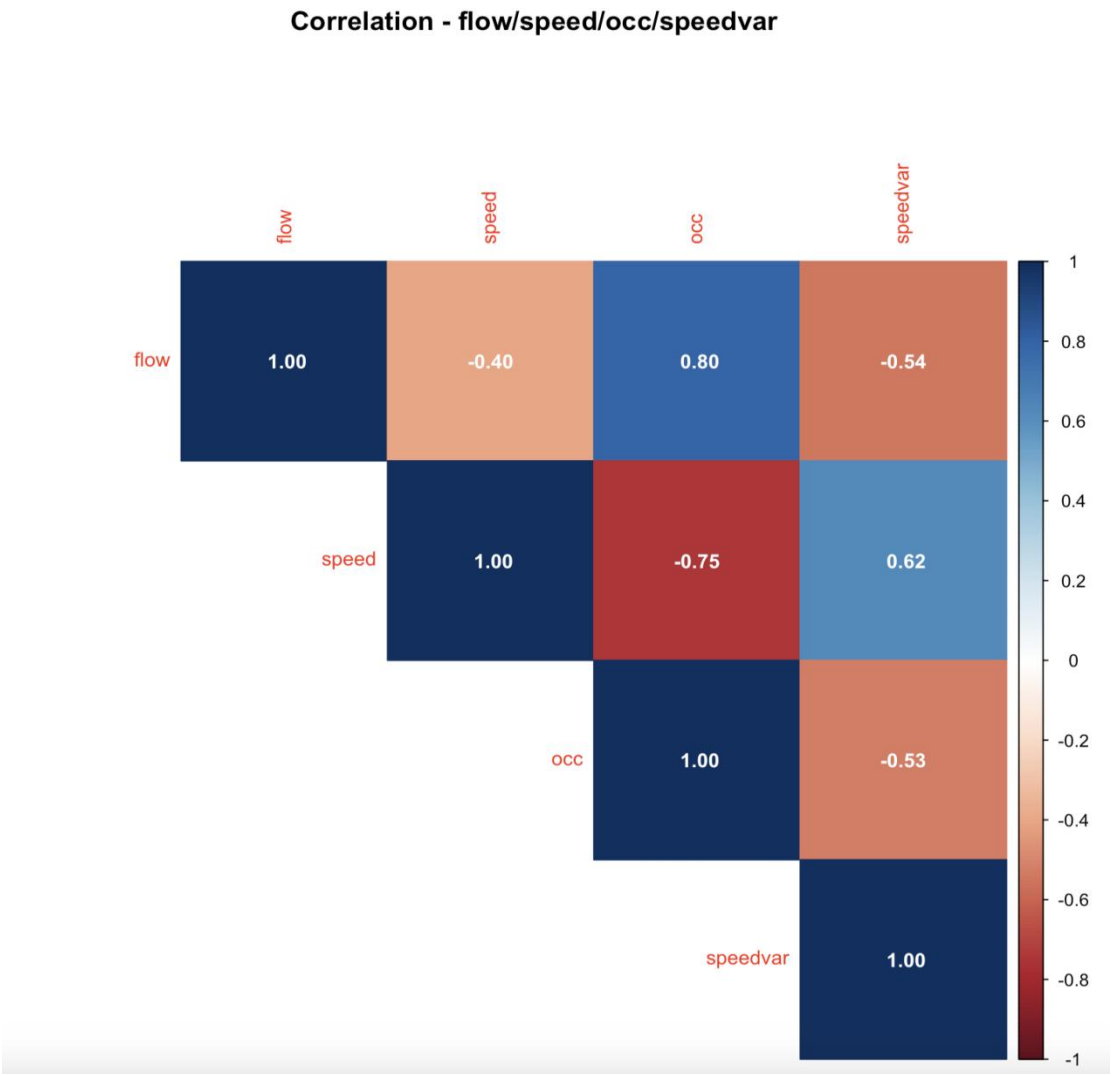



Figure 8.8 The correlation of explainatory variables

Similar to the variable correlation plot in the north direction, it can be seen that lane occuapncy is highly correlated to traffic volume and speed variance is also correlated with speed.

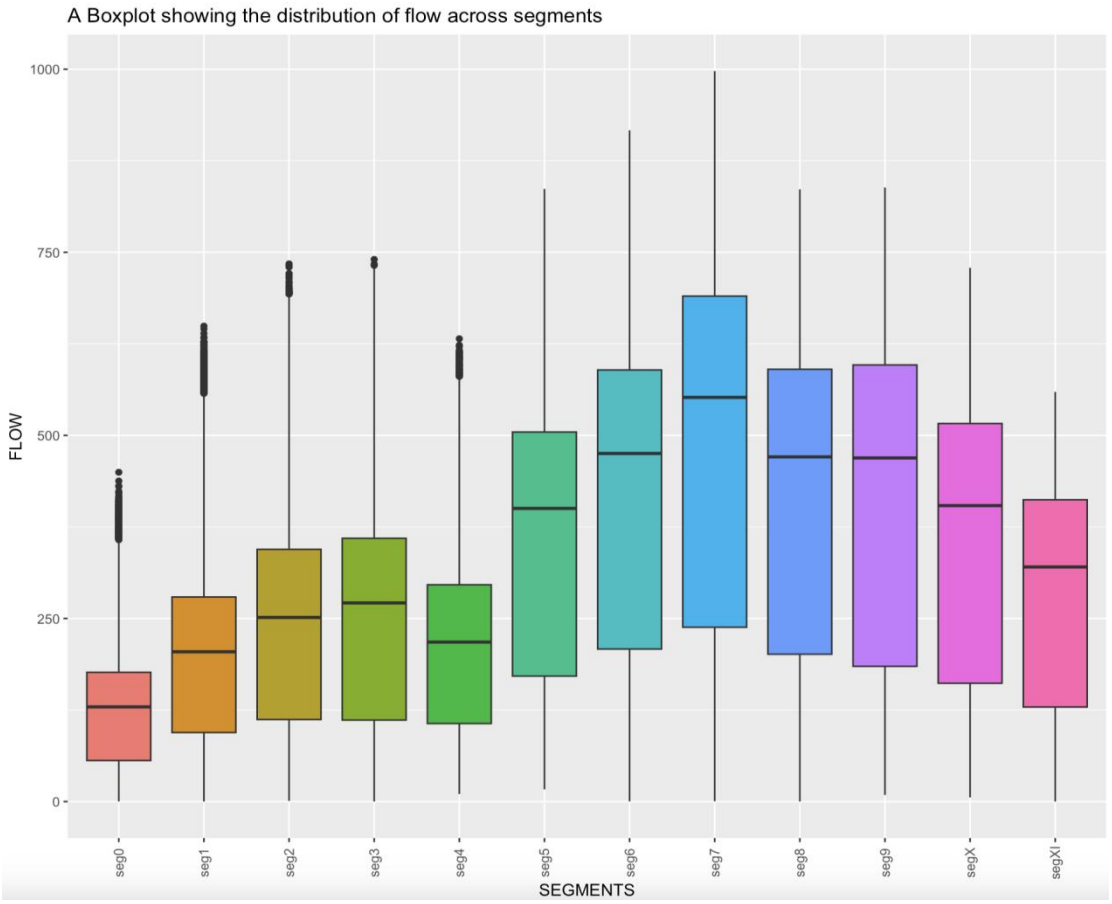



Figure 8.9. Boxplot showing the distribution of flow across segments

It can be seen that spatial correlation is significant among segment 0 to segment 4, and is also prominent among segment 5 to segment 11. However, no correlation is detected between road section of segment 0 to segment 4, and segment 5 to segment 11.

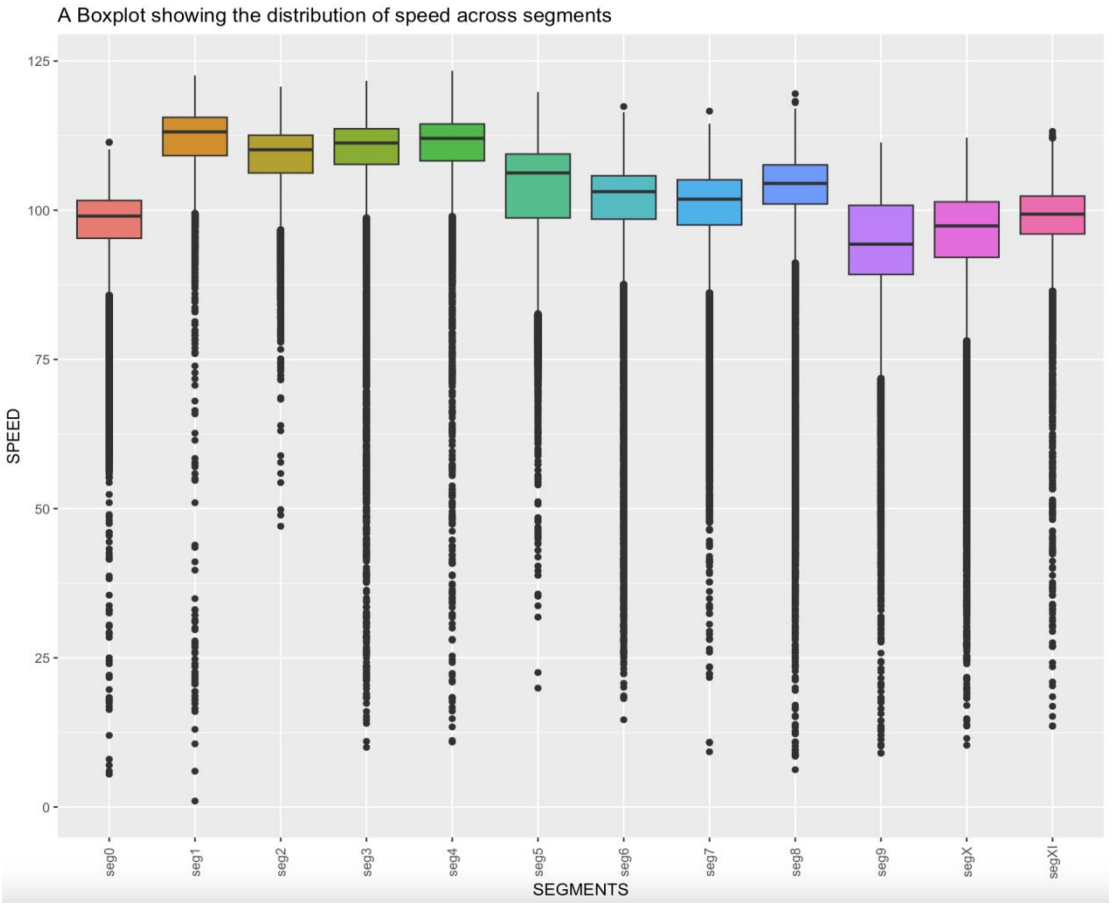



Figure 8.10. Boxplot showing the distribution of speed across segments.

It can be seen that spatial correlation is significant among segment 1 to segment 4. Similarly, correlation is also prominent among segment 5 to segment 8, and among segment 9 to segment 11 as well. However, no correlation is detected among segment 0, road section of segment 1 to segment 4, road section of segment 5 to segment 8, and segment 9 to segment 11.

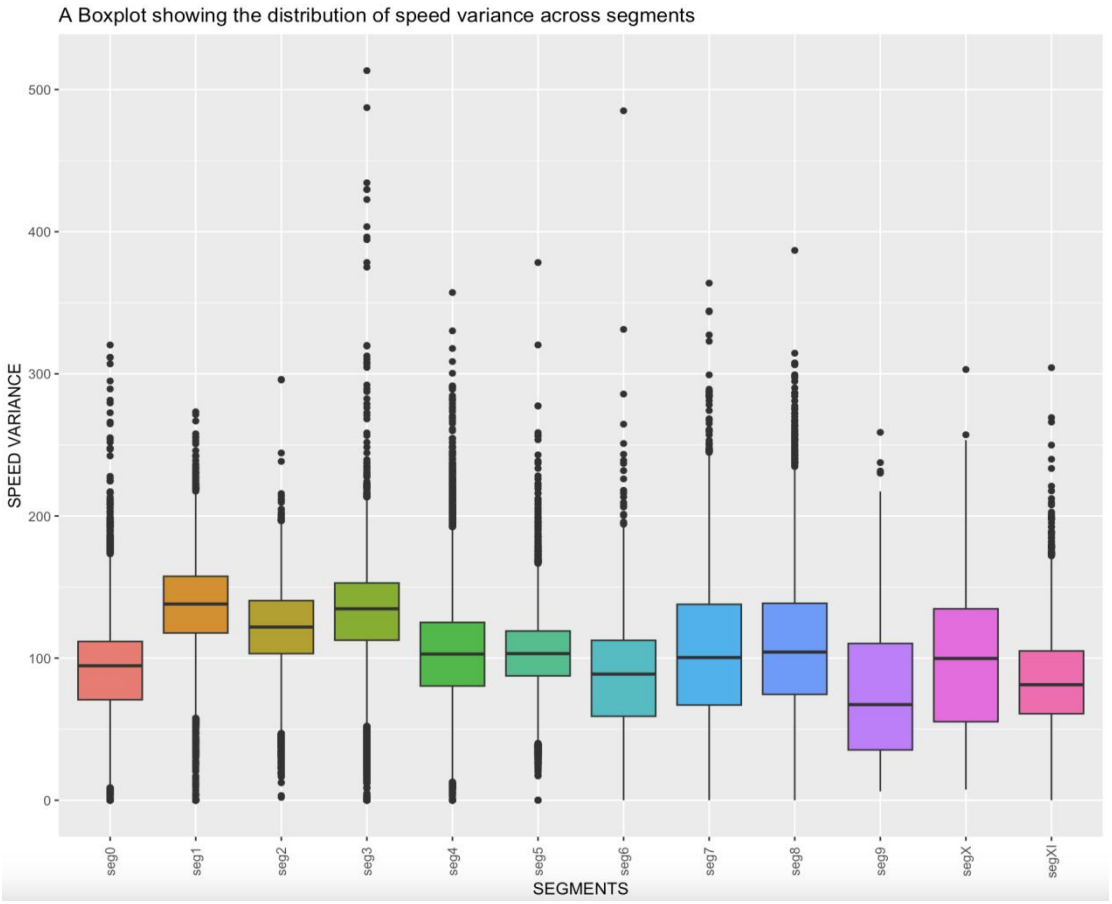



Figure 8.11. Boxplot showing the distribution of speed variance across segments.

It can be seen that spatial correlation is significant among segment 1 to segment 3, segment 4 to segment 8, and is also prominent among segment 9 to segment 11. However, no correlation is detected segment 0 and others.

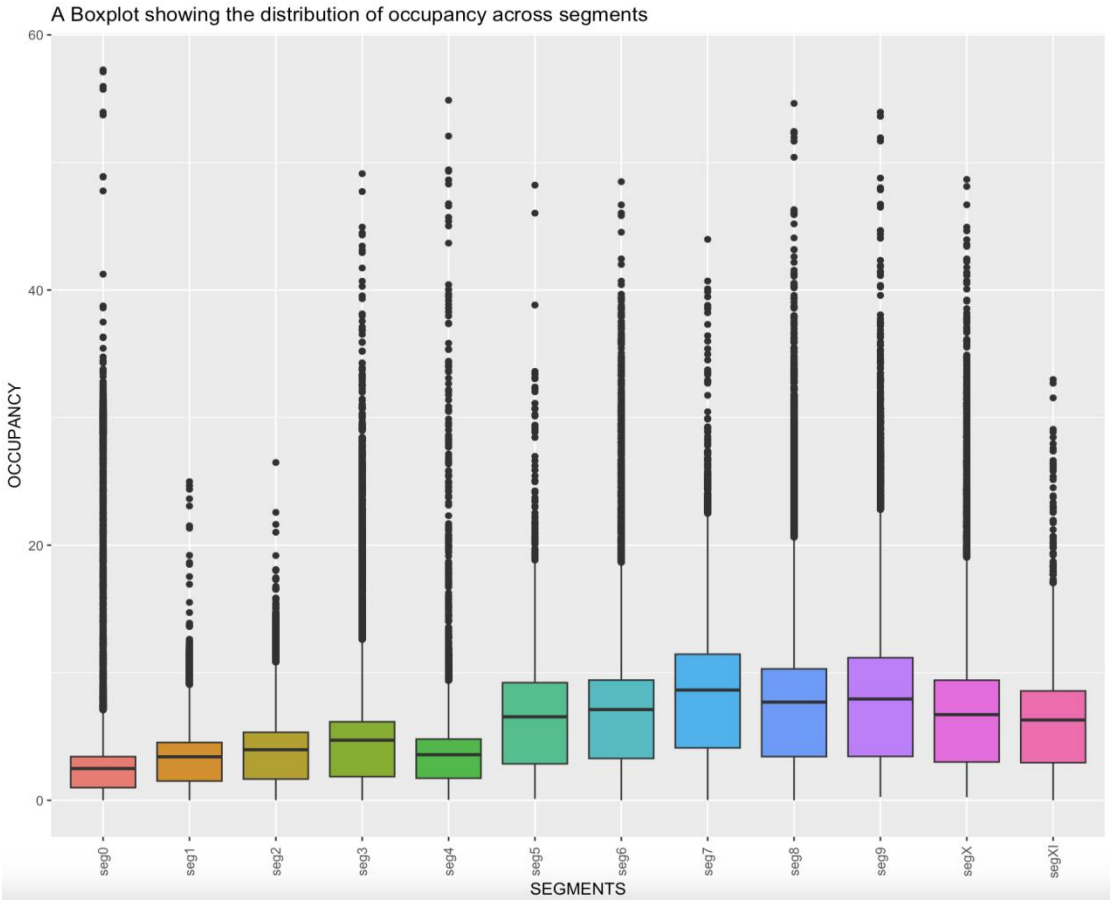



Figure 8.12 Boxplot showing the distribution of occupancy across segments

It can be seen that spatial correlation is significant among segment 0 to segment 4, and is also prominent among segment 5 to segment 11. However, no correlation is detected between road section of segment 0 to segment 4 and road section of segment 5 to segment 11.

The following plots show the temporal analysis in the north direction by analysing dynamic changes of different traffic parameters among consecutive time stamps all over the year. Because there are too many observations, loess smoothing technique was applied to smooth time series to make it clearer to visualize.

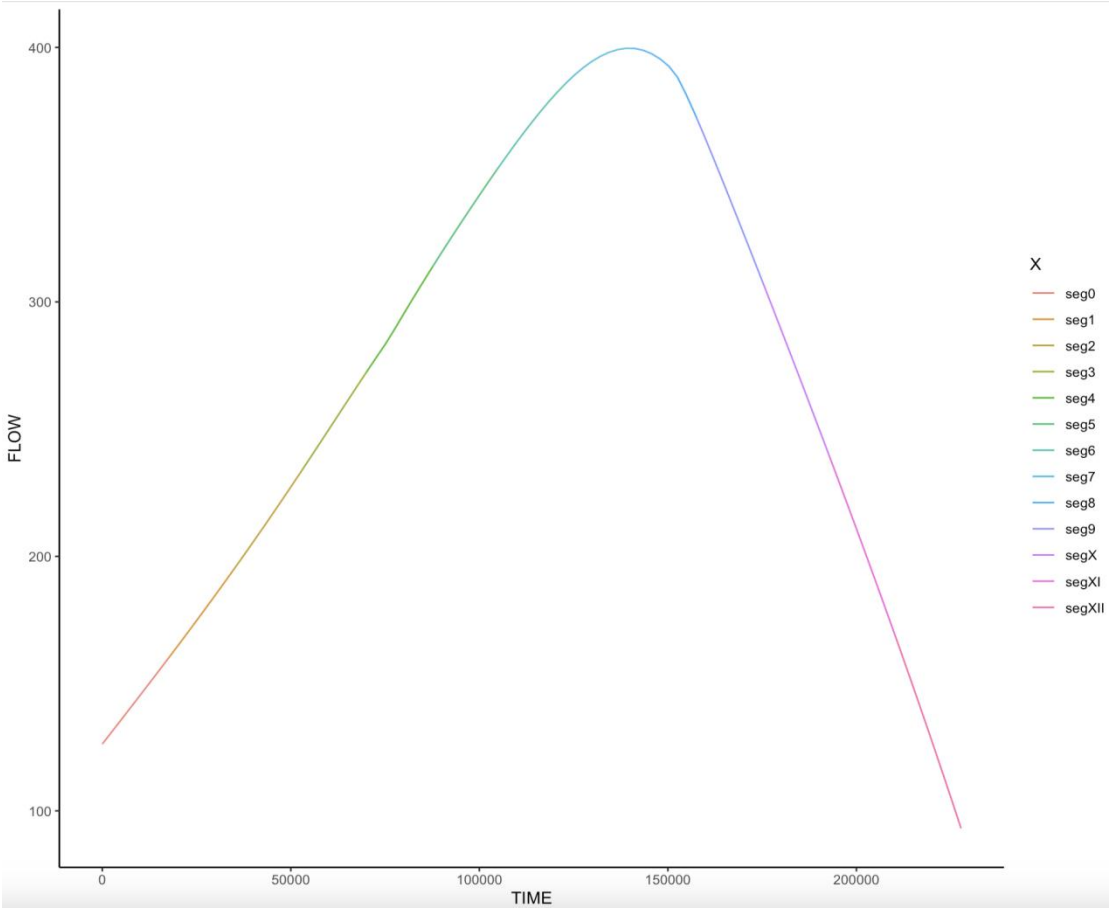



Figure 8.13 Traffic flow vs. Time in the north direction

It can be seen that traffic flow keeps increasing in the period of January to July. However, it starts to drop down since August.

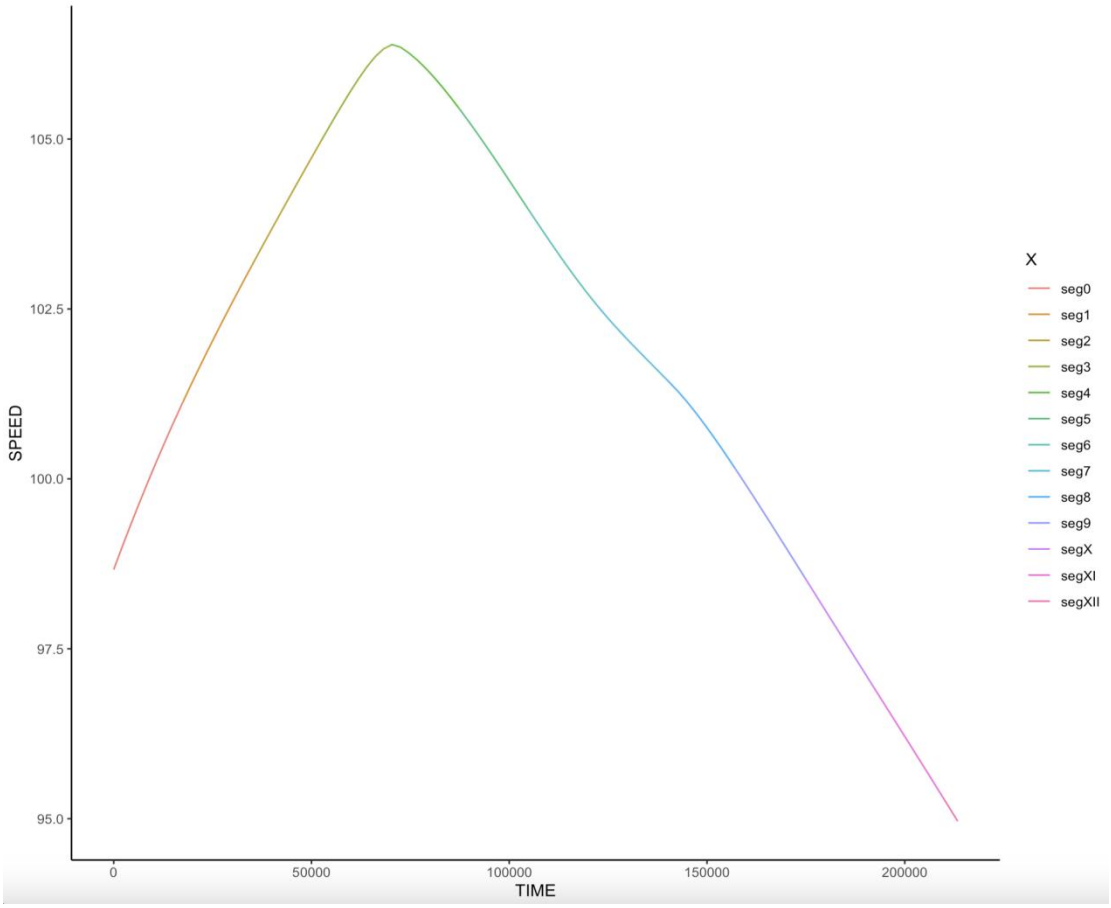



Figure 8.14. Speed vs. Time in the north direction

It can be seen that speed keeps increasing in the period of January to April. However, it starts to drop down since May.

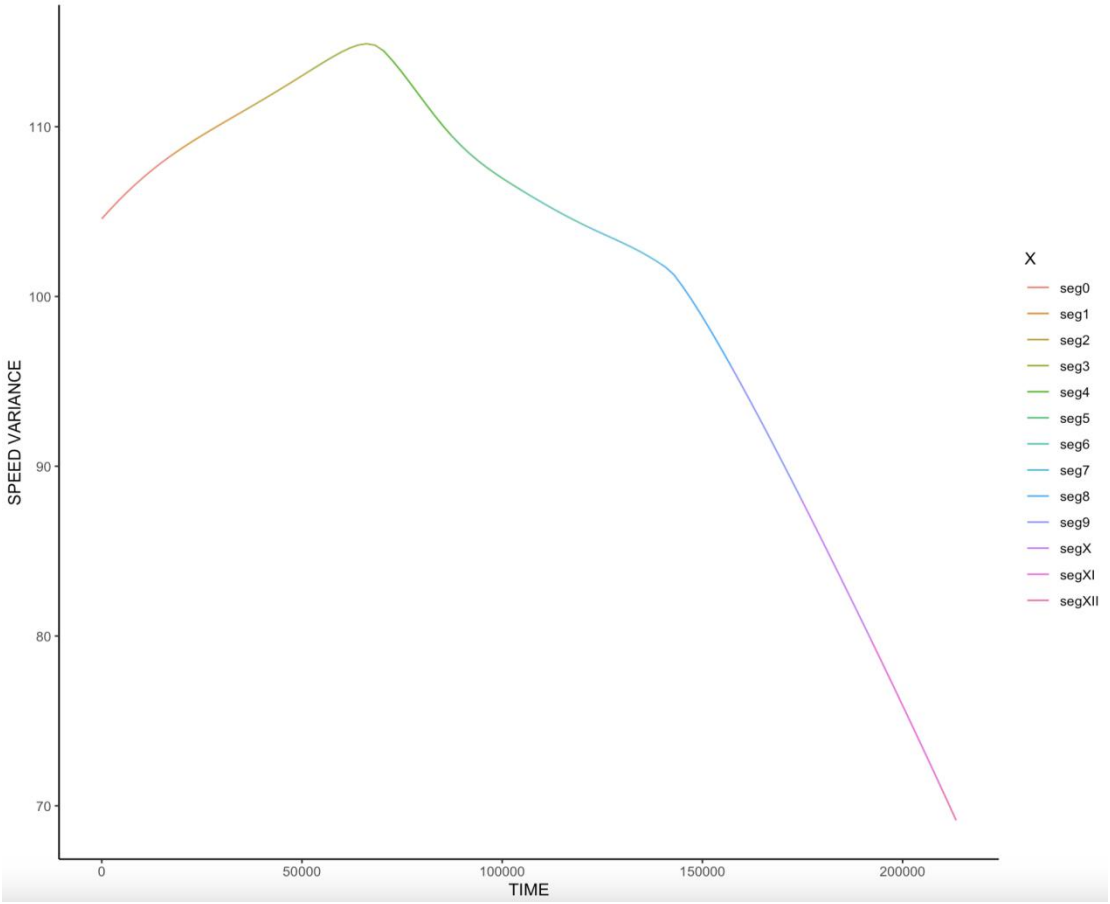



Figure 8.15 Speed variance vs. Time in the north direction

It can be seen that speed variance keeps increasing in the period of January to March. However, it starts to drop down since April.

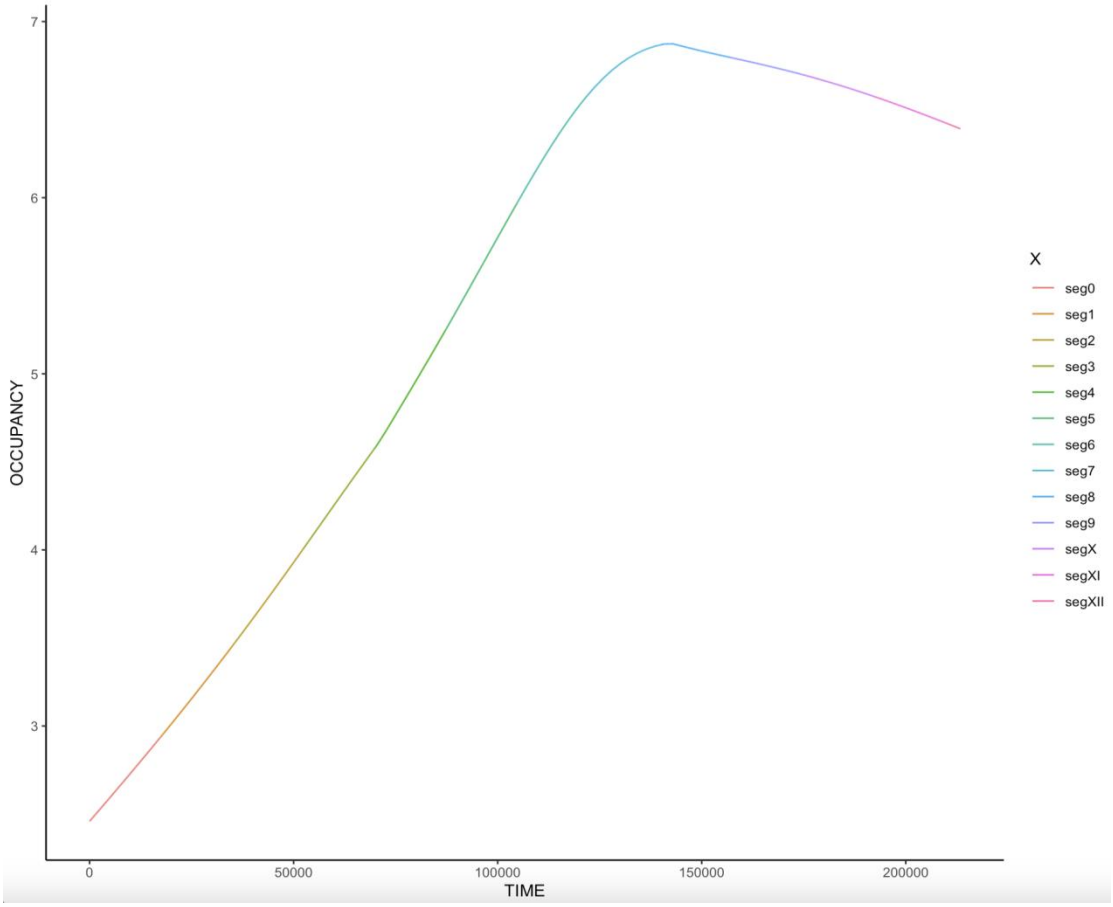



Figure 8.16 Occupancy vs. Time in the north direction

It can be seen that lane occupancy keeps increasing in the period of January to September. However, it starts to drop down after it reaches its peak in October.

The following plots show the temporal analysis in the south direction by analysing dynamic changes of different traffic parameters among consecutive time stamps all over the year.

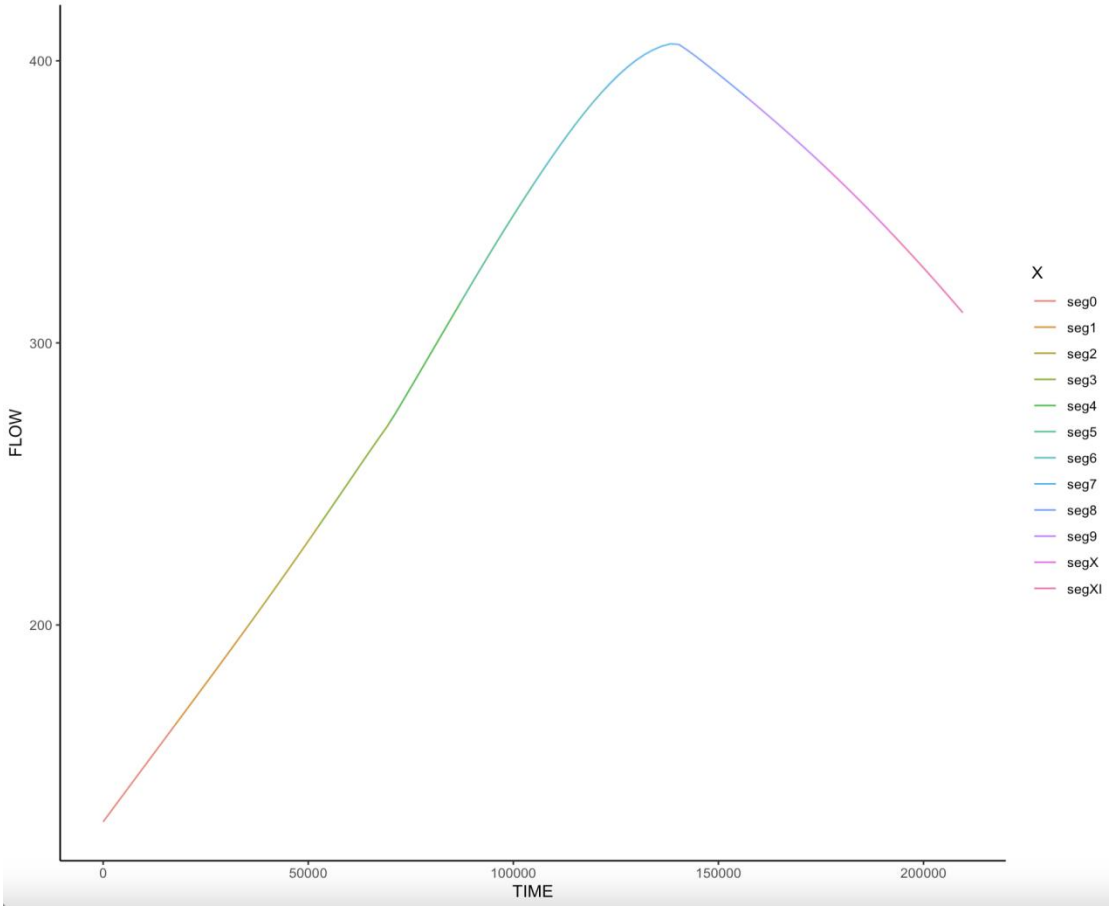



Figure 8.17 Flow vs. Time in the south direction

It can be seen that traffic flow keeps increasing in the period of January to September. However, it starts to drop down after it reaches its peak in October.

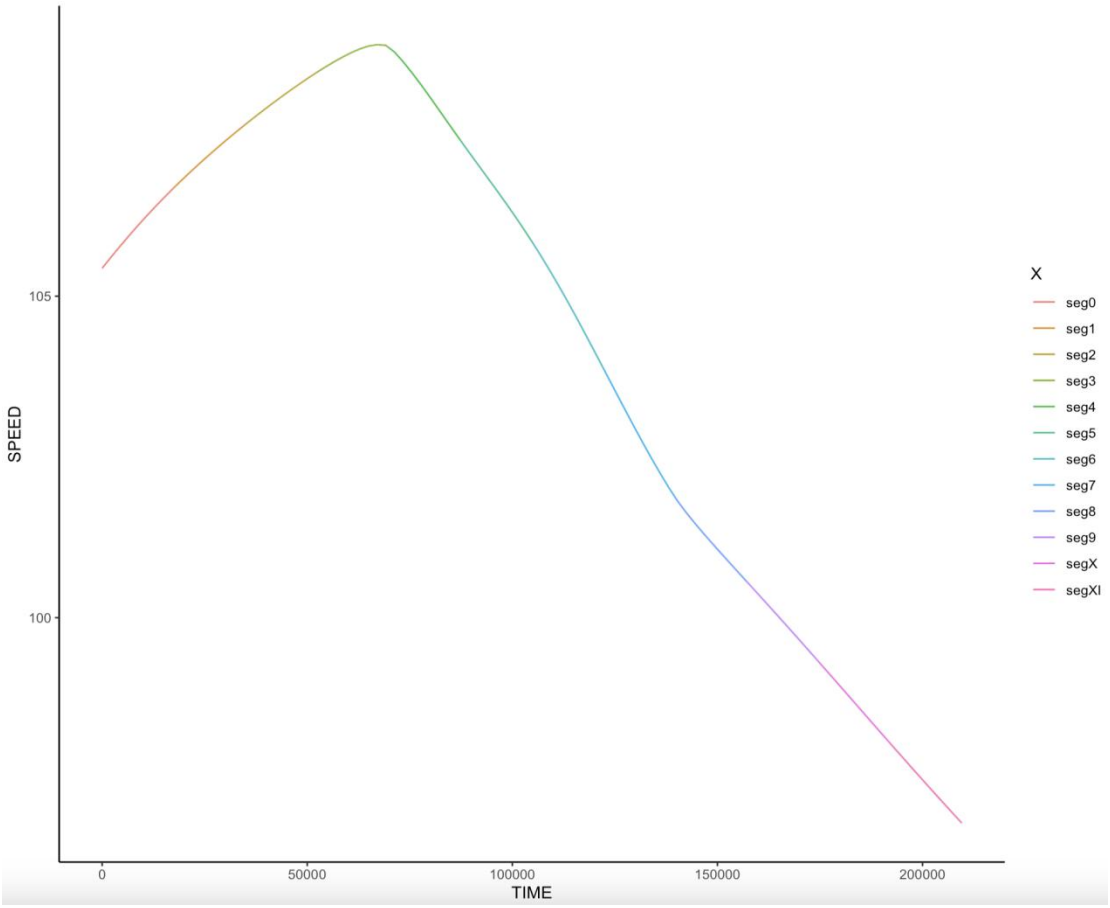



Figure 8.18 Speed vs. Time in the south direction

It can be seen that traffic speed keeps increasing in the period of January to March. However, it starts to drop down after it reaches its peak in April.

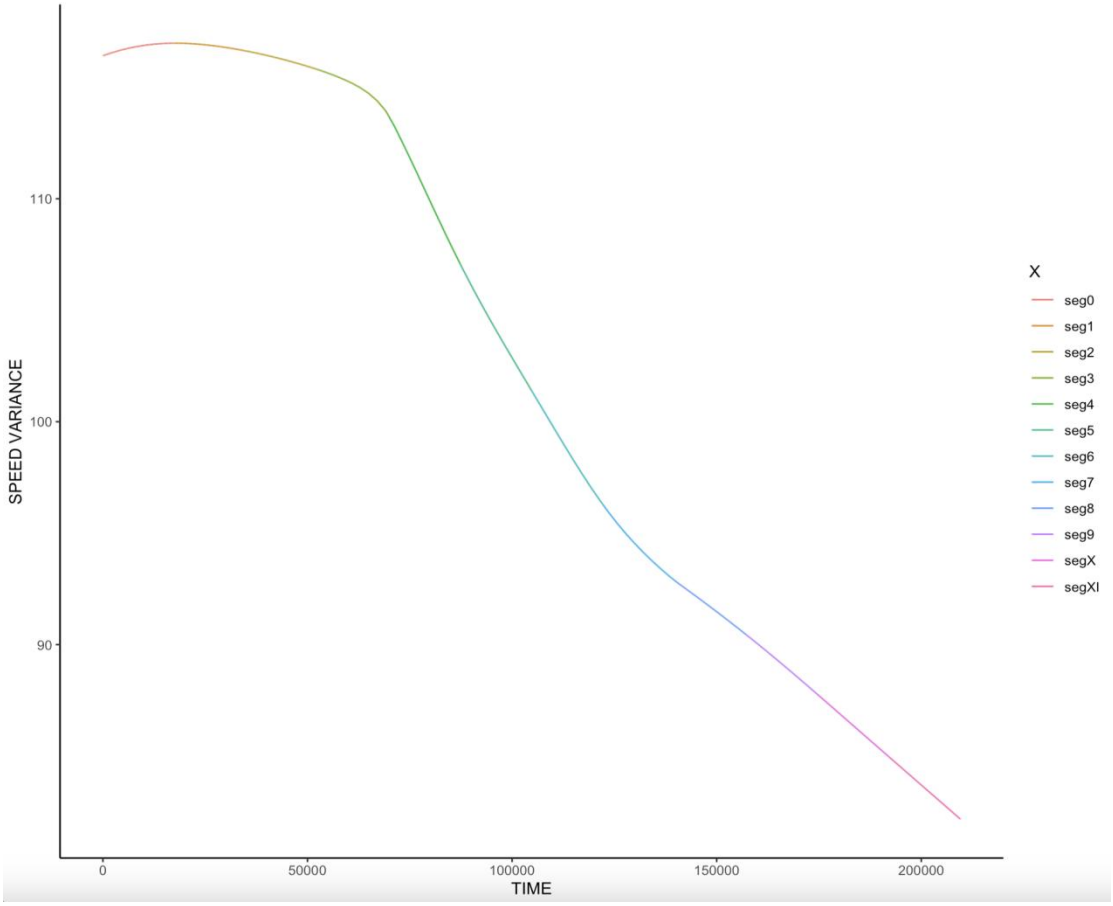



Figure 8.19 Speed variance vs. Time in the south direction

It can be seen that speed variance keeps decreasing in the beginning and all the way to end of the year.

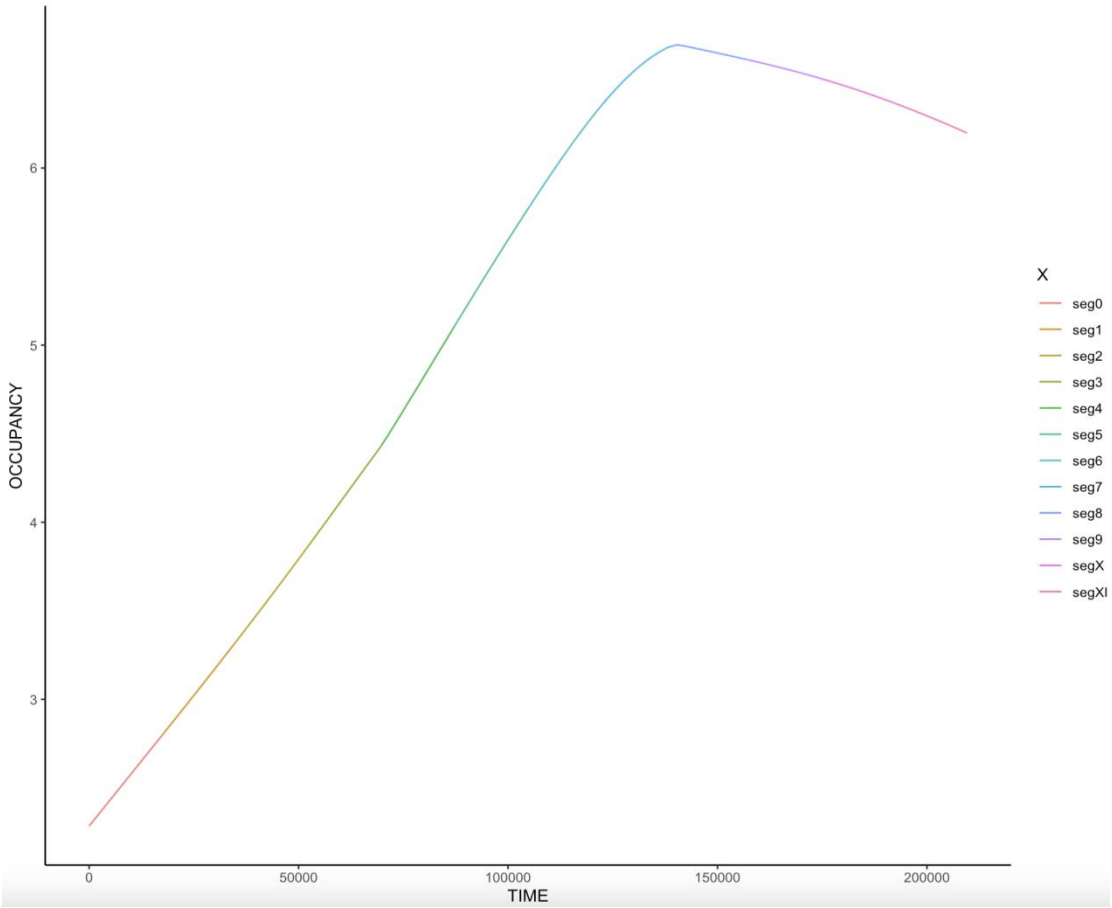



Figure 8.20 Occupancy vs. Time in the south direction

It can be seen that lane occupancy keeps increasing in the period of January to September. However, it starts to drop down after it reaches its peak in October.

For the purpose of stabilising the prediction model, half a year's worth of data was used as the training dataset. To fine-tune the model parameters during the fitting process, three months of data were designated as the validation dataset. The remaining three months of data were set aside as the test dataset to evaluate the actual prediction accuracy. As discussed earlier, the TSGRNN model was applied to make prediction of dynamic traffic variables at a rolling base of 30 minutes from time t-1 to time t. Tuning parameters of autocorrelation lags and weights were trained by the TSGRNN model by fitting a regression model with the training dataset. In the validation set, smoothing and centre parameters that control autocorrelation and seasonality in TSGRNN were fine tuned for optimization. In the testing dataset, the tuned parameters were fixed at the optimal values to make prediction of traffic variables in the next half hour.

Initially, a WCNN model was trained on an oversampled training dataset generated by employing the Synthetic Minority Over-sampling Technique (SMOTE) method to training dataset. The purpose was to create a robust classifier capable of handling the extreme class imbalance in the data. Subsequently, the trained model was validated using a three-month validation set. This validation dataset consisted of predicted dynamic traffic data obtained from the TSGRNN which served as input variables for the weighted convolutional neural network. The validation process aimed to assess the generalizability and prediction accuracy of the model and fine-tune the initial weights for both class and non-class events. TGRCN model was built to make crash occurrence prediction in the following thirty minute time window in the unseen test set. Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV) and Accuracy are selected as measuring criteria as employed in Formosa et al. (2023). The results are presented in Table 8.5.

Table 8.5 Prediction accuracy comparison for TGRCN and other predictive models for the northbound and the southbound data of M1 Motorway, UK.

| Method | Direction | Metrics employed to compare the predictive performance | | | | |
|---|---|---|---|---|---|---|
| | | Sensitivity | Specificity | PPV | NPV | Accuracy |
| STGCN | the north | 0.351 | 0.944 | 0.863 | 0.589 | 0.644 |
| | the south | 0.292 | 0.958 | 0.874 | 0.572 | 0.622 |
| MLP | the north | 0.086 | 0.972 | 0.754 | 0.532 | 0.529 |
| | the south | 0.078 | 0.935 | 0.545 | 0.504 | 0.507 |
| LSTM | the north | 0.382 | 0.862 | 0.735 | 0.582 | 0.622 |
| | the south | 0.366 | 0.881 | 0.755 | 0.582 | 0.624 |
| GARCH | the north | 0.252 | 0.956 | 0.852 | 0.561 | 0.5 |
| | the south | 0.233 | 0.964 | 0.867 | 0.557 | 0.599 |
| ARIMA | the north | 0.121 | 0.97 | 0.801 | 0.525 | 0.545 |
| | the south | 0.118 | 0.962 | 0.756 | 0.522 | 0.54 |

| | | | | | | |
|---|---|---|---|---|---|---|
| TGRCN (Developed in the thesis) | the north | **0.781** | **0.802** | **0.798** | **0.786** | **0.792** |
| | the south | **0.753** | **0.816** | **0.812** | **0.768** | **0.789** |

As shown in Table 8.5, the TGRCN model demonstrates a successful prediction rate of approximately 78% for crash events and 80% for non-crash events at the the north direction versus 75% for crash events and 81% for non-crash events at the the south direction. It is important to note that the results displayed in the table correspond to the proportion of events from the initial real-world dataset and not the oversampled data. Considering that over 99.99% of the data comprises non-crash events, the model's ability to accurately classify the majority of crash and non-crash events within the next thirty minutes is commendable. This performance opens up potential applications for real-time short-term traffic forecasting scenarios, where accurate classification is crucial.

For comparison purposes, the STGCN model was also applied to the same dataset to test the prediction accuracy. To strengthen classification ability, the SMOTE technique was used to generate pseudo crash data in the training set as an oversampling technique for model comparability. Weights inversely proportional to class frequency were also assigned to create attention mechanism in training STGCN model. Prediction results are not satisfactory compared to that of TGRCN which is also shown in Table 23. STGCN model achieves quite a high accuracy in non-crash prediction but fails to extract characteristics in crash data by classifying the majority of crash events wrongly. Therefore, the TGRCN model outperforms STGCN in short period crash prediction. Similarly, MLP and LSTM predict noncrash data precisely, but lack of the ability to differentiate crash data by utilising dynamic traffic parameterss. Traditional time-series models such as ARIMA and GARCH are also used to test the prediction accuracy in near future traffic crash analysis. Nevertheless, their ability to predict near future traffic crashes are inferior to deep learning based neural network models. It may be ascribed to the lack of feature capturing ability for conventional time series models in the scenarios that exhibit excess of zeros. Although TGRCN slightly sacrifices its ability to predict accurately non-crash data, it achieves a good trade-off in forecasting more crash

incidents.

The thesis developed an integrated method consisting of a time series generalised regression neural network and weighted convolutional neural network to make short-term crash predictions of 30-minute interval. The joint model termed as time-series generalised regression convolutional neural network (TGRCN) can capture both spatial and temporal features present in segment-based crash data. Results show that the TGRCN model outperforms other state-of-the-art models such as STGCN, MLP, and LSTM in predicting near future crashes. Speed variances is the most important factor contributing to crash occurrence. The literature has focused importantly on traffic conflicts due to the shortcomings of collecting historical crash data, however predicting real crashes is more difficult as the occurrence likelihood is significantly lower. Additionally, it holds the advantage of being more applicable to real-world scenarios.

The integrated method TGRCN developed in this study is a novel approach to combining TSGRNN with WCNN for tackling crash features. However, more options of different and generalised CNN structures should be assessed for their appropriateness in crash prediction. Dynamic threshold in classifying crash versus non-crash data in the test set should also be studied in future research since the middle value of 0.5 as a threshold may not be the best choice in predicting crashes with imbalanced data.

To validate the robustness of the proposed TGRCN model in different datasets, the Sutong Bridge Freeway hourly traffic data is used. Sutong Bridge is a freeway cable-stayed bridge with a length of 32.4km (20.2 mi) located on the Yangtze River connecting Nantong and Suzhou in China (Cai et al., 2024). The extracted hourly traffic data covers 9 month period from July 2020 to April 2021, wherein 91% of data is non-crash. Various econometric and deep learning prediction and classification methods are tested and compared. Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), and Accuracy are selected to make comparisons. The results are presented in Table 8.6.

Table 8.6 Prediction accuracy comparison for TGRCN and other predicting models for Sutong Bridge traffic data

| Methods | Sensitivity | Specificity | PPV | NPV | Accuracy |
|---|---|---|---|---|---|
| MLP | 0.028 | 0.98 | 0.583 | 0.502 | 0.504 |
| GARCH | 0.393 | 0.917 | 0.826 | 0.602 | 0.655 |
| ARIMA | 0.101 | 0.89 | 0.479 | 0.497 | 0.496 |
| STGCN | 0.455 | 0.891 | 0.807 | 0.621 | 0.673 |
| LSTM | 0.567 | 0.902 | 0.852 | 0.676 | 0.735 |
| TGRCN | 0.667 | 0.909 | 0.879 | 0.732 | 0.788 |

In alignment with the previous results, TGRCN still outperforms other candidate methods, which shows the model structure has good transferability and robustness to other scenarios. In addition, deep learning neural network related models exhibit stronger prediction and classification ability compared to conventional econometric time series methods.

Some limitations of the TGRCN model are identified as follows: (i) the predicted dynamic traffic parameterss by the GRNN have some degree of error. Although it transfers predictors to the same dimension, using predictors with a margin of error to make prediction in the near future may bring more uncertainty and noise, which is hard to measure, (ii) WCNN is used in this study, but the structure of CNN is not complicated. Deeper networks are more suitable to other input data types such as images or audio data, however in the case of numeric data, deeper networks would result in overfitting. generalised parallel network structures such as inception net or networks with attention mechanisms such as ‘transformers’ should be taken into analysis to test their suitability and (iii) currently, the number of crashes covered in the data set is not sufficient, more data covering wider scenarios should be collected and utilised for further enhancing the performance of the TGRCN model.

In summary, while most existing studies have approached crash prediction as a classification problem and utilised various classification methods to distinguish crash events from

non-crash events without considering temporal structures in crash data, the thesis introduces the use of time-series generalised regression neural networks to account for temporal dependencies. Additionally, a weighted CNN model is incorporated, which samples dynamic weights inversely proportional to class frequency to optimise gradient descent toward classifying as many crash events as possible by learning spatial features. Although GRNN has been initiated for some time, the application of time-series based GRNN in crash prediction is a novel technique that has not been previously explored. The joint model - TGRCN utilises dynamic traffic data at time t to predict real-time crashes in the same time dimension, transferring t-1 traffic data to predict values at time t using GRNN.

The insights gained from the thesis will aid freeway operators in predicting the likelihood of a crash in advance and implementing interventions such as enforcing speed limits to reduce speed variances between and within lanes, to prevent such crashes.

## 8.3 Contributing Factors for Near Future Traffic Crashes

As discussed in Chapter 5 (section 5.3 Model Interpretability and page 127), the ICAV-LIME method was applied to analyse dynamic traffic variable importance to crash occurrence. Results show that speed variance plays the most important role in crash prediction. Besides speed variances, average speed, time headway, occupancy, and traffic flow are all contributing factors to crash occurrence and exhibit similar effects. The ranking order of variable contribution is as follows: speed variances, speed, headway, occupancy, and traffic flow (see Figure 8.21).

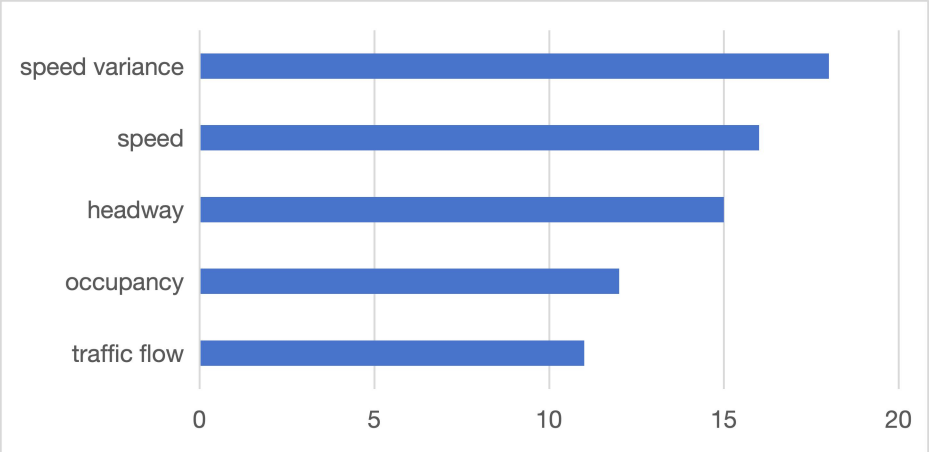



Figure 8.21 Variable importance for explanatory variables

The ICAV-LIME method was employed for model interpretability. Speed variance, average speed, and headway are found to be the three most significant variables related to traffic crash. Apart from speed and headway, the fact that speed variance is the most influential factor in traffic crash occurrence demonstrates its significance as a traffic characteristic affecting road safety. Many studies have also validated the quantified positive relationship between speed variance and crash rates (Nicholas & Ravi, 1989). Solomon (1964) and Cirillo (1968) also concluded that, as vehicle speeds deviated from the average speed of the traffic stream, crash involvement rates increased.

Different road environments possess varying geometry and traffic characteristics, while vehicle behaviour and kinematics parameters exhibit significant variations across distinct road types. Safety surrogate measures are widely used safety indicators, albeit their significance and performance in different road environments are rarely investigated by researchers. The thesis not only initiates a novel stacked ensemble learning model to predict traffic conflicts but also ranks SSM importance in different road scenarios during training, enabling more interpretable use of black-box algorithms to avoid the trade-off between accuracy and interpretability. The novel stacked ensemble model achieves prediction accuracies of 99%, 88%, and 87.5% for vehicle-based motorways, urban junctions, and infrastructure-based motorways respectively.

Future improvements for this study include splitting training data and constructing a weighted hierarchical stacked ensemble model to capture various aspects of traffic conflicts and assign different weights to individual models based on their respective performances. Additionally, expanding the data pool by recording more videos and identifying additional conflicts could further enhance the performance of the prediction models.

## 8.4 Traffic Conflict Prediction: Freeway and Urban Junctions

In chapter 6, a noval stacked ensemble model is put forwarded. In the first layer, three models run in parallel: (i) Random Forest (RF), (ii) Support Vector Machine Radial (SVM-R), and (iii) deep neural network comprising of three hidden layers. The results generated by these three models serve as inputs to the second layer which is a Gradient Boosting Machine (GBM) model whose output is the final binary prediction detecting the presence or absence of a conflict. Conflicts data were collected from various infrastructure and vehicle-based sensors, including drones, lidars, radars, and cameras, across different scenarios in China and the UK: urban junctions (5 urban junctions in Shanghai), motorway segments (Sutong Bridge Freeway) and vehicle-based data from instrumented vehicles (UK naturalistic driving data from instrumented vehicles). Actual traffic conflicts were identified by human perspectives and dynamic traffic parameterss were extracted through computer vision techniques introduced in chapter 4. Traffic conflicts were identified through human judgment by experts in transportation fields. Experts were trained to identify traffic conflicts using TTC first, and then let humans make judgments. The TTC threshold used in previous studies has varied from 2 to 4 s (Mahmud et al., 2017, Li et al., 2014). In order to include a greater number of conflict samples in this research, TTC* was set as 3 s at junction scenarios for the UAV data. (Guo et al., 2016). The reason why TTC was not used directly as a judgment standard is due to the potential correlation between conflicts and conflict affecting factors. If TTC was used directly to identify conflicts and TTC, MTTC, and other SSMs were used as independent variables to predict conflicts, the prediction accuracy would be very high but it is meaningless because a

strong correlation existed between the independent variables and the dependent variable.

For UAV data, human observers' perception of traffic conflicts should be an appropriate way to determine ground truth at junction scenarios (Diwakar et al., 2023). Lots of studies have proved this and suggest that human judgments are reliable and valid for detecting severity in traffic events (Diwakar et al., 2023). Hyden (1987) showed that with the right initial training, there is good agreement reached between observers in terms of identifying traffic conflicts. Horst (1984) also showed that humans have an innate ability to assess the level of danger in a traffic situation especially when it is based on an actual observation.

The vehicle-based motorway scenario achieved the highest overall accuracy of 99.3% with a sensitivity rate of 99% for conflict detection. The infrastructure-based motorway and urban junctions' scenarios also demonstrated relatively high accuracy, reaching 87.5% and 88% respectively, with a sensitivity rate of 87.9% and 89.6% for correctly classified conflicts. Vehicle-based scenarios demonstrate high classification accuracy. However, predicting conflicts using infrastructure-based sensors poses slightly more difficulty. This is attributed to the higher number of conflicts present in the infrastructure-based data and the higher heterogeneity in driving behaviour captured by the drones compared to the five different drivers collecting the vehicle-based data. Another potential factor is that conflicts defined from a human perspective may not always equate to actual conflicts, and the prediction model struggles to adequately account for tolerance. Sensitivity and specificity precision closely mirror the accuracy of predictions, indicating minimal disparity in false positive and false negative ratios. Table 8.7 displays the results of the stacked ensemble model for each scenario.

Table 8.7. Results of the stacked ensemble learning model for each scenario

| Scenario | Accuracy | Sensitivity | Specificity | F1 Score | Pos Pred Value | Neg Pred Value |
|---|---|---|---|---|---|---|
| Urban junctions – | 0.88 | 0.896 | 0.865 | 0.8823 | 0.8600 | 0.9000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| infrastructure-based | | | | | | |
| Motorway segments – infrastructure based | 0.875 | 0.879 | 0.871 | 0.8756 | 0.8700 | 0.8800 |
| Vehicle-based motorways | 0.993 | 0.99 | 0.986 | 0.9932 | 0.9884 | 1 |

The proposed stacked ensemble model exhibits low computation time and robust performance for different road scenarios. The results show high accuracy for vehicle based motorways but it is not because of overfitting. The reason is that we form a balanced dataset by selecting the same amount of non-conflicts randomly to match the number of conflicts data. Once the imabalanced dataset is scaled to balanced dataset, it would be much easy to differentiate conflict and nonconflict data since noises are filtered through under-sampling method.

The thesis highlights the significance of recognising the varying efficacy of SSMs across different road environments, directly influencing their utility in real-world applications such as Advanced Driver Assistance Systems (ADAS) or roadside monitoring using smart infrastructure such as sensors developed by Vivacity Labs for promoting smarter, safe and sustainable cities. However, the study faced limitations due to the size of the dataset (1,454 conflicts over more than 10 hours of video recording, less than 0.1% of total observations). Future investigations could strengthen the reliability of findings by expanding the scope to larger datasets. Additionally, further exploration could seek to identify the most effective SSMs in specific road environments. Furthermore, enriching the categorisation of road environments with more detailed classifications and considering diverse countries and levels of rurality could yield deeper insights into SSM performance across various contexts. Subsequent studies can incorporate additional enhancements, including assigning varying weights to individual ensemble models, establishing a hierarchical stacking framework through data partitioning, and employing counterfactual causal inference for enhanced interpretability of variables.

Different road environments possess different geometry and traffic characteristics, while vehicle behaviour and kinematics parameters exhibit significant variations in distinct road types. Safety surrogate measures are widely used safety indicators, albeit their significance and performance in different road environments are rarely investigated by researchers. This thesis not only initiates a novel stacked ensemble learning model to predict traffic conflicts but also ranks SSM importance in different road scenarios during training, enabling more interpretable uses of black-box algorithms to avoid the trade-off between accuracy and interpretability. The novel stacked ensemble model achieves 99%, 88%, and 87.5% prediction accuracy for vehicle-based motorways, urban junctions, and infrastructure-based motorway respectively.

## 8.5 Contributing Factors Relating to Traffic Conflicts

Analysis of the ablation study revealed that gap time, DRAC and CAI emerged as the most effective measures both for infrastructure-based urban junctions and motorway segment data. However, disparities were observed between motorway segments (infrastructure) and vehicle-based data: while time-based measures exhibited superiority for the latter, a mix of different measure types was evident for the former. Conversely, the primary influencing factors for vehicle-based conflict detection differed from those in infrastructure-based urban and motorway contexts. Specifically, the deceleration rate emerged as more critical in infrastructure-based urban and motorway scenarios, whereas vehicle-based conflicts were more closely associated with time-based SSMs. The reason that Gap time, DRAC, and CAI are more influential for infrastructure-based conflicts while TTC, MTTC, and PET are more influential for vehicle-based conflicts is possibly due to their belongings of different classes of SSM. TTC, MTTC, PET, and Gap time are time based SSM, but DRAC belongs to the deceleration based SSM and CAI belongs to energy-based SSM (Wang et al., 2021). For vehicle-based conflicts, time based SSM are major safety indicators to measure the time proximity to a crash occurrence. However, for infrastructure-based conflicts, various SSM

should be involved to measure different aspects of a crash occurrence. It also indicates that the causes of infrastructure-based conflicts are more complicated than vehicle-based conflicts since more interactions (vehicle to vehicle and vehicle to person) occurred in infrastructure based scenarios than vehicle based scenarios (ego vehicle video collection). It can be also be ascribed to external drones capture all roadway conditions in all lanes contrast with just using single-lane following scenario for ego vehicle video. Ego vehicle video recording may ignore the surrounding situations so that energy based metrics are not relevant.

In addition, the significant contribution of CAI indicates higher variability in crash energy for larger traffic flows especially in urban junctions and dense motorways since congested traffic roadways are the places where interactions are more likely to happen. Frequent lane changes, vehicle merging, the conflict between vehicle passing and pedestrian crossing in the intersections, emergency braking due to fewer cars following distance, frequent acceleration and deceleration, and multi-directional flows in urban junctions and motorways all increase the likelihood of collision occurrences especially for rear-end collision and vehicle merging collisions. Therefore, CAI becomes a good indicator to measure traffic characteristics in infrastructure based scenarios as more complicated behaviours (merging, crossing, lane changing) are taking place.

Furthermore, there are more sidesweep conflicts in intersections which could be more difficult to detect using only one type of SSM, for example just time based SSMs.
Results are displayed in Table 8.8.

Table 8.8. Results of the feature contribution assessment for each scenario

| Scenario | Criteria | RF | SVM | DNN | Five most significant variables |
|---|---|---|---|---|---|
| Urban junctions – | Model contribution | 87% | 12% | 1% | |

| | | | | | |
|---|---|---|---|---|---|
| infrastructure-based | Most significant variables per model | GAP, DRAC, CAI, PSD, Speed | GAP, CAI, TIT, TTC, MTT | DRAC, Speed, MTTC, TIT, PIUCD | **GAP, DRAC, CAI, PSD, Speed** |
| Motorway segments – infrastructure based | Model contribution | 84% | 13% | 3% | |
| | Most significant variables | GAP, DRAC, CAI, TTC, TIT | GAP, CAI, TTC, TIT, MTTC | CAI, DRAC, DSS, GAP, Distance | **GAP, DRAC, CAI, TTC, TIT** |
| Motorway segments - Vehicle-based | Model contribution | 70% | 26% | 4% | |
| | Most significant variables | TTC, MTTC, PET, CIF, Speed Variances | TTC, MTTC, PET, CIF, Speed Variances | CIF, SpeedCar, Speed Relative variance, SD Density, Headway | **TTC, MTTC, PET, CIF, Speed Variances** |

Ablation study results show that Gap time, CAI and DRAC are the three most significant SSMs for infrastructure-based motorway and urban junction scenarios. Conversely, significant variables for vehicle- differ considerably, with TTC, MTTC, PET, CIF, and PSD being the five most significant. Plots for depicting influential factors in different scenarios are also displayed as follows.

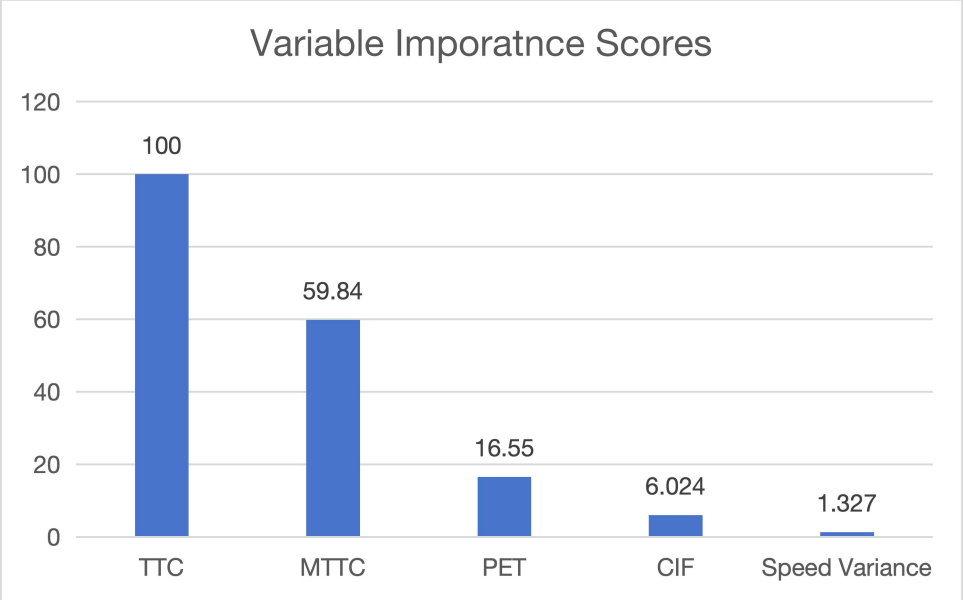



Figure 8.22. Visualization of influential features in vehicle-based motorway scenario.

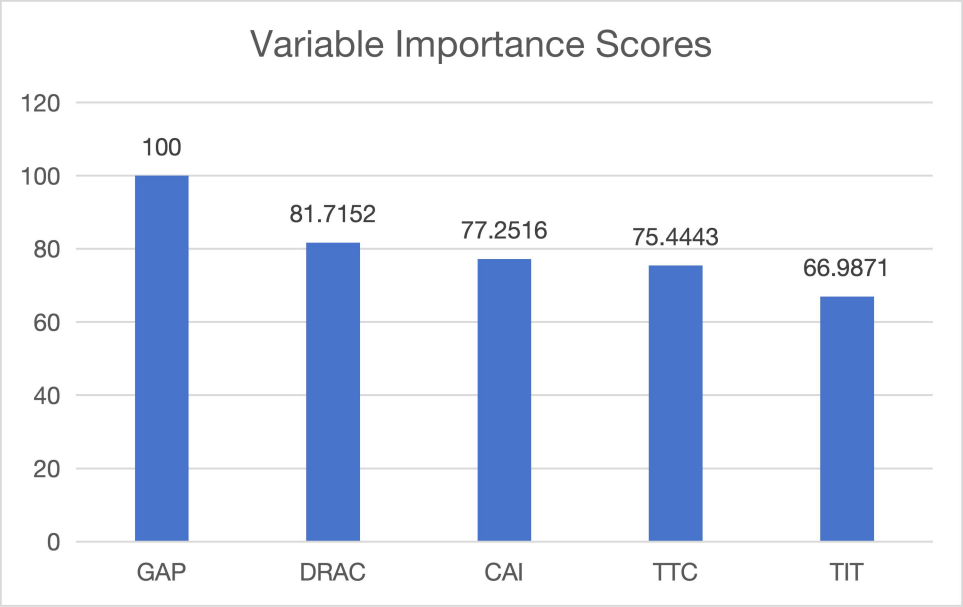



Figure 8.23. Visualization of influential features in infrastructure-based motorway scenario.

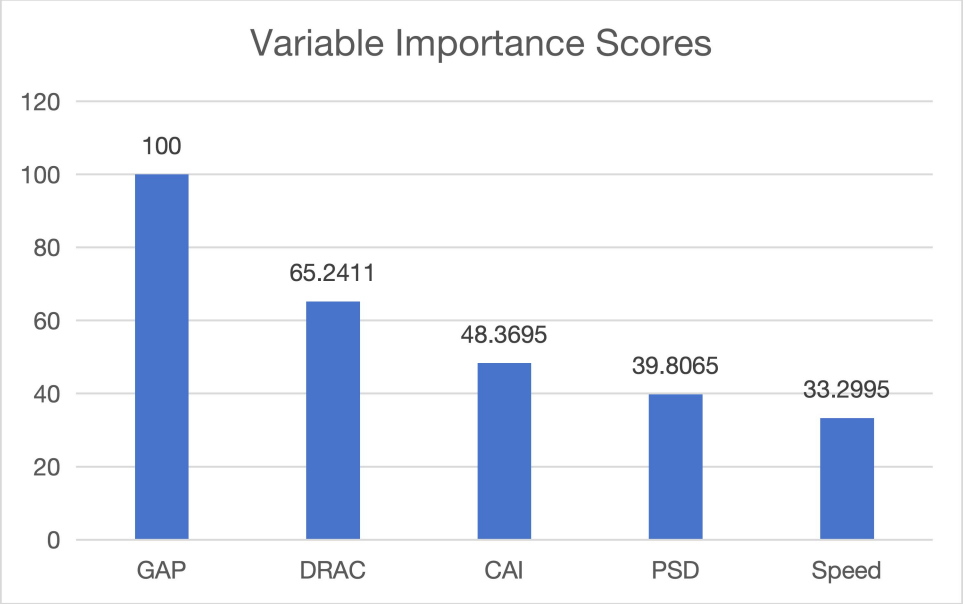



Figure 8.24. Visualization of influential features in urban junction scenario.

Variable correlations are also investigated. As shown in Figure 8.25, significantly positively correlated features are Speed and Flow, Occupancy and Density, Density and Flow. It shows that as speed increases, traffic volume may also increase. As traffic volume increases, density increases, followed by the increase of occupancy. Significantly negatively correlated features are Flow and Headway, Occupancy and Average Speed, Speed and Density, Speed and Occupancy. When traffic volume increases, headway decreases. When occupancy increases, average speed decreases, followed by the increase of density.

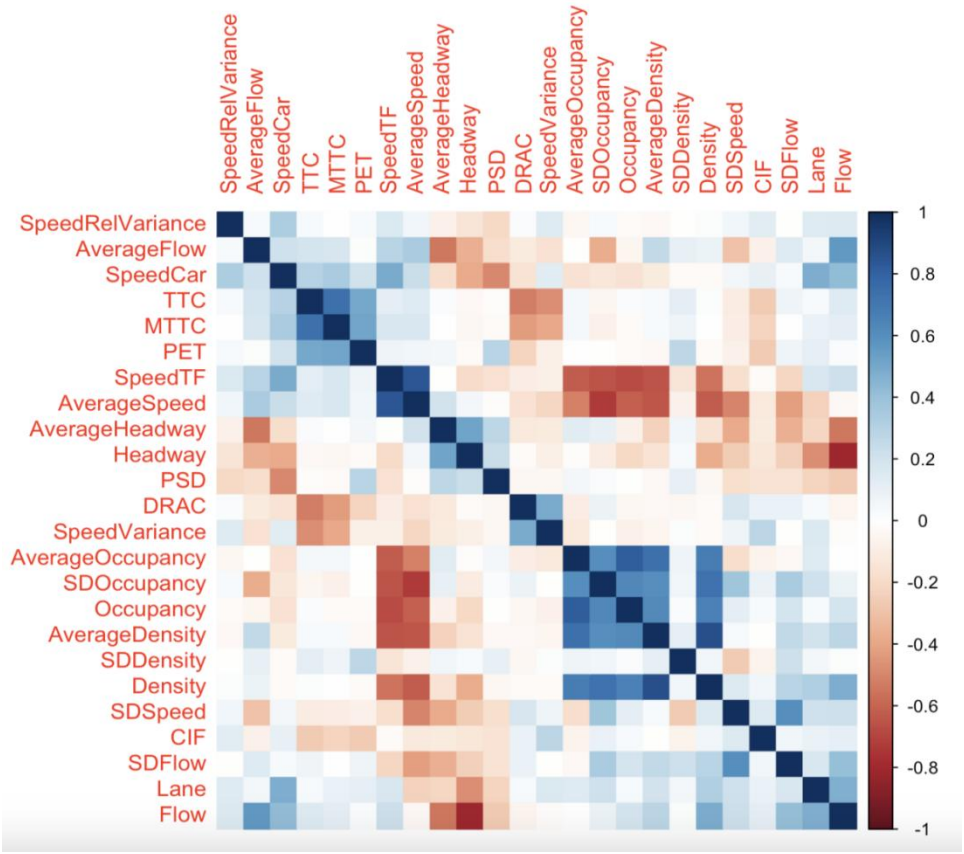



Figure 8.25. Correlation plot of features

For importance rankings, interactions, and correlations can affect the stability of importance rankings (Darst et al., 2018). If SSMs are interdependent, small changes in the data or model might lead to significant changes in rankings. Correlation and interactions among variables may also lead to overfitting in high-dimensional SSMs data. Therefore, regularisation techniques of Lasso regression is applied to handle multicollinearity and improve the stability of importance rankings. Cross validation and Bootstrapping tests across different scenarios have been conducted to evaluate how consistently certain SSMs are ranked as important. It shows that the top six most important variables are consistent in all scenarios. However, the latter variables vary from scenarios. It means that important variables truly capture SSM data characteristics and can indicate the occurrences of traffic conflicts.

This paper highlights the significance of recognising the varying efficacy of SSMs across different road environments, directly influencing their utility in real-world applications such

as Advanced Driver Assistance Systems (ADAS) or roadside monitoring using smart infrastructure such as sensors developed by Vivacity Labs for promoting smarter, safe and sustainable cities. However, the study faced limitations due to the size of the dataset (1454 conflicts over more than 10 hours of video recording, less than 0.1% of total observations). Future investigations could strengthen the reliability of findings by expanding the scope to larger datasets. Additionally, further exploration could seek to identify the most effective SSMs in specific road environments. Furthermore, enriching the categorisation of road environments with more detailed classifications and considering diverse countries and levels of rurality could yield deeper insights into SSM performance across various contexts. Subsequent studies can incorporate additional enhancements, including assigning varying weights to individual ensemble models, establishing a hierarchical stacking framework through data partitioning, and employing counterfactual causal inference for enhanced interpretability of variables.

Additionally, in this study, we tried as many SSMs as possible, but a few of them were not selected due to unable acquirement of the missing parameters by virtue of video analysis only. It possibly creates selection bias for choosing more longitudinal SSMs than cross sectional SSMs, which may be a potential limitation. For future research, sensors such as LiDar and Radar will be utilised to collect more sufficient traffic data and calculate corresponding SSMs.

The real-world width of the junction is measured and compared with the pixel width in the image to compute the scale parameter. This scale parameter is applied for all distance estimations as the drone height is fixed during data collection. The speed is calculated every second by using the difference in position per second. The smoothed distance is employed to ensure reliable speeds. The accuracy of the obtained speed values is computed by comparing them with speed measurements collected using a handheld speedometer simultaneously with drone data collection. The accuracy is presented in Table 2. Detection accuracy in different scenarios for UAV data.

Regarding the data balancing, random under-sampling of the non-conflict majority class was systematically employed to balance the data. Current real-time crash risk analyses primarily use undersampling methods to create equivalent ratios (commonly 1:1 or 1:4) between crash and non-crash samples through matched case-control techniques or by randomly discarding excess non-crash data (Abdel-Aty et al., 2004; Yang et al., 2018; Yu et al., 2020). Yu et al. (2020) conducted a further investigation to find proper crash to noncrash ratio in the classification problem and 1:1 exhibits highest performance in all metrics: Sensitivity, FAR, and AUC. Therefore, the number of conflicts in the dataset was calculated and the same amount of non-conflicts were selected to constitute a 1:1 ratio of conflicts versus non-conflicts in the dataset.

Table 7. Data Distribution

| Types | Conflict vs. Non-conflict Ratio | Ratio after undersampling |
|---|---|---|
| Vehicle based motorway | 193:39017 | 193:193 |
| Infrastructure based motorway | 5181:147948 | 5181:5181 |
| Urban junction | 621:53070 | 621:621 |

Once the imbalanced dataset is scaled to a perfectly balanced dataset, differentiating between conflicts and nonconflicts data is easier since noises are filtered through during the under-sampling method.

The built stacked ensemble model has been tested in three scenarios: Vehicle based motorway, Infrastructure based motorway, and urban junctions. The detection accuracies cross validate each other. Due to distinct driving behaviours in conflict driving scenario and non-conflict driving scenarios across different environments, conflict prediction accuracy may vary as well. For vehicle-based data, it seems a bit overfit for traffic conflict prediction for having exceptionally high accuracy for both sensitivity and specificity. It probably ascribes to the limited size of the dataset, which may also be a possible limitation of this study. In future

research, an extra vehicle based dataset will be collected and cross validated with the proposed model to optimise robustness and test its suitability in various scenarios.

A stacked ensemble model excels individual ensemble model in traffic conflict prediction which is the case involves a mix of structured numerical data (SSMs) and unstructured data (temporal relationships and complex patterns). Component of the stacked ensemble model compensates each other to make complementary effects to capture temporal dependencies, handle complex patterns, achieve scalability to high-dimensional data, and ensure model transferability. Random Forest works well for tabular data with clear feature interactions and when model interpretability is important. SVM is useful for datasets where non-linear relationships and some temporal patterns can be captured through feature engineering. DNN is ideal for raw sequential or multi-modal data where temporal dependencies automatic feature learning are critical. GBM works well for classification and interpretability. Therefore, by combining these models, a more comprehensive approach to traffic conflict prediction can be achieved, leveraging the strengths of each method to address the specific characteristics of the data.

## 8.6 Summary

This chapter presented the accuracy of various hourly and half-hourly crash prediction models and also analysed traffic conflict prediction results and contributory factors affecting unsafe traffic conditions. Different test scenarios are used to evaluate model performances: the application of ZILT model to make hourly crash predictions at Sutong Bridge Freeway; the application of TGRCN model to make semi-hourly crash predictions at London M1 motorway; the application of the stacked ensemble learning model to make real-time traffic conflict predictions at both Sutong Bridge Freeway and Shanghai urban city junctions. This chapter also discusses model interpretation of using feature importance selection algorithm for analysing influencing contributing factors affecting unsafe traffic conditions.

For traffic crash prediction, this chapter evaluated the effectiveness of ZILT and TGRCN employing real-world highly disaggregated traffic datasets collected from the Sutong Bridge Freeway in China in 2021 with surveillance camera data to extract traffic parameterss (see Chapter 4) and M1 motorway in the UK in 2019 with crash data extracted from the UK national accident database for the same year. Short-term intervals were defined as 60 minutes and 30 minutes, respectively, providing sufficient time for a traffic control centre to implement interventions and mitigate potential traffic hazards. The dataset was highly imbalanced, with over 99.99% non-crash samples after being segmented from yearly crash distribution into short time intervals. Feature importance analysis and model interpretation were employed to analyse the relative importance of explanatory variables contributing to crashes. Results reveal that speed variance, speed, and traffic volumes are the most influential factors contributing to crash occurrence.

For traffic conflict prediction, real-time traffic operation data are collected using UAV drones. Conflicts are identified from a human perspective, with vehicle kinematics and traffic flow data extracted using computer vision techniques. A stacked ensemble model comprising SVM, Random Forest, DNN as the first layer, and GBM as the second layer, is built to classify traffic conflicts. GAP, DRAC, CAI, PSD, and Speed are identified as the five most significant variables for urban junction, while GAP, DRAC, CAI, TTC, and TIT are the five most significant variables to motorways. Future improvements include splitting the training data and constructing a weighted hierarchical stacked ensemble model to capture various aspects of traffic conflicts, assigning different weights to individual models based on their performances. Additionally, recording more videos and identifying additional conflicts will expand the data pool, thereby enhancing the performance of the prediction models even further.

# Chapter 9 Discussion

Traffic situation analysis and prediction are fundamental to daily freeway operation supervision. In-depth data mining and multi-factor association analysis construct short-term and long-term traffic crash prediction models using machine learning algorithms. By analysing real-time and historical road traffic data, combined with traffic flow, weather, and crash data, traffic parameterss and trends are understood. Prediction results are transmitted to traffic information and management systems, allowing management personnel to foresee changes in traffic operation status and undertake timely traffic controls such as speed limit control, lane control, ramp block, etc, providing drivers with real-time effective information, aiding route selection, and enabling dynamic route guidance to reduce travel time and traffic congestion. Effective traffic situation analysis and condition prediction can greatly enhance freeway operation and management levels, ensuring freeway safety and rapid passage, evaluating traffic status, predicting traffic conditions, sensing traffic risks, and controlling traffic incidents.

This chapter discusses difficulties in predicting unsafe traffic conditions including near future crashes and real-time traffic conflicts. It retrospects factors that influence prediction accuracies in both crash and conflict prediction models. It discusses the advantages and disadvantages of different crash or conflict prediction models proposed in previous chapters. It also compares the suitability and transferability of each model in different scenarios. In addition, the implementation of pertinent interventions is reviewed to initiate effective ways to prevent crash and other traffic incidents. The relationship between crash prevention and environmental and traffic factors is investigated. The policy implication is also made on how to get improved with the reflection of prediction accuracies and model interpretation of contributory factors. In the end, further development in the future studies of near future crash prediction and traffic conflict prediction models are discussed in terms of additional multi-dimensional data collection, existed model upgrading, and new advanced model introduction such as the Large language model (LLM).

## 9.1 Difficulty in predicting unsafe traffic conditions

Near future crashes are a small likelihood and highly random event. Unlike traffic conflict which can be defined by driver maneuvers and vehicle interactions with other road users through safety surrogate measures, accurately predicting the likelihood of a traffic crash in the near future is extremely difficult. The shorter the time period, the harder it is to predict crashes. Studies typically define 5-minute, 15-minute, and 30-minute periods for near future crash prediction. While these time settings are reasonable for traffic analysis or traffic conflict prediction, they may not make sense for predicting actual crashes, because no pertinent intervention or actions can be taken since the reaction time is insufficient for traffic police or traffic management control centres. Crash data is always faced with inaccurate recording issues such as missingness and erroneous. Additionally, dynamic traffic parameterss are not easy to collect. Therefore, putting forward a near future crash prediction model with integrating dynamic traffic parameterss and environmental factors should be indispensable for proactive crash management and predictive crash prevention.

For hourly or semi-hourly time intervals, statistical methods can predict crash trends more precisely due to data sufficiency, the regression to mean effect over time, and seasonal periodic effects. Many factors contribute to crash occurrences and are closely related to crash rates. During our research, vehicle operation speed, vehicle-to-vehicle interaction, segment traffic dynamics, driver driving status, roadway geometric design features, and weather conditions, all play important roles in traffic safety and influence crash occurrences. Small changes in these influencing factors can instantly change the crash rate. Although some factors are not directly extracted from this study, their characteristics are reflected in dynamic traffic parameterss such as speed, speed variances, traffic flow, etc. Using computer vision techniques to extract dynamic traffic data contributes to capturing crash characteristics and therefore getting more accurate prediction results.

Traffic conflicts as proper surrogate measures of traffic crashes, are widely used in proactive traffic management. Surrogate safety measures (SSMs) along with other environmental and traffic operation factors are indicators of traffic conflicts. Typically, conflicts are calculated in vehicle base to assist drivers with the safe operation and build proactive crash prevention systems such as Advanced driver-assistance systems (ADAS). However, traffic environmental based traffic conflict prediction models lack of research. The author spent efforts in collecting traffic conflicts data as well as real-time traffic operation data in both infrastructure based freeway and urban city junctions to analyse contributory variables (causal factors) affecting traffic conflicts and make comparisons of prediction accuracies in three diverse road environments: (a) urban intersection data, (b) infrastructure-based motorway data, and (c) vehicle-based motorway data by using the same independent variables including SSMs and other traffic operation parameters. A new stacked ensemble learning model was developed to predict conflict accurately and assess the transferability of a common model and then conduct an exhaustive comparative analysis of various SSMs to evaluate their effectiveness in identifying conflicts across different scenarios.

## 9.2 Data-driven Transport AI – Properties of accuracy, causality, transferability, explainability and uncertainty

### 9.2.1 The necessity of applying data-driven methods

The growing accessibility of various sensor and image recognition technologies that can be used for collecting roadway traffic safety data, combined with recent advancements in modern data-driven methods, especially in Time Series Modelling, Machine Learning, and Deep Learning, has led to a surge of interest in data-driven road safety research in recent years (Sohail et al., 2022). A data-driven method is a powerful approach that leverages data to make informed decisions, build predictive models, and uncover insights (Papathanasopoulou et al., 2019). Using data-driven methods for traffic crash prediction involves leveraging

historical and real-time traffic data to build models that can predict the likelihood of crashes. These methods are highly effective because they can capture complex patterns and relationships in the data that traditional rule-based or theoretical approaches might miss.

This thesis focuses on utilising data-driven approaches including time series modelling, statistical machine learning, and deep learning models to predict the likelihood of traffic crashes or conflicts occurring at a specific location and time to devise proactive interventions to promote traffic safety. The reason that this thesis intensively uses data-driven methods can be ascribed to the following points:

1. Ability to Capture Complex Patterns

Traffic crash data is highly complex, with interactions between multiple factors (e.g., speed, weather, road geometry). Data-driven methods, especially machine learning and deep learning, excel at capturing these non-linear and high-dimensional relationships.

2. Real-Time Prediction

Data-driven methods can process real-time traffic data (e.g., from sensors or cameras) to predict crashes as they are about to occur, enabling timely interventions.

3. Handling Imbalanced Data

Crashes are rare events, leading to imbalanced datasets. Data-driven methods like SMOTE (Synthetic Minority Over-sampling Technique) or weighted loss functions can handle this imbalance effectively.

4. Spatio-Temporal Analysis

Traffic crashes often have both spatial (e.g., location) and temporal (e.g., time of day) dependencies. Data-driven methods like CNN, LSTM or graph neural networks (GNNs) can model these dependencies effectively.

5. Scalability

Data-driven methods can handle large volumes of heterogeneous data from multiple sources (e.g., sensors, cameras, IDLs), making them scalable for freeway or regional crash prediction.

6. Proactive Safety Management

By predicting crashes before they happen, data-driven methods enable proactive safety measures, such as dynamic speed limits, traffic signal adjustments, or emergency response planning.

7. Continuous Improvement

Data-driven models can be continuously updated with new data, improving their accuracy and adaptability over time.

### 9.2.2 Addressing Properties of accuracy, causality, transferability, explainability and uncertainty

Addressing accuracy, causality, transferability, explainability, and uncertainty is essential for developing effective and trustworthy AI models in transport applications. By leveraging techniques like ensemble learning, variable importance analysis, deep neural network, transfer learning, and uncertainty quantification, the proposed novel advanced prediction models demonstrated its ability to predict unsafe traffic conditions accurately, generalize across regions, and provide interpretable insights. These properties are critical for real-world deployment and adoption of AI solutions in transport systems.

**Hourly crash prediction in ZILT:**

Accuracy:

The ZILT model is designed to handle excessive zeros and temporal-spatial correlations in hourly crash data, which are common challenges in crash prediction. The model's performance is evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which are standard metrics for assessing prediction accuracy. The ZILT model is compared with traditional models like Zero-Inflated Poisson (ZIP) and Hurdle models, and it demonstrates superior performance with lower MAE and RMSE values.

Causality:

The study incorporated traffic operation variables (e.g., traffic flow, speed, truck-to-car ratio) and temporal factors (e.g., hour of the day, holidays) to identify potential causal relationships between these factors and crash occurrences. Statistical significance testing was performed to

determine the influence of each variable on crash predictions. Variables like traffic flow, speed, and truck-to-car ratio were found to be statistically significant in predicting crashes. The relationship between independent variables and dependent variable can also be interpreted. For example, higher truck-to-car ratios were positively correlated with crash occurrences, while higher speeds were negatively correlated, suggesting smoother traffic flow reduces crash likelihood.

Transferability:
The study focused on data from the Sutong Yangtze River Bridge, but the ZILT model's design is generalizable to other locations and contexts. The ZILT model was tested on data from the Sutong Yangtze River Bridge in China, and was also validated using Guidu mountainous freeway. However, further testing on datasets from different geographical locations (e.g., intersections, ramps) to validate the model's transferability are still needed. The model's ability to handle excessive zeros and temporal-spatial correlations makes it applicable to other transportation networks with similar data characteristics.

Explainability:
The ZILT model is based on a log-linear extension of INGARCH, which provides a clear mathematical framework for understanding how predictions are made. The model's structure separates the prediction of crash occurrence (zero-inflation component) from the prediction of crash counts (count component), making it easier to interpret. Statistical significance testing and coefficient estimates for covariates (e.g., traffic flow, speed) provide insights into the factors influencing crash predictions. For example, the study found that traffic flow in the outer lane (closer to the shoulder) was positively correlated with crashes, while flow in the inner lane (closer to the median) was negatively correlated. This finding is explainable by the differing driving behaviors and interactions in these lanes.

Uncertainty:
The study used quasi-maximum likelihood estimation for parameter estimation, which is robust to certain types of uncertainty in the data. The model's ability to handle overdispersion (common in crash data due to excessive zeros) and temporal autocorrelation reduces uncertainty in predictions. Diagnostic plots (e.g., autocorrelation function (ACF) and probability integral transform (PIT)) were used to assess model fit and uncertainty.

Summary of How Each Property Was Addressed:

| Property | How It Was Addressed |
|---|---|
| Accuracy | ZILT outperformed ZIP and Hurdle models in MAE and RMSE, demonstrating higher accuracy. |
| Causality | Incorporated traffic and temporal variables, with statistical significance testing. |
| Transferability | Model design is generalizable, but further testing in other locations is needed. |
| Explainability | Clear model structure, coefficient estimates, and significance testing provided insights. |

| Property | How It Was Addressed |
|---|---|
| Uncertainty | Used quasi-maximum likelihood estimation and diagnostic plots to assess and reduce uncertainty. |

These properties are addressed through a combination of time series method, rigorous validation, and interpretable model design, making the proposed ZILT model robust and reliable for hourly traffic crash prediction.

**Semi hourly Crash Prediction with application of TGRCN model:**

Accuracy:

The proposed TGRCN (Time-Series Generalized Regression Convolutional Neural Network) model achieved high accuracy in predicting crashes, outperforming state-of-the-art models like STGCN, MLP, GARCH, ARIMA, and LSTM. Metrics like sensitivity, specificity, and precision were used to evaluate accuracy. The model was built using UK M1 motorway dataset in 2019. Model transferability and prediction accuracy was also tested and validated using Sutong Bridge freeway in China.

Causality:

Variable importance analysis and model-based interpretation were used to identify the relative importance of explanatory variables (e.g., volumes, speed variance, speed) in contributing to crashes. It helped establish cause-and-effect relationships between traffic dynamics and crash likelihood.

Transferability:

The model was tested on data from the M1 Motorway in the UK and validated on the Sutong Bridge Freeway in China, demonstrating its transferability to different regions and scenarios.

Explainability:

Model interpretation method ICAV-LIME (Intermediate Convnet Activation Visualization - Local Interpretable Model-agnostic Explanations) was employed to visualize feature maps and interpret the contributions of input variables. It made the model's decision-making process more transparent and interpretable.

Uncertainty:

The model's ability to handle temporal-spatial correlations and data imbalance indirectly addresses uncertainty by improving the robustness of predictions:

TSGRNN: Captures temporal dependencies (e.g., autocorrelation, seasonality) in traffic data, which helps reduce uncertainty related to time-varying traffic dynamics.

WCNN: Uses binomial sampling weights to handle the extreme class imbalance in crash data, which reduces uncertainty in classifying rare crash events.

Uncertainty of missing data: Addressed in the data preprocessing stage, where missing traffic data (approximately 0.5%) is imputed using the MissForest method, a non-parametric imputation technique based on random forest ensemble learning. The imputation accuracy is

validated by intentionally generating missing values and comparing the imputed values with the actual values. This process helps quantify and reduce uncertainty arising from missing data.

| Property | How It Was Addressed |
|---|---|
| Accuracy | ZILT outperforms ZIP and Hurdle models in MAE and RMSE, demonstrating higher accuracy. |
| Causality | Incorporates covariates and lagged effects to capture causal relationships in crash data. |
| Transferability | Model design is generalizable, but further testing on other datasets is needed. |
| Explainability | Clear model structure, statistical significance testing, and interpretation of lagged effects. |
| Uncertainty | Handles excessive zeros and temporal-spatial correlations, but acknowledges limitations. |

These properties are addressed through a combination of advanced machine learning techniques, rigorous validation, and interpretable model design, making the proposed TGRCN model robust and reliable for semi-hourly crash prediction.

**Conflict Prediction:**

Accuracy:

Model Performance: The proposed stacked ensemble learning model achieves high accuracy in predicting traffic conflicts across different scenarios. Specifically, the model achieves 88% accuracy for urban junctions, 87.5% for motorway segments, and 99% for vehicle-based conflicts. These results demonstrate the model's effectiveness in accurately predicting traffic conflicts.

Ablation Study: The study conducts an ablation study to evaluate the contribution of different Safety Surrogate Measures (SSMs) to the model's performance. It helps in understanding which SSMs are most influential in different scenarios, further enhancing the model's accuracy.

Cross-Validation: The model's performance is validated across different datasets (urban junctions, motorway segments, and vehicle-based data), ensuring that the accuracy is consistent across various road environments.

Causality:

Feature Importance: The study uses Recursive Feature Elimination (RFE) to identify the most influential SSMs for conflict prediction. By understanding which features (e.g., Gap Time, DRAC, CAI) contribute most to the model's predictions, the study provides insights into the causal factors behind traffic conflicts.

Scenario-Specific Analysis: The study highlights that different SSMs are more effective in different scenarios (e.g., time-based SSMs for vehicle-based conflicts vs. deceleration-based SSMs for infrastructure-based conflicts). It suggests that the model captures the causal relationships specific to each scenario.

Transferability:

Cross-Scenario Validation: The model is tested across three different scenarios (urban junctions, infrastructure-based motorway segments, and vehicle-based motorway data). The high accuracy across these diverse environments suggests that the model is transferable to different road types and conditions.

Generalizability of SSMs: The study emphasizes that different SSMs are effective in different scenarios, which implies that the model can be adapted to various road environments by selecting appropriate SSMs. This adaptability enhances the model's transferability.

Real-World Data: The model is trained and tested on real-world data collected from different countries (China and the UK), which further supports its transferability to different geographic and traffic conditions.

Explainability:

Feature Contribution Analysis: The study uses RFE to evaluate the contribution of each feature to the model's predictions. It provides a clear understanding of which SSMs are most important in different scenarios, making the model's predictions more interpretable.

Bootstrap is also used to evaluate the consistency of contributing variable importance scores. We set the number of bootstrap samples to be 100, and define the sample size the same as the original dataset with replacement. Bootstrap results return the confidence interval of each variable and show that the top five most important variables keep the same across different

bootstrapped samples, which matches with cross validation results. The reason is that the importance scores of the top five variables are much different from the latter ones. A big gap of important scores exists.

Uncertainty:

Early Stopping Mechanism: To mitigate overfitting, an early stopping mechanism is employed during model training. This ensures that the model generalizes well to unseen data, reducing uncertainty in its predictions.

Data Balancing: The study addresses class imbalance by using random under-sampling of the non-conflict majority class. This ensures that the model is not biased towards the majority class, reducing uncertainty in its predictions.

Hyperparameter Tuning: The study uses grid search and other hyperparameter tuning techniques to optimize the model's performance. This reduces uncertainty by ensuring that the model is trained with the best possible parameters.

Cross-Validation: The model's performance is validated across different datasets, which helps in assessing the uncertainty of its predictions in various scenarios.

Summary of How Each Property Was Addressed:

| Property | How It Was Addressed |
|---|---|
| Accuracy | High prediction accuracy across different scenarios. |
| Causality | Feature importance analysis and human judgment for conflict identification. |
| Transferability | Cross-scenario validation and adaptability to different road environments. |
| Explainability | Feature contribution analysis and hierarchical model structure. |
| Uncertainty | Early stopping, data balancing, hyperparameter tuning, and cross-validation. |

These properties are addressed through a combination of advanced machine learning techniques, rigorous validation, and interpretable model design, making the proposed stacked ensemble model robust and reliable for traffic conflict prediction.

## 9.3 Validation test of near future crash prediction model

The main purpose of this thesis is to discuss the prediction and analysis of unsafe traffic conditions, several models are proposed to make crash predictions in hourly and semi-hourly based, and real-time traffic conflict prediction. Along with modelling procedure, near future crash characteristics and real-time conflict characteristics are captured and extracted, the relationships between contributory factors and unsafe traffic conditions are investigated, model interpretation and variable importance are analysed.

In the near future crash prediction, this thesis:

1) Developed Zero-inflated log count data time series (ZILT) models to predict traffic crashes in the next hour;

2) Developed the combined methods TSGRNN-WCNN (TGRCN) for semi-hourly crash prediction.

While both ZILT and TGRCN make crash predictions, ZILT excels at capturing crash trends and modelling crash rates over longer periods. On the other hand, TGRCN, a neural network based model, focuses more on predicting crashes in the near future. TGRCN operates in two stages: predicting independent variables such as speed, and traffic volumes for the next time step as the first stage, and then forecasting crashes using these predicted values as independent variables. ZILT, on the other hand, is a time series model that incorporates periodicity and seasonality features, gaining robustness with longer periods.

To validate the effectiveness of ZILT model in monthly prediction, the 80km Guidu Freeway in Guizhou Province, China was used as a test case. Video processing was applied to extract traffic features and build daily and monthly crash prediction models to forecast crash numbers for each road segment in both directions. This validation process spanned more than a year, from 2020 to 2021. Initially, data from 2018 to 2019 were used to build ZILT model, which was then used to predict monthly traffic crashes starting in 2020. The crash data for the next month was collected to validate the model's predictions for the previous month. This experiment continued for a two years period from 2020-2022. The purposes of this

experiment are:

1) Test ZILT model effectiveness and stability;

2) Assess the utility of using video analytics to extract dynamic traffic data for improving crash prediction in real-world applications.

The Guidu Mountainous Freeway was completed in March 2011, with a total length of 80km. It connects Guiyang to Duyun, forming a crucial part of the Guizhou section of the Xiamen-Chengdu freeway. It generally consists of a two-way, four-lane road with 18 tunnels, 54 bridges, 5 interchange hubs, and 3 parking service areas distributed along its length. The overall speed limit is 110km/h. The tunnel speed limit is 80km/h. The road profile is displayed as follows in Figure 9.1.

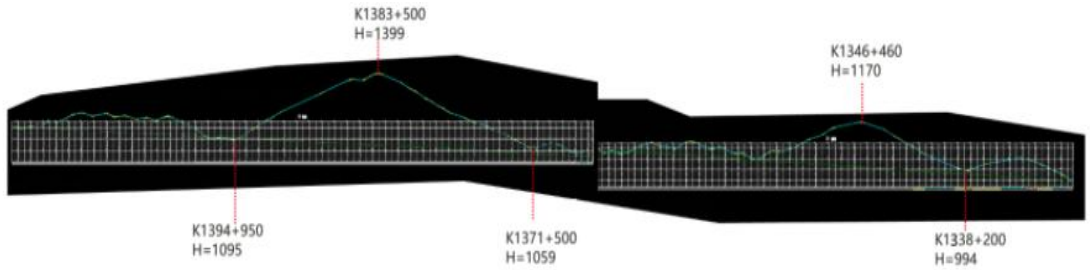



Figure 9.1. Road Profile of Guidu Freeway

Dynamic traffic features, including vehicle speed, traffic volume by direction, and truck-to-car ratio (extracted via video processing), along with weather conditions, historical crash data, and the impact of holidays and special events such as Covid-19 regulations, were selected as independent variables for crash prediction. A Zero-Inflated Logarithmic Link for Count Time-Series (ZILT) model was developed, assuming a negative binomial distribution for crash occurrences, to account for spatio-temporal dynamics and enable monthly crash predictions. For comparison, the same model was also applied to predict crashes without incorporating the dynamic traffic variables. The prediction results are displayed in Figure 9.2.

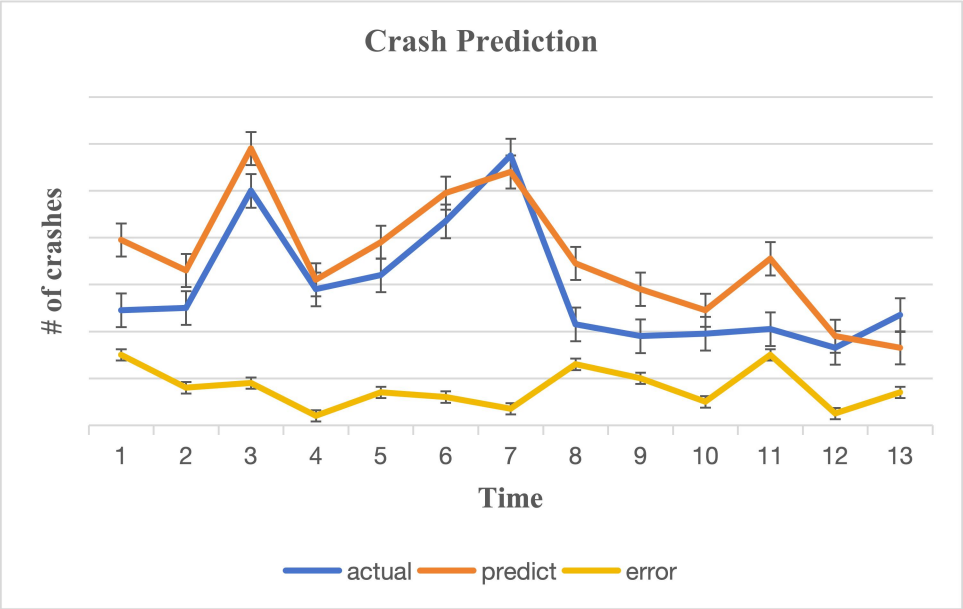



Figure 9.2. The comparison of actual data vs prediction

Crash prediction accuracy is compared with and without involving dynamic traffic data as displayed in Table 9.1.

Table 9.1. Prediction Accuracy on Different Perspective Settings (based on the Ground Truth data)

| | Prediction Accuracy | Mean Square Error |
|---|---|---|
| Prediction without Dynamic Traffic Data | 78.5% | 0.96 |
| Prediction with Dynamic Traffic Data | 83.1% | 0.88 |

For the model without dynamic traffic features, predicted results are more viable and R-squares value is significantly lower than the model with dynamic traffic features. This indicates that the inclusion of dynamic traffic features (obtained through the video analytics presented earlier) as independent variables can explain more variances in crash occurrences. Video analytics plays an important role in traffic crash prediction by extracting additional

dynamic motion parameters to gather information.

### 9.3.1 Justification on the stacked ensemble models in handling temporal dependencies and feature interactions of traffic conflict prediction

Traffic conflict prediction involves complex, high-dimensional data with temporal dependencies, non-linear relationships, and interactions between features. The selection of Random Forest (RF), Support Vector Machines for Regression (SVM-R), Gradient Boosting Machine (GBM), and Deep Neural Networks (DNNs) for traffic conflict prediction is justified by their complementary strengths in handling the specific characteristics of traffic data. RF provides robustness to noise and also the interpretation of the model. SVM-R captures non-linear relationships and temporal structures of sequential data. GBM deals with high-dimensional data and excels at dealing with multicollinearity that existed in the dataset, and DNNs model temporal dependencies and complex patterns existing in the conflict datasets. The stacked ensemble of these models offers a comprehensive approach to addressing the challenges of traffic conflict prediction, ensuring both accuracy and interpretability.

Safety Surrogate Measures (SSMs) data is high-dimensional, non-linear, and contains noises. Curse of dimensionality is usually the problem with high-dimensional data. Random Forest model can handle with high-dimensional data through feature selection and ensemble of trees. The interaction between the random forest model with high-dimensional SSM data are explained in details as follows (Beest, et al., 2017):

Non-linearity: SSMs often capture complex, non-linear relationships between variables. Random Forest can model these non-linear interactions effectively by capturing different aspects of the data.

Robustness to Noise: SSM data can be noisy due to measurement errors or variability. Random Forest's ensemble approach averages out the noise across multiple trees, leading to more reliable predictions.

Interpretability: Feature importance scores returned by Random Forest can be valuable in understanding which SSMs are more influential in predicting safety outcomes.

Overfitting: High-dimensional SSM data is prone to overfitting during model training. By randomly selecting subsets of features, the model introduces variability, preventing it from becoming overly dependent on any single feature and thereby reducing the risk of overfitting.

In addition, the random forest can be parallelized, making it scalable to large, high-dimensional datasets, which is just the case for extensive SSM data. Therefore, Random Forest should be suited for handling high-dimensional Safety Surrogate Measures data due to its inherent feature selection, robustness to noise, and the ability to model complex, non-linear relationships. Its ensemble nature and bagging technique make it resistant to overfitting, while its scalability and interpretability make it practical in explaining models built with high-dimensional SSM data.

DNN is suited for capturing temporal dependencies in traffic data by modelling how a sequence of events leads to a conflict. The architecture of neural network can capture temporal features by neurons and transmit model weights from long sequence to make prediction.

In order to avoid overfitting issue, we managed to make DNNs effective through:

- using simpler DNN architectures with fewer parameters to avoid overcomplexity and better suit the smaller dataset size.
- using augmentation techniques like time-warping, adding Gaussian noise in the process of model training.

- using pre-trained models from other traffic prediction use cases.
- using regularisation techniques such as L1/L2 regularisation to penalize large weighs in the network
- using dropout technique to randomly drop neurons during training and using early stopping technique when validation performance stops improving.

This study applies 1), 4), and 5) techniques in the above to avoid overfitting and make DNNs effective.

Deep Neural Networks (DNNs) excel at automatically extracting and learning features from one-dimensional sequence data, such as univariate time series (Fawaz et al., 2018). They inherit the advantages of Multilayer Perceptrons (MLPs) for time series forecasting, including support for multivariate inputs, multivariate outputs, and the ability to model complex, arbitrary functional relationships (Fawaz et al., 2018). Unlike traditional methods, DNNs do not need to rely solely on lagged observations for learning (Fawaz et al., 2018). Instead, they can learn a meaningful representation from a large input sequence, focusing on the aspects most relevant to the prediction task (Fawaz et al., 2018).

SVMs is a popular tool for analysing temporal data with a timestamp for each record. SVMs are well-suited to temporal data because they can handle large, high-dimensional data sets, and are effective for classification, regression, and time series prediction (Thissen et al., 2003).

SVMs use a risk function that combines empirical error and a regularised term.
SVMs can handle high dimensional data well, even with relatively small training samples.
SVMs can exhibit good generalisation ability for complex models.

SVM uses feature engineering to convert time series data into a format involving lagged variables, rolling statistics, and seasonal indicators (Tajiri et al., 2010). Specifically, lagged variables (e.g., speed at time t−1, t−2) can be created to capture past behaviour. Rolling

statistics (e.g., average speed over the last few seconds) can be computed to summarize temporal trends.

In addition, SVM's regularisation parameter helps prevent overfitting, which is useful when dealing with high-dimensional temporal features. SVM does not inherently model sequential data. It relies on feature engineering to incorporate temporal information, which can be labour-intensive and may not capture long-term dependencies effectively, but is good at short-term time series analysis (Thissen et al., 2003).

SVM and DNN can Compensate for RF's limitations in temporal dependencies from the following aspects:

Capturing Temporal Dependencies:

SVM: Although not inherently designed for temporal data, SVMs can model temporal relationships through careful feature engineering, such as incorporating lagged variables or rolling statistics (Thissen et al., 2003).

DNN: DNNs, are specifically designed to handle sequential data and can capture both short-term and long-term temporal dependencies without extensive feature engineering.

Handling Complex Patterns:

SVM: SVM's kernel functions allow it to model non-linear relationships and also short-term temporal patterns.

DNN: DNNs work well at modeling complex, non-linear relationships and can automatically learn hierarchical features from raw data. It makes them applicable to traffic conflict prediction where temporal and spatial patterns are existed simultaneously (Fawaz et al., 2018).

Scalability to High-Dimensional Data:

SVM: SVM performs well in high-dimensional spaces, making it suitable for datasets with many features, including engineered temporal features (Thissen et al., 2003).

DNN: DNNs can handle high-dimensional raw data and learn relevant temporal features directly from the data.

In terms of complementary use cases, Random Forest works well for tabular data with clear feature interactions and when model interpretability is important. SVM is useful for datasets where non-linear relationships and some temporal patterns can be captured through feature engineering. DNN is ideal for raw sequential or multi-modal data where temporal dependencies and automatic feature learning are critical. GBM works well for model interpretation and high-dimensional data. Therefore, by combining these models, a more comprehensive approach to traffic conflict prediction can be achieved, leveraging the strengths of each method to address the specific characteristics of the data.

However, variables in the same domain: time based SSMs, energy based SSMs, and acceleration based SSMs, exist correlations. Interpretability and importance rankings may get impacted by the interactions and correlations among SSMs (Darst et al., 2018). In terms of interpretability, high correlations or interactions can make it difficult to isolate the individual effect of each SSM (Darst et al., 2018). If two SSMs are highly correlated, RFE might arbitrarily select one over the other, leading to misleading interpretations.

For importance rankings, interactions and correlations can affect the stability of importance rankings (Darst et al., 2018). If SSMs are interdependent, small changes in the data or model might lead to significant changes in rankings.

In addition, correlation and interactions among variables may also lead to overfitting in high-dimensional SSMs data. Therefore, regularisation techniques of Lasso regression are applied to handle multicollinearity and improve the stability of importance rankings. Cross validation tests across different scenarios have been conducted to evaluate how consistently certain SSMs are ranked as important. It shows that the top six most important variables are consistent in all scenarios. However, the latter variables vary from scenarios. It means that important variables truly captures SSM data characteristics and can indicate the occurrences

of traffic conflicts.

Bootstrap is also used to evaluate the consistency of contributing variable importance scores. We set the number of bootstrap samples to be 100, and define the sample size the same as the original dataset with replacement. Bootstrap results return the confidence interval of each variable and show that the top five most important variables keep the same across different bootstrapped samples, which matches with cross validation results. The reason is that the importance scores of the top five variables are much different from the latter ones. A big gap of important scores exists. The following plot shows the important variable ranking in the vehicle based motorway scenario through bootstrapping method. Bootstrap returns the average ranking scores and confidence interval of each explainatory variable.

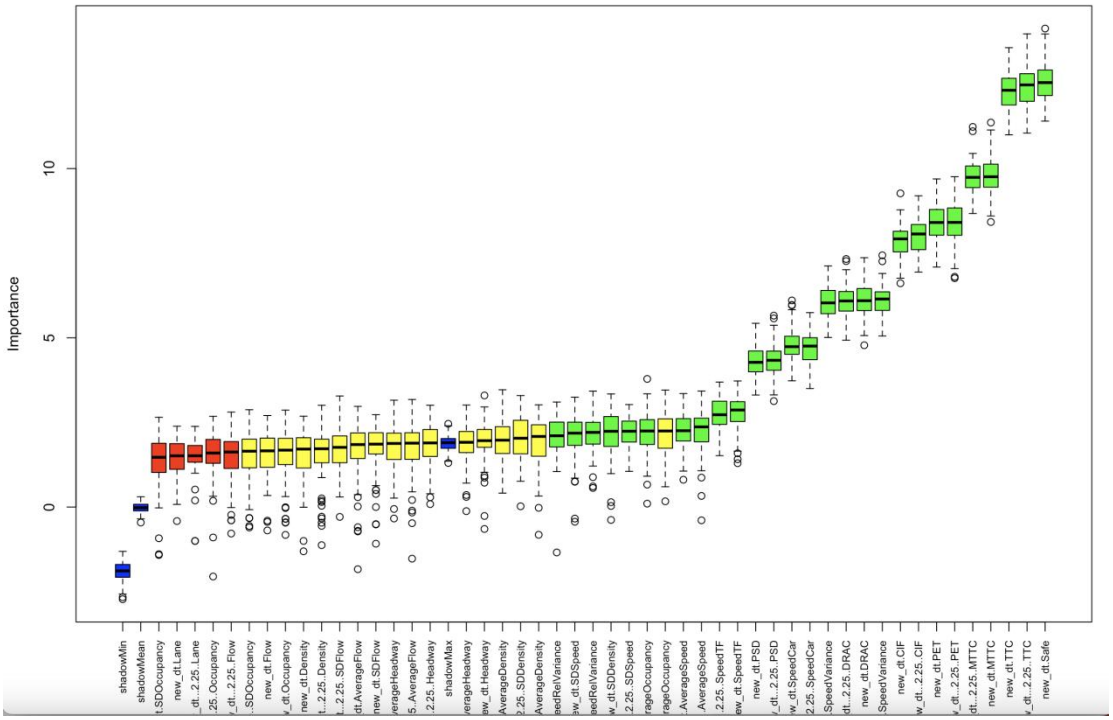



Figure 9.3 Variable importance plot in vehicle based scenario

## 9.4 Implementation of pertinent interventions

For traffic prevention, pertinent interventions should be designed according to significant influential factors affecting crash and conflict occurrences respectively. Therefore, identifying essential traffic parameterss related to crash and conflict occurrences are important. The

following table exhibits contributory factors for traffic crash and conflict by key findings from previous chapters.

Table 9.2 Contributory factors from previous chapters.

| | 1st factor | 2nd factor | 3rd factor | 4th factor | 5th factor |
|---|---|---|---|---|---|
| Crash | speed variance | speed | headway | occupancy | Traffic flow |
| Conflict (urban junctions) | GAP | DRAC | CAI | PSD | Speed |
| Conflict (motorway) | GAP | DRAC | CAI | TTC | TIT |
| Conflict (vehicle based) | TTC | MTTC | PET | CIF | speed variances |

From previous studies, we have found that for short-term crash affecting factor analysis, speed variance explains the most for crash occurrences. Speed, headway contribute significantly to crash occurrences. Occupancy and traffic flow are also influential factors for traffic crashes. Speed variances, speed and headway are variables related to vehicle speed. Lane occupancy and traffic volume are variables related to traffic flow. Hence, pertinent interventions can be designed to control vehicle operation speed, speed variances and traffic flow (volume) to prevent crash occurrences.

For real-time conflict analysis, at urban junction, it is found that GAP, DRAC, CAI, PSD, Speed are influential SSM variables contribute to crash occurrences. Similarly, GAP, DRAC, CAI, TTC, TIT are contributing SSM factors for motorway segments of infrastructure based analysis. For motorway segments of vehicle based, influential factors are different, TTC, MTTC, PET, CIF, Speed variances are the most important variables. Although contributing factors vary for different roadway scenarios, speed is the common base variable deriving the explanatory SSMs. Therefore, devising pertinent interventions concerning speed, speed variances, and traffic flow (volume) can increase traffic operation efficiency and promote traffic safety.

### 9.4.1 Overview of pertinent interventions

Proactive and predictive traffic safety management system can monitor real-time traffic conditions, detecting abnormal traffic scenarios, identifying unsafe traffic dynamics, predicting traffic conflicts and crashes in short time span, and implement pertinent interventions to bring back normal traffic status from unsafe conditions (Hossain et al., 2019). Accurate and reliable traffic conflict and crash prediction models with uitlising sensor fusion techniques and deep learning neural networks evaluate incident severity and crash risk. Traffic dynamic parameters, crash precursors, classification of abnormal incidents, and influential crash affecting variables, provide abundant pre-crash information to assist traffic

police and road control centre to make up instant and suitable pertinent interventions to prevent crashes.

Traffic safety is affected by traffic factors negatively or positively, as indicated by an increase or reduction in crash frequency by change of factor influence. Traffic volumes, signalized intersections, and access point densities have negative influence on traffic safety, as increase of their values is expected to raise the number of crashes due to the numerous traffic conflicts under heavy traffic conditions, especially at signalized intersections and access points where conflicts are concentrated (Al-Omari et al., 2021). A perfect pavement condition may also increase the likelihood of crashes as drivers are encouraged to drive at high speeds (Al-Omari et al., 2021). The presence of a raised median can lead to vehicle rollovers in case of a crash, while an unraised median is not considered an obstacle for vehicles (Al-Omari et al., 2021).

On the contrary, improvements of road conditions and necessary information signs related to speed can lead to a decrease in the number of crashes. Roads with a large number of lanes offer smooth movement without congestion, thus reducing vehicle conflicts (Al-Omari et al., 2021). High posted speed limits are only set on roads with low intersection and access point densities, ensuring continuous traffic with fewer interruptions (Al-Omari et al., 2021). Unpaved roads may cause confusion for drivers, but wide paved, hard shoulders, sidewalks and vegetation median types provide good separation between the road and opposite traffic as well as the roadside environment (Al-Omari et al., 2021).

However, some factors have a dual safety effect. The fluctuation in the impact of these factors on crash occurrence is due to the different road environments among road classes (Al-Omari et al., 2021). For example, increase speed is positively correlated with crash occurrences in most of cases, but when traffic congestion existed, increasing speed indicates congestion status is mitigated and thereby crash is not likely to take place.

Therefore, formulation of pertinent interventions should take considerations into various traffic, vehicle, geometry, and environmental factors. A list of these factors is displayed in the

following figure (Hossain et al., 2019).

Table 9.3. List of considered factors in the formulation of pertinent interventions.

| Crash and Incident data | Traffic flow data | Detector sensing location | Environmental data | Other data |
|---|---|---|---|---|
| Time | Speed, Lane change information, Volumes and Occupancy/ Density | Longitudinal: 2 detectors at upstream and downstream from crash | Roadway Geometry | Surrogate safety measures |
| Location | Their lateral and longitudinal differences | Lateral: detector data for each lane | Weather | Human factors |
| | | | Interaction with other vehicles | |

Pertinent interventions majorly include: road infrastructure interventions, vehicle based interventions, speed related interventions, environmental based interventions, and other interventions such as driver monitoring. These interventions are instant reactive correspondence to the contributing factors (causes) of traffic conflict. Key findings from previous chapters suggest interventions related to speed, speed variances, and traffic flow are pertinent to accident prevention. Implementation of effective interventions plays an important role in traffic management and traffic safety promotion. Speed related interventions involve changing or lowering speed limits, implementing dynamic speed limit adjustments, and employing traffic calming techniques. Speed variance related interventions are similar to speed control interventions, aiming to promote safety by reducing the difference between design speed and the posted speed limit (Garber and Gadiraju, 1989). Typical interventions include variable speed limit at hazardous sites, lane level speed limit control, application of adaptive speed control systems with vehicle tracking to dynamically capture speed variation and change speed limits (Federal Highway Administration, 1998). Typical traffic flow related interventions include traffic light adjustments, lane blocks, and the use of open emergency hard shoulders during rush hours. Additional applicable interventions to prevent accidents

include roadside and central barrier systems, grade separation, the separation of bicycle and motorcycle lanes, traffic sign updates, and lane markings. These interventions are also related to the management and control of speed and traffic flow, but they are not in general and particularly specific to certain traffic conditions.

Dynamic traffic interventions are significantly better than static or fixed traffic intervention strategies. Emerging technologies provide the accessibility to real-time traffic operation parameters, such as speed, speed variances, trajectories, traffic volumes and the detection of abnormal incidents. The intelligent freeway control platform can be built to integrate dynamic traffic information. Based on real-time traffic conditions data collected by external sensing devices, the intelligent freeway control platform judges and evaluates the current traffic operation status using built-in crash and conflict prediction models.

It analyses abnormal traffic conditions' duration and severity. The assessment mainly relies on empirical based algorithms designed by researchers, dynamically analysing road transportation capacity, design speed, real-time average speed of traffic flow, real-time vehicle events, and vehicle trajectories. It computes multiple indicators such as interruption rate, congestion severity, saturation status, traffic characteristic index, and traffic meteorological index to complete an overall assessment of traffic operation status. Following assessment, targeted traffic control strategies, dynamic variable speed limits, road traffic induction, and other measures are implemented to address slow traffic, congestion, and accident sensitivity resulting from mixed traffic flows on main routes. Traffic induction instructions are issued through road control lights, variable information signs, third-party platforms, and roadside broadcasts. During congestion, traffic control instructions are transmitted through lane controllers and variable information signs at lane level, with dynamic shoulders activated to coordinate and control vehicle speeds. Traffic congestion control along with lane change control are the key interventions of traffic flow. Traffic flow interventions aim to reduce traffic volume, and lane occupancy in congested traffic and accelerate traffic operation efficiency in peak hours. Speed and speed variance interventions focus on speed limit control. For speed limit control execution strategy, corresponding

information is optimized and coordinated spatially and temporally to manage speed. Different speeds apply varying pressures to the road. By analysing speed differences during distinct traffic flow fluctuations, traffic attenuation can be reduced and overall road traffic efficiency can then be improved. During congestion, road-level variable speed limit signs are displayed hierarchically based on proximity to congestion points and the requirements of different road segments.

### 9.4.2 Implementation of pertinent interventions

Traffic situation analysis and prediction are fundamental to daily freeway operation supervision. Based on real-time detection of abnormal scenarios, and the predicted results of traffic conflicts, crashes, congestion, and flow, multidimensional traffic evaluation and prediction systems can be built with the integration of pertinent intervention strategies. This section introduces the actual implementation of pertinent interventions for speed control, speed variance control, traffic volume control, severe weather condition control, presence of traffic police, and the application of smart traffic management systems.

#### 9.4.2.1 Pertinent interventions for speed control

Wang et al. (2018) investigates the relationship between crash rates and mean speed, speed variation, geometric design features, and traffic volume, concluding that relevant policy should be formulated in speed management and speed variation control, concluding that it is important to post proper speed limits along with matched enforcement for example detecting vehicles exceeding the speed limit so as to restrict the travel speeds to a reasonable range. They also found that lower speed resulted in lower crash rates. Federal Highway Administration (1998) concludes that crashes increased on the average 7 percent at sites where the speed limits were lowered and decreased on the average 11 percent where the speed limits were increased. Shinar and Stiebel (1986) found compliance with speed limits to be greatest in the vicinity of police vehicles and diminish with increasing distance. The halo

effect is more significant for mobile police vehicle than stationary polic vehicles. Federal Highway Administration (1998) found that in USA increasing speed limits generally raises freeway average speeds simultaneously. Although vehicle operating speed is distinct in different road geometric when speed limits in the United States were raised from 55 mph (89 km/h) to 65 mph (105 km/h), changes in mean speeds ranged from 1 to 4 mph in average (Federal Highway Administration, 1998). Therefore, posting speed limit pertinent to different road segments and roadway geometric features should be a contributory safety intervention and are important to reduce crash rates.

Speed limits are set for the maximum safe speed on roadways. Speed limit controls can smooth traffic flow and reduce traffic collisions. Contrast with traditional speed limit sign that written on the board, current speed limit control uses a digital dashboard to convey messages. Changeable message signs can be used to give drivers travel-time information, weather condition, congestion information, and other details (Transportation Policy Research centre, Texas A&M Transportation Institute). Nowadays, variable speed limit is more popular than traditional speed limit signs which convey more dynamic traffic information and use changeable speed limit signs to slow drivers to avoid creating heavy traffic congestion. For example, sensors along the roadway detect when congestion or weather conditions are dangerous. They then automatically lower the speed limit in stages to slow traffic evenly and delay the onset of congestion (Transportation Policy Research centre, Texas A&M Transportation Institute).




Figure 9.4 Two types of Speed Limit Information Signs

Figure 9.4 shows the display of speed limit information signs in freeways. There are typically two speed limit signs. One is digital dashboard hanged in the middle of freeway. The other is traditional roadside speed limit sign. Digital dashboard speed limit signs are also used for variable speed limit (VSL) applications. Speed limit can be changed according to weather condition, congestion, and road geometric.

### 9.4.2.2 Pertinent interventions for speed variance control

Speed variance is defined as a vehicle's deviation from the mean speed of free-flowing traffic (Federal Highway Administration, 1998). Garber and Gadiraju (1989) found that the discrepancy between the design speed and the posted speed limit is a significant factor affecting speed variance. Research indicates that speed variance approaches minimum levels when the posted limit is between 5 and 10 mph lower than the design speed; beyond this

range, variance rises as the gap widens (Garber and Gadiraju, 1989). Additionally, drivers are likely to accelerate as roadway geometric features improve, independent of the posted limits. While crash rates do not always rise with higher average speeds, crash rates increase with greater speed variance (Garber and Gadiraju, 1989). Wang et al. (2018) terms reduction in speed variation as the key component of proactive arterial safety management. In contrast with speed intervention by simply posting the speed limit, speed variance intervention should estimate optimal speed for given traffic conditions in real-time and displays dynamic traffic operation information through variable message signs since even when drivers observe the speed limit, speed variation can still exist (Wang et al., 2018). Lave (1985) suggests taking action against slow drivers as well as fast drivers in order to reduce variances not just average speed.

Speed intervention usually relies on stationary speed limit control. However, in order to reduce speed variance among vehicles, variable speed limits should be considered. Variable speed limits (VSL) play a crucial role in enhancing traffic safety by significantly influencing speed variations and headways. Variable speed limits increase average headways and reduce variances in speed, leading to fewer short headways and lower mean speeds (Borrough, 1997; Ha et al., 2003; Pilli-Sivola, 2000). Such changes are directly linked to safety improvement as they result in fewer crashes. Moreover, Borrough (1997) found that the use of VSL along with strong enforcement measures like video cameras greatly reduced the number of crashes (by 28% over 18 months). This positive impact on safety is attributed not only to the smoothing of traffic conditions through longer following distances but also to the reduction in the number of lane changes during congestion. In essence, the control of speed variations through variable speed limits has a profound and positive impact on overall traffic safety (Abdel-Aty et al., 2006). Abdel-Aty et al. (2006) recommends implementing Variable Speed Limits (VSL) with several considerations: Firstly, speed limit changes should be introduced gradually over time, at a rate of 5 mph every 10 minutes. Secondly, there should be an abrupt change in the speed limit in space with no gap distance. Thirdly, speed limits should be reduced upstream and increased downstream of the location of interest. Fourthly, the speed limit changes both upstream and downstream should be significant in magnitude (15 mph) and implemented

within a short distance (2 miles) of the location of interest. Abdel-Aty et al. (2006) also concludes that in addition to providing safety benefits, this VSL implementation strategy will result in travel time savings. In England, VSL systems have been shown to reduce injury crashes by 10%. and reduce noise, and reduce emissions by 2% to 8% (Public Roads, Federal Highway Administration, 1995). The following figure shows the installation of VSL on freeways.

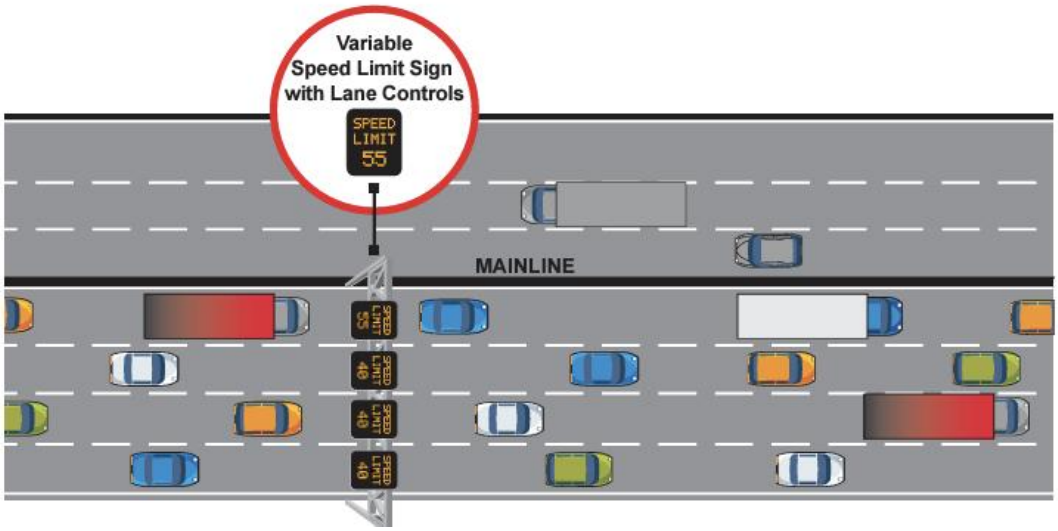








Figure 9.5 Variable Speed Limit Sign with Lane Controls

Figure 9.5 shows the exhibition of VSL digital dashboard in freeways. VSL digital dashboard not only displays speed limit information, but also conveys messages about traffic congestion, road construction, lane closure information, crash information, etc. VSL digital dashboard improves traffic safety by conveying real-time traffic status to drivers. It is the improvement of conventional speed limit signs.

VSL is controlled by national freeways in most countries. For example, in the United Kingdom, the speed limit for cars, motorcycles, and dual-purpose vehicles on single carriageways is set at 60 miles per hour. However, when towing a caravan or trailer, the speed limit is reduced to 50 mph. On motorways, the speed limit for these same vehicle types is 70 mph. If towing on a motorway, the speed limit drops to 60 mph (GOV.UK, 2018). The variable speed limit is beneficial to traffic safety promotion. Abdel-Aty et al. (2006) conducted a study examining the effects of changing speed limits on traffic safety and behaviour at peak hours. They found that abrupt changes in speed limits had a more significant positive impact than gradual changes and could mitigate traffic congestion. Additionally, larger differences in speed limits (15 mph) were more effective than smaller differences (10 mph) in influencing driver behaviour. The test scenarios are displayed in the following figure. (See Figure 9.6)

| | Upstream Lowering Distance | Downstream Raising Distance |
|---|---|---|
| M2_Case 1 | 4 mi | 5.5 mi |
| M2_Case 2 | 6 mi | 5.5 mi |
| M2_Case 3 | 2 mi | 5.5 mi |
| M2_Case 4 | 4 mi | 4 mi |
| M2_Case 5 | 6 mi | 4 mi |
| M2_Case 6 | 2 mi | 4 mi |
| M2_Case 7 | 4 mi | 2 mi |
| M2_Case 8 | 6 mi | 2 mi |
| M2_Case 9 | 2 mi | 2 mi |

Figure 9.6 Different Scenarios Based on Changing Distance for Speed Limit Change (Abdel-Aty et al., 2006)

VSL is usually applied to congested traffic to accelerate traffic operation efficiency. This suggests that more noticeable speed limit changes can enhance compliance and potentially improve safety outcomes on the road. Moreover, decreasing speed in upstream improves the effectiveness of the VSL. The effectiveness is the most significant at the beginning and ending periods of the speed limit change (Abdel-Aty et al., 2006). The following Figure 9.7 depicts the above mentioned test in peak hours when traffic congestion occurs.

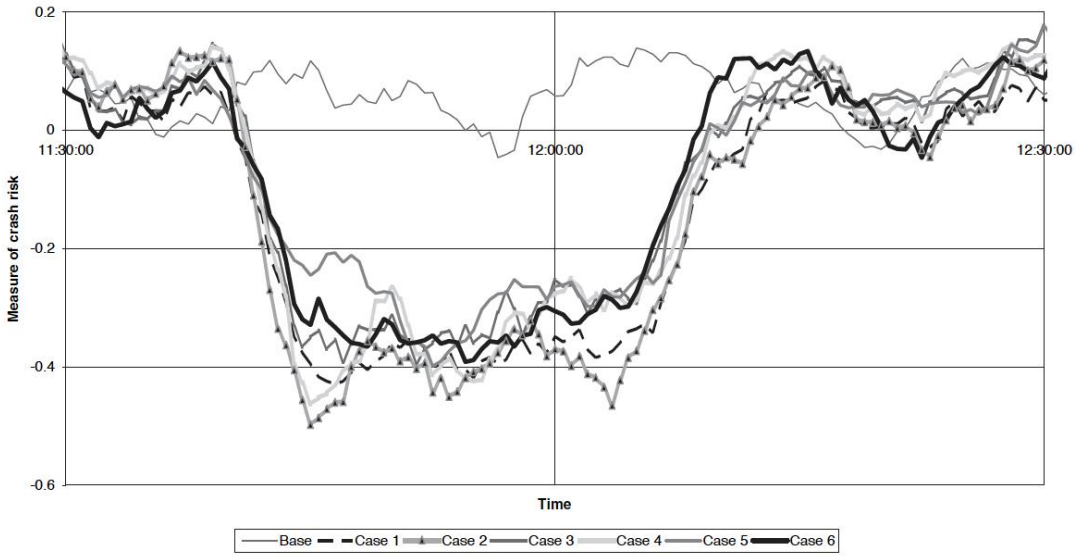



Figure 9.7. Crash risk for strategy scenarios is described in Figure 9.3 at peak hours (Abdel-Aty et al., 2006).

Multiple tests show that the best strategy of VSL was an abrupt 15-mph change in the speed limit, both decreasing 2 mi upstream and increasing 2 mi downstream, applied in 5-mph increments every 10 min. The change in crash risk is shown in Figure 9.7 for the best strategy in peak hours of congested traffic.

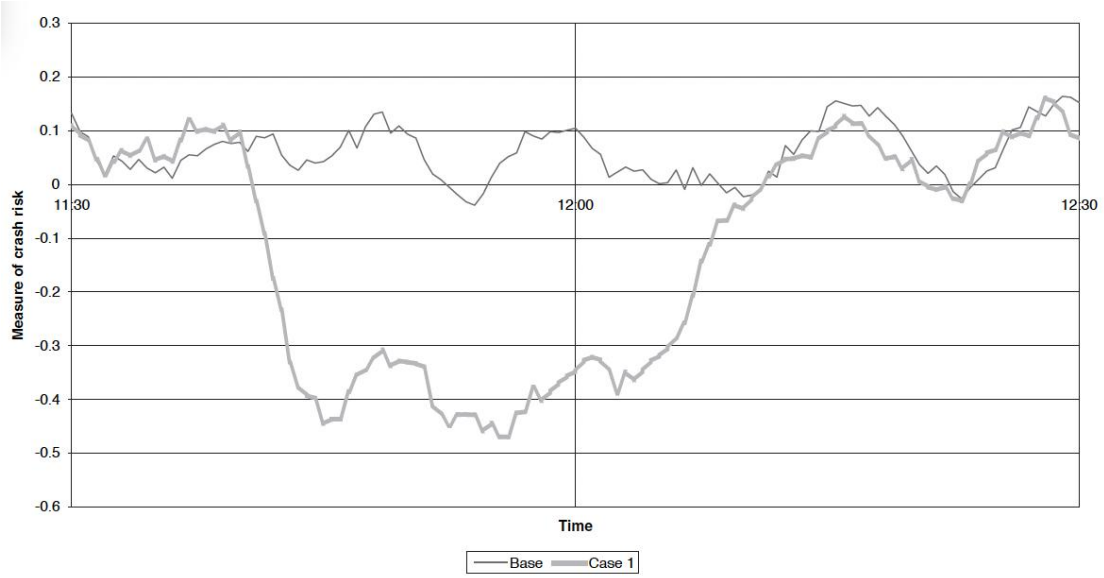



Figure 9.8 Crash rate for the best case (Abdel-Aty et al., 2006).

Seen from the above Figure 9.8, after application of VSL as safety intervention strategy, crash risk is significantly reduced. It shows that VSL should be an effective pertinent intervention to mitigate crash potential and improve traffic safety in general. Rather than solely employing Variable Speed Limits (VSLs) during periods of high congestion, they can also be beneficial during off-peak times. Instead of focusing exclusively on reducing congestion, VSLs can be utilised to effectively mitigate hazards at specific locations (Abdel-Aty et al., 2006). The study found that implementing VSLs during off-peak conditions had a positive impact on travel times (Abdel-Aty et al., 2006). As a result, this best practice determination for existing VSL can be thought of in a new light.

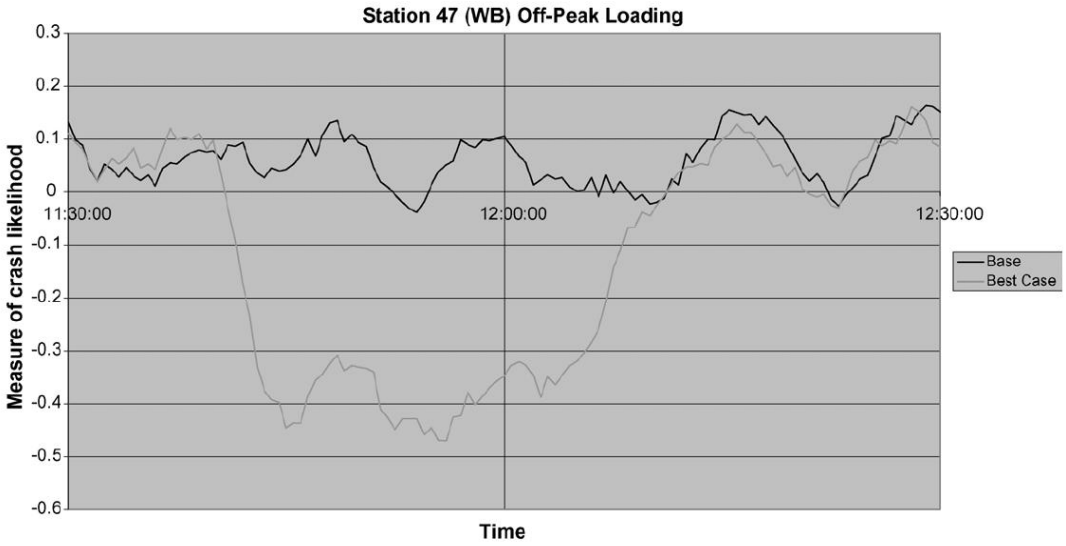



Figure 9.9 Crash potentials at the detector of interest for best case and base case (Abdel-Aty et al., 2006).

Instead of aiming to reduce congestion time only, the VSL can be used to effectively reduce the hazard at certain locations (Abdel-Aty et al., 2006). This research also concluded that by using VSL in off-peak conditions, travel time is positively affected (Abdel-Aty et al., 2006). Abdel-Aty et al. (2006) conducts a t-test to assess the improvement of travel time with the presence of the VSL strategy application. Figure 9.9 indicates a consistent and significant reduction in travel time, as the t-test reveals a notable negative value for travel time in the system due to the implementation of Variable Speed Limits (VSL). This suggests that the approach of adjusting speed limits not only reduced crash potential but also enhanced freeway efficiency. The overall t-test results show significant differences, with a t-value of 14.61. (See Figure 9.11)

| Base scenario | Best scenario | Difference (best case – base case) | Base scenario | Best scenario | Difference (best case – base case) |
|---|---|---|---|---|---|
| 36776.3 | 36655 | −121.3 | 36603.5 | 36456.5 | −147 |
| 36868.9 | 36754.5 | −114.4 | 36712.5 | 36563 | −149.5 |
| 36510.6 | 36526.3 | 15.7 | 36759.9 | 36577.1 | −182.8 |
| 36632.9 | 36529.3 | −103.6 | 36696.4 | 36616.8 | −79.6 |
| 36775.7 | 36763.6 | −12.1 | 36712.6 | 36510.2 | −202.4 |
| 36718.4 | 36563 | −155.4 | 36814 | 36703.7 | −110.3 |
| 36823.4 | 36644.9 | −178.5 | 36892.2 | 36756.5 | −135.7 |
| 36683.6 | 36456.4 | −227.2 | 36856.1 | 36637.5 | −218.6 |
| 36789.9 | 36612.5 | −177.4 | 36959.4 | 36711.4 | −248 |
| 36838.6 | 36628.1 | −210.5 | 36701.5 | 36513.8 | −187.7 |
| 36954.3 | 36618.8 | −335.5 | 36757.6 | 36583.1 | −174.5 |
| 36943 | 36487.8 | −455.2 | 36834.7 | 36615.3 | −219.4 |
| 36733.1 | 36598.8 | −134.3 | 36837.3 | 36687.3 | −150 |
| 36844.5 | 36645.4 | −199.1 | 36749.2 | 36652.4 | −96.8 |
| 36810.1 | 36743 | −67.1 | 36854.9 | 36510.9 | −344 |
| 36799.5 | 36720 | −79.5 | 36814 | 36703.7 | −110.3 |
| 36626.4 | 36444.7 | −181.7 | 36892.2 | 36756.5 | −135.7 |
| 36818.2 | 36795.3 | −22.9 | 36856.1 | 36637.5 | −218.6 |
| 36733.7 | 36551.4 | −182.3 | 36959.4 | 36711.4 | −248 |
| 36886.8 | 36419.8 | −467 | 36701.5 | 36513.8 | −187.7 |
| 36590.2 | 36406.5 | −183.7 | 36757.6 | 36583.1 | −174.5 |
| 36763.5 | 36534.7 | −228.8 | 36834.7 | 36615.3 | −219.4 |
| 36951.2 | 36689.4 | −261.8 | 36837.3 | 36687.3 | −150 |
| 36719.8 | 36642.7 | −77.1 | 36749.2 | 36652.4 | −96.8 |
| 36715.3 | 36444.4 | −270.9 | 36854.9 | 36510.9 | −344 |
| 36807.6 | 36529.6 | −278 | 36714.7 | 36707.3 | −7.4 |
| 36682.2 | 36526.9 | −155.3 | 36760.5 | 36573.1 | −187.4 |
| 36748.3 | 36526.8 | −221.5 | 36884.7 | 36699.5 | −185.2 |
| 36635.9 | 36468.8 | −167.1 | 36799.5 | 36783.1 | −16.4 |
| 36776.8 | 36612.7 | −164.1 | 36678.8 | 36533.7 | −145.1 |
| 36835.6 | 36673.2 | −162.4 | 36785 | 36530.8 | −254.2 |
| 36685.1 | 36591.5 | −93.6 | 36695.5 | 36457.7 | −237.8 |
| 36845.1 | 36649.3 | −195.8 | 36819.6 | 36425.5 | −394.1 |
| 36660.6 | 36503 | −157.6 | 36799.7 | 36441.8 | −357.9 |
| 36884.8 | 36475.7 | −409.1 | 37099.7 | 36561.9 | −537.8 |

Figure 9.10 t-Test for the network Travel time in minutes.

When implementing VSL, the recommendations of this study are as follows (Abdel-Aty et al., 2006):

• Gradually introduce speed changes in time (5 mph every10 min).

• Abruptly introduce speed changes in space (no gap distance).

• Use upstream reductions in speed and downstream increases in speed.

• Change speed limit by large values (15 mph).

• Short up- and downstream distances are sufficient (2 miles each).

### 9.4.2.3 Pertinent interventions for traffic flow control

Traffic flow is important contributing factor to both crash and conflict occurrences according to our previous findings in earlier chapters. Traffic flow interventions concentrates in two ways: congestion intervention and lane change control.

1) Congestion intervention

Congestion causes can be divided into two categories: recurring and nonrecurring. Recurring congestion refers to predictable delays that occur due to high vehicle volumes during specific times, such as peak commuting hours, holidays, or special events, particularly at critical locations like intersections, interchanges, major construction zones, or toll plazas. Nonrecurring congestion, on the other hand, is characterized by unpredictable delays caused by unexpected events, such as traffic accidents, emergency maintenance, or adverse weather conditions. Recurring congestion can often be addressed through traffic planning and infrastructure improvements, while nonrecurring congestion typically necessitates real-time responses and effective incident management (Public Roads, Federal Highway Administration, 1995). However, evidence proves that traffic congestion problems cannot be simply solved by expanding the road infrastructure (Public Roads, Federal Highway Administration, 1995). Besides increasing the use of alternative transportation models and altering trip patterns, measures such as traveler information services, route guidance systems, traffic signal adjustments, and incident management are conducive to improving traffic flow efficiency (Public Roads, Federal Highway Administration, 1995).

Sun et al. (2024) proposes a combined method to address congestion through ramp traffic flow restrictions, ramp closures, plot traffic flow restrictions, plot closures, and fast access to plots without railing. Fast access, implementing dynamic traffic flow restrictions, and adjusting auxiliary road inflows during peak hours are the most effective ones to achieve optimal traffic flow efficiency at ramp and plot entrances (Sun et al., 2024). Fast access without railing can mitigate congestion and reduce local bottlenecks in upstream traffic flow. Dynamic traffic flow restriction or closure measures can adapt to the dynamic process of congestion formation and dissipation to ensure optimal travel speed and efficiency (Sun et al., 2024). Controlling and adjusting auxiliary road inflows with consideration of varying traffic volumes in different scenarios can promote traffic flow efficiency at ramp and plot entrances (Sun et al., 2024).

Temporary shoulder use, often referred to as hard shoulder running or dynamic shoulder use, allows vehicles to drive on the shoulder at reduced speed limits to temporarily increase road

capacity. This approach helps accommodate more traffic and alleviate congestion, either fully or partially, during peak times. The decision to implement temporary shoulder use on a specific stretch of road is made by an operator in the traffic management centre, based on current traffic conditions and established operational policies (Transportation Policy Research centre, Texas A&M Transportation Institute). Temporary shoulder use involves two conditions, shoulder use for all vehicles and transit-only shoulder use for bus or purposed vehicles. Figure 9.11 displays a sample for temporary shoulder use for buses.




Figure 9.11 Temporary Shoulder Use for Buses

The Federal Highway Administration (FHWA) estimates that 40 percent of all congestion in the U.S. is due to recurring congestion, which can manifest as significant problems when traffic demand exceeds the capacity of entire interchanges or corridors (Transportation Policy Research centre, Texas A&M Transportation Institute). These recurring bottlenecks are often predictable in terms of their causes, locations, times of day, and durations. Some are periodic issues where traffic volume temporarily exceeds road capacity (Transportation Policy Research centre, Texas A&M Transportation Institute).

Common bottleneck locations include areas where lanes narrow, ramps and interchanges, and regions with sharp curves or steep inclines (Transportation Policy Research centre, Texas A&M Transportation Institute). Low-cost solutions to address these issues may involve

restriping roads, adding travel lanes by reducing lane widths or converting shoulders, accommodating entering and exiting traffic, and modifying ramps (Transportation Policy Research centre, Texas A&M Transportation Institute). By doing so, localized congestion can be mitigated and traffic safety can be improved. Figure 9.12 shows the locations of in total 26 freeway bottleneck removal projects conducted in the DallasFort Worth urban area of the United States. It has been found that 35% of injury crash rates have been reduced average (Transportation Policy Research centre, Texas A&M Transportation Institute).

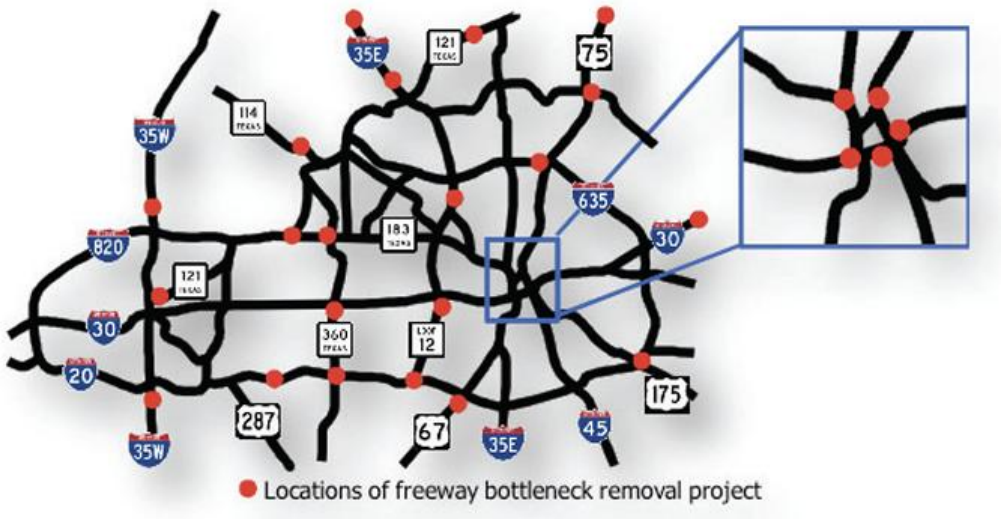



Figure 9.12 Locations of Freeway Bottleneck Removal Project

2) Lane change control

The lane-changing trend is defined as “an act of driving practice that changes a vehicle from one lane to another as both lanes travel in the same direction” (National Highway Traffic Safety Administration, 2004). Farooq et al. (2021) developed a lane-change model featuring key factors organized in a three-level hierarchical structure for evaluation, as shown in the following Figure 9.13. The first level includes four primary factors related to road safety: traffic characteristics, human factors, road characteristics, and light conditions (Farooq et al., 2021). A descriptive-analytic study identified three main categories contributing to crashes linked to fatigue and sleepiness—human, road, and light conditions, along with vehicle-related factors (Farooq et al., 2021; Ghasemi et al., 2020). In level 2, these main

factors were divided into fourteen sub-factors, and in level 3, they were further categorized into eight sub-factors (Farooq et al., 2021).

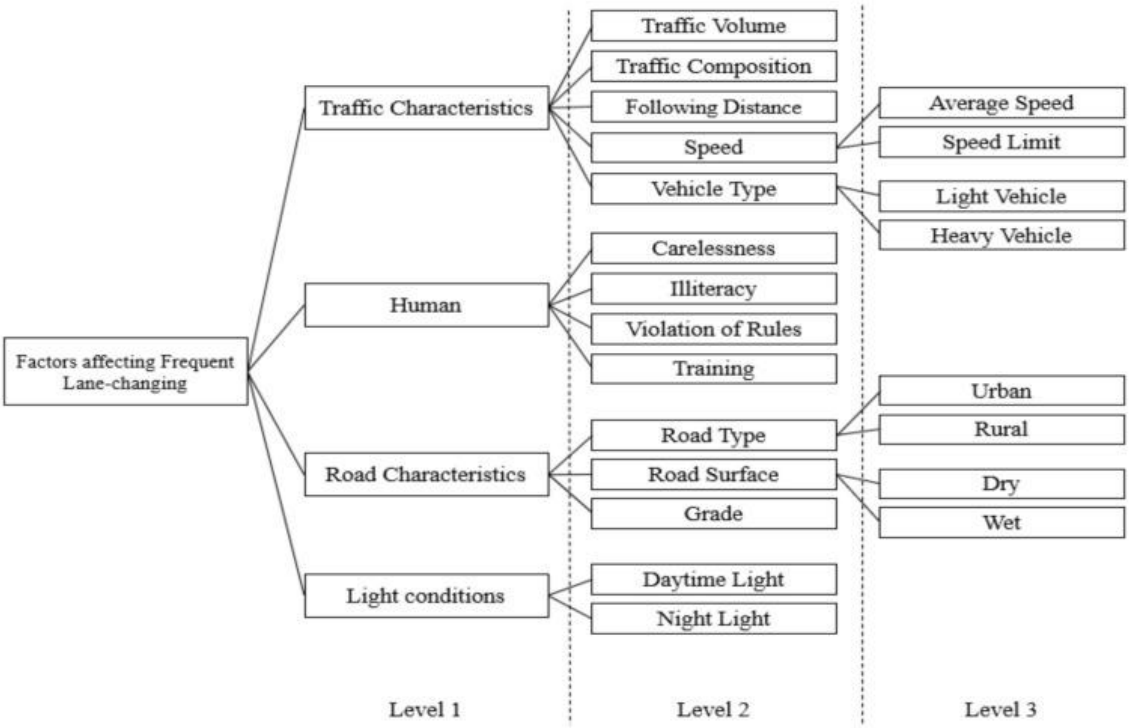



Figure 9.13 Three-level hierarchical structure of the factors affecting frequent lane-changing.

Lane change behaviours are related to crash occurrences. Frequent lane changes are likely to increase crash risk, especially in congested traffic conditions. Dynamic lane management operations can be deployed to reduce roadway congestion by freeway control centres. For example, a hard shoulder can be opened during congested traffic. Aron et al. (2013) used a French urban motorway as a studied case to conduct an observational before-after assessment to compare the empirical number of crashes that would have happened in a hard shoulder open during congestion. Research shows that a reduction in congestion occurs and results in a decrease of the crash occurrences (Aron et al., 2013). In addition, change of lane widths and shoulder widths may also influence crash risk. Pokorny et al. (2020) conducted research to analyse safety effects of the traffic lane and shoulder widths on rural roads and found that the lane widths of 1.50-2.50 m and shoulder widths of 0.50-0.75m were relatively safer than other categories on two-lane rural undivided roads in Norwegian.

The lane-level intelligent control module achieves active lane-level control under heavy

traffic, events, maintenance and construction, and adverse weather conditions. Built on the lane-level real-time traffic flow control strategy algorithm, the module transmits traffic perception data to the road management centre at regular intervals. It calculates real-time probabilities of traffic accidents and congestion on freeways based on multi-source heterogeneous data such as weather and road conditions using traffic prediction models. Corresponding solutions are provided once risk values exceed thresholds. Lane controllers and variable information boards automatically adjust display content upstream and downstream to manage traffic volume and flow by implementing traffic control strategies such as rear-end collision prevention, lane-specific dynamic speed limits, truck lane management, and emergency lane opening and closing in adverse weather. Active traffic flow and speed adjustments at lane level significantly reduce traffic accident risks and improve traffic efficiency.




Figure 9.14 Lane Control Information Dashboard

Figure 9.14 shows the lane control information dashboard in freeway. Lane control dashboard usually applies together with VSL controls. Information of speed limits, lane closures, high-occupancy vehicle lanes, high-occupancy toll lanes, bus lanes, truck lanes will all be displayed.

Managed lanes are specialized lanes offering access to vehicles with the purposes of selecting

a preferred travel method Such lanes include High-occupancy vehicle (HOV) lanes, High-occupancy toll (HOT) lanes, Express toll lanes, Truck-only lanes, and Bus-only lanes. Utilising managed lanes can maximize the use of existing roadway space, encourage transit use, carpools, and vanpools, improve travel time reliability, and increase speed and efficiency. As a result, the traffic congestion problem can be reduced and safety levels will be promoted.




Figure 9.15 Instances for HOV and HOT Managed Lanes

### 9.4.2.4 Severe Weather Environment Control

In the ZILT model for hourly crash prediction in Sutong Bridge Freeway and Guidu Mountainous Freeway, weather conditions were set as categorical variables consisting of 12 classes: Sunny, Partially cloudy, Cloudy, Drizzle, Rainy, Heavy Rainy, Stormy, Shower, Riany-Shower, Drizzle-Rainy, Sleet, Snow. Although the weather condition variable is not as significant as other traffic operating variables such as speed, speed variances, and traffic volume, the weather condition variable is still a potential factor influencing crash occurrences. The insignificant weather effect is probably due to the fact that weather is recorded daily, but the prediction model is based on hourly observations. Another possible reason is that class proportion is not even. Most of the categories fall into Sunny and Rainy classes. Other classes are less representative. However, the weather effect should not be ignored in the crash and conflict prediction modelling procedures.

Weather is widely acknowledged as a significant environmental factor that increases the risk of roadway crashes and contributes to crash severity and frequency (Xing et al., 2019). According to the Federal Highway Administration (FHWA), there are more than 6.3 million road crashes in the United States annually. Among these, 24% (i.e., 1.5 million) are weather-related (Goodwin, 2012). Understanding the relationship between weather and road safety is important so as to formulate effective countermeasures to alleviate weather-related road safety hazards, particularly under adverse weather conditions (Xing et al., 2019). Xing et al. (2019) also finds that the lag effect of weather in the preceding period has a non-linear exposure response relationship with the crash risk in the current period. The design of weather warning and proactive road safety management systems is indicative of mitigating possible hazards on the road under adverse weather conditions (Xing et al., 2019). Given that the instant effect and the lag time effect of possible road safety hazards after the presence of extreme weather warnings simultaneously exist, it is necessary to disseminate advance road safety warning messages through various media such as the internet, in-vehicle driver assistance systems, and variable message signs (Xing et al., 2019). To alleviate severe weather impact on traffic operations, measures such as information release, traffic diversion, vehicle induction, speed and lane control, entrance and exit control, and safety facility activation should be developed for various weather conditions. Warning and control strategies also need to be formulated for different weather types and levels, establishing corresponding disposal systems. It is worth exploring the effects of different dissemination strategies for different inclement weather conditions so that safety effectiveness can be maximized (Xing et al., 2019).

#### 9.4.2.5 Presence of traffic police in freeway management

Traffic police are responsible for road traffic management, including planning, directing traffic flow, setting traffic signs, etc., to ensure that road traffic is carried out in an orderly manner (Xinhua, 2024). Traffic crashes are closely related to traffic violations. Traffic police can reduce the occurrence of crashes by cracking down on illegal behaviours. Traffic police

correct traffic violations such as speeding, running red lights, drunk driving, etc. through patrolling and monitoring to maintain traffic order and safety (Xinhua, 2024). The presence of a traffic police force at the crash venue can effectively relieve traffic congestion and quickly handle accidents. In China, traffic police is responsible for:

(i) Formulate policies and regulations for road traffic management.

(ii) Guide and supervise local public security organs to investigate and deal with road traffic violations in accordance with the law, prevent and handle traffic accidents, and maintain road traffic orders and highway public security orders.

(iii) Guide local public security organs to implement road transportation approval for highly toxic chemicals.

(iv) Guide and supervise the registration, safety inspection and driver examination, and certification of motor vehicles (excluding tractors).

(v) Organize and guide road traffic safety publicity and education work.

(vi) Organize and guide road traffic management science and technology work.

(vii) Guide local public security organs to organize urban road traffic, participate in urban road traffic planning and construction, and the planning of road traffic safety facilities.

Presence of a traffic police force enhances traffic education, policy enforcement, traffic management, policy formulation, technology investment, and violation correction, which contributes to crash reduction and traffic safety promotion. (See Figure 9.16 )



Figure 9.16 Chinese traffic police flying UAV objects to supervise freeway operation

### 9.4.2.6 Smart Freeway Management Systems

Besides enhancing the traffic police force to prevent and minimize damages from traffic emergencies and crashes, the smart freeway control platform should also be built to promote traffic safety. It is a comprehensive travel information service platform generates various types of information based on big data analysis results and real-time internet map road condition collection. It actively releases various information types through multiple means and channels throughout the process and in real-time to enhance public travel convenience and safety, optimizing public travel experiences.

The smart freeway control platform establishes a knowledge base focused on road perception, problem prevention and control, and event management. It is a multi-source data collection platform for real-time access to freeway sensing equipment. The platform stores dynamic data from meteorological monitoring, traffic flow, vehicle speed, video surveillance, weather information, environmental conditions, and static data such as infrastructure facilities, roadway geometric design features, and milestones. Serving as the system's foundational layer, the platform supports real-time intelligent model computing and functional applications.

Ideally, the system should include four main modules: display function, early warning function, safety control, and disposal management. The display function module maps sensing facilities' location, facilities operational status, dynamic traffic flow, vehicle operation data, and checkpoint video on a map. The early warning function module computes early warning models based on various sensor real-time data, issuing alarms upon reaching warning values like fog, ice, and rainfall warnings. The early warning function module also calculates crash risk and the probability of real-time conflicts. Once the likelihood of crash incidents is beyond a specific threshold, the early warning system will send updated information to traffic police station so as to conduct immediate interventions. Safety control manages warning events, recommending plans, releasing plans, and cross-departmental linkages. Disposal management tracks event handling processes from start to finish, including process evaluation. The essence of the smart traffic management platform is statistical machine learning algorithms, data visualization models, and a large computing centre. Figure 9.17 shows the smart traffic management platform installed in Beijing University of Technology.




Figure 9.17 Smart Traffic Management centre Platform in Beijing, China

For instance, UK National Highways developed smart motorways, including All Lane

Running (ALR) and Dynamic Hard Shoulder Running (DHSR), in 2017 (NFCC, 2022). These smart motorways utilise various technologies and traffic management strategies to monitor and respond to fluctuating traffic conditions (NFCC, 2022). Signals are used to inform drivers about network status and to display lower Variable Mandatory Speed Limits (VMSL) in response to congestion or incidents (NFCC, 2022).

On ALR and DHSR smart motorways, additional capacity is provided by either temporarily or permanently opening the dynamic hard shoulder to traffic (National Highways, 2024). National Highways employs systems like SVD (Stopped Vehicle Detection) and MIDAS (Motorway Incident Detection and Automatic Signaling) to automatically detect events such as stopped vehicles, queuing traffic, and congestion (National Highways, 2024). These systems can promptly set signs or signals to warn and inform drivers while adjusting speeds to facilitate smoother traffic flow (National Highways, 2024).

For every incident, multiple signs and signals are activated, spaced between 1,000 and 1,500 meters apart, ensuring that even if one device fails, others can still function. National Highways invests £105 million to enhance the resilience of operational technology systems on traffic management platforms, including warning signs, speed control signals, CCTV, and MIDAS, aiming for 97% availability across ALR sections. (Response to BBC Panorama's 'Smart Motorways: When technology fails'). There are currently three types of smart motorway (Allen, 2023):

Controlled Motorway (e.g., the western section of the M25): This system features variable speed limits that are monitored via a regional traffic centre. The hard shoulder is only permitted for use in emergencies, such as vehicle breakdowns (Allen, 2023).

Dynamic Hard Shoulder (e.g., junctions 10-13 on the M1): During peak times, vehicles can use the hard shoulder to alleviate congestion. The traffic control centre displays a speed limit sign on the gantries above the shoulder when it is in use and a red X when it is not. Driving on the hard shoulder when a red X is displayed can result in fines. Emergency refuge areas

(ERAs) are located at intervals for breakdowns. Concerns about the inconsistent use of the hard shoulder have led to a halt in constructing new dynamic hard shoulder sections, with existing roads being converted to all lane running (Allen, 2023).

All Lane Running (e.g., M6 junctions 16-19): On these stretches, the hard shoulder is permanently used as an additional lane. ERAs are still present at regular intervals. If there is an incident, the hard shoulder lane may be closed, as indicated by a red X displayed on the gantries above (Allen, 2023).

Currently, there are 44 stretches of smart motorway either in operation or under construction, all located in England. Most of these are concentrated on the M1, M6, and M25, but a total of 14 motorways feature some aspect of smart motorway technology, covering approximately 500 miles of road. The majority of these smart motorways are found in the the south-east of England, as well as around Manchester, Birmingham, and Sheffield. Below Figure 9.18 shows the map of smart motorways in the UK (Allen, 2023).

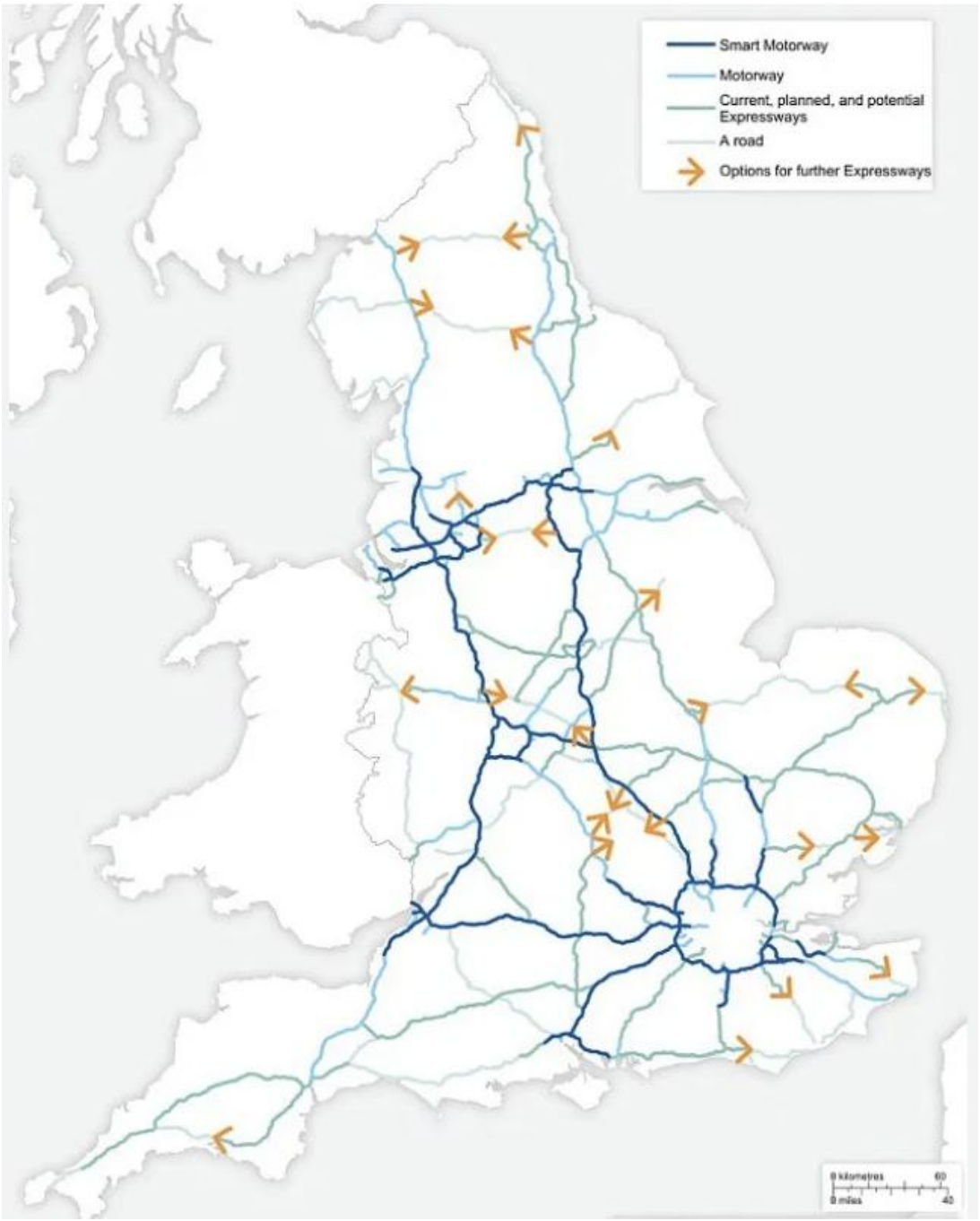


Figure 9.18 Map of smart motorways in the UK.

## 9.5 Future Research on Unsafe Traffic Conditions Prediction

Crashes are complex traffic incidents caused by multiple independent variables, such as environmental conditions, driver status, vehicle interactions, and overall traffic operations. Increasing the number of factors analysed can improve the accuracy of traffic crash prediction

models. Conflicts as crash surrogates are indicator of crash occurrences and also closely related to real-time dynamic vehicular and infrastructure based parameters. Therefore, collecting data from various sources and aspects is essential for developing integrated crash prediction and conflict detection models that incorporate dynamic traffic characteristics.

This thesis proposes practical methods for extracting dynamic traffic data in both segment-based and vehicle-based scenarios using video processing and data mining techniques. For segment-based infrastructure data, includes lane-specific speeds, speed variances across lanes, vehicle trajectories, vehicle types, traffic volumes, and acceleration. These parameters can be computed by analysing videos recorded by roadside surveillance cameras. For vehicle-based operational data, the focus is on relative traffic parameterss to the operation of both the ego vehicle and preceding vehicles. These data are extracted from videos recorded by in-vehicle front cameras. The thesis introduces computer vision methodologies to detect various traffic scenarios, and extract real-time vehicular and infrastructure parameters, enabling the incorporation of multifaceted data into crash and conflict prediction models that account for human factors, roadway conditions, environmental influences, and vehicle interactions.

Due to challenges in real-time data acquisition and feature extraction, few studies have simultaneously analysed multidimensional data to predict near-future traffic crashes and real-time traffic conflict detection. This thesis proposes a holistic approach to short-term crash prediction and conflict prediction by integrating dynamic features from both segments and vehicles into analysis. Future research will focus on:

1. Detection of preceding and following traffic scenarios using front and rear in-vehicle cameras.
2. real-time driver emotion expressions and abnormal driving patterns will be recognised by developing a deep convolutional neural network.
3. Fusion of data from multiple sources, such as in-vehicle cameras, roadside surveillance cameras, UAV drones, radar, LiDar, and different kinds of environmental sensors.
4. Development of statistical machine learning models to account inherit heterogeneous

structures in crashes and conflicts.

5. Establishment of crash prediction models for imminent crash risk, considering human factors, traffic conditions, environmental variables, and vehicle interactions.

6. Multi-faceted cross-sectional analysis to determine variable importance in explaining crash occurrences.

7. Development of causal inference models to explain crash and conflict causation and capture contributing factors.

8. Development of Spatio-temporal Large Language Models to redefine unsafe traffic condition problem as a language modelling problem. Timesteps can be treated as tokens. Spatial location and global temporal patterns of timesteps at each location can be learned and more detailed information of spatial-temporal dependencies will be captured to build unsafe traffic conditions prediction models.

More in-depth explainations of future research development will be elabourated in the conclusion parts.

## 9.6 Policy Implications and Crash Prevention Strategies for Traffic Management

To effectively manage the freeway system and meet goals of security, safety, and reliability, it's essential to keep track of real-time multi-dimensional information in order to understand freeway current status. Access to real-time information about freeway performance and weather conditions is crucial for professionals to optimize capacity, address disruptions (such as emergencies, evacuations, and security threats), and help users plan their trips regarding timing, mode, and route (FHWA TEA-21).

Various technologies are employed to gather detection and surveillance data, including in-roadway and over-roadway sensors that measure traffic flow (ILDs, Radars, LiDars), vehicle probes for tracking travel times and origin-destination patterns, closed-circuit

television (CCTV) systems for real-time freeway monitoring, road weather information systems (RWIS) for assessing pavement and weather conditions, and manual collecting methods (Freeway Management and Operations Handbook, 2006).

Intelligent transportation systems (ITS) and freeway management strategies can help alleviate congestion, enhance safety, and improve mobility. However, the potential advantages of these strategies and technologies can only be fully realised with a clear understanding of current freeway operating conditions and effective pertinent interventions by roadway management centres or traffic police.

With dependence on data-gathering methods by virtue of various sensors and computer vision techniques, benefits arise from freeway management strategies and ITS technologies (Freeway Management and Operations Handbook, 2006):

- ✓ Decreased delays and congestion due to timely detection and resolution of incidents.
- ✓ Fewer secondary accidents resulting from prompt incident identification.
- ✓ Lower road maintenance costs (labour, materials, and equipment) facilitated by RWIS technologies and effective winter road management strategies (like anti-icing and snow plowing).
- ✓ Enhanced traveler information.

Based on data collection and modelling results analysis in the previous study, some implications for policy making in ITS traffic management are as follows (Freeway Management and Operations Handbook, 2006):

- ✓ Regional Coordination: Effective traffic management necessitates collabouration across various jurisdictions and agencies, fostering information sharing among stakeholders.
- ✓ Adoption of ITS Standards: Policies should require the implementation of national ITS standards to facilitate interoperability and seamless data exchange.
- ✓ Performance Monitoring and Evaluation: Stress the importance of monitoring and evaluating performance to gauge the success of regional integration and ITS implementations.

- ✓ Investment in Technology and Infrastructure: Support the introduction of advanced technologies and infrastructure essential for regional integration.
- ✓ Training and Education: Encourage training and education for transportation professionals to effectively manage and operate integrated systems.
- ✓ Flexibility and Scalability: Ensure that regional ITS architectures are adaptable and scalable to meet future demands and technological advancements.
- ✓ Integration of Freeway Management: Treat freeway management as part of the broader transportation network, incorporating strategies like ramp and incident management.
- ✓ Safety and Mobility: Focus on enhancing safety and mobility through strategies aimed at reducing congestion and improving road safety.
- ✓ Environmental Considerations: Consider the environmental impacts of traffic management strategies.
- ✓ Public Information and Outreach: Include measures for informing the public about traffic management strategies.
- ✓ Legislative and Regulatory Support: Ensure that traffic management strategies have legislative and regulatory backing.
- ✓ Managed Lanes: Support the creation and implementation of managed lanes to optimize freeway efficiency and safety.
- ✓ Technology Integration: Promote the integration and standardization of advanced technologies.
- ✓ Advanced Communication Technologies: Encourage the adoption of advanced communication technologies to improve freeway management systems.
- ✓ System Design and Implementation: Advocate for a holistic approach to system design, considering long-term needs and future expansions.

In addition, crash blackspot identification and analysis is crucial for promoting traffic safety. Crash blackspot identification involves safety precautions, management decision-making, and predictive traffic crash modeling. Managing hidden dangers on crash-prone roadways entails data collection, traffic management, resource allocation, improvement planning, and evaluation. Integration of traffic data collection, analysis, and crash modeling enhances

implementation efficiency. Road traffic crash identification and safety assessment requires comprehensive analysis of different road types and traffic characteristics. Statistical and machine learning models analyse crash causation through collected traffic operation data, crash data, violation records, and traffic flow data, identifying hidden hazards and proposing effective improvement plans for crash blackspots road segments.

Using systematic safety engineering principles, potential traffic hazards can be identified, diagnosed, and analysed through qualitative and quantitative methods. Multi-dimensional crash data can be processed using statistical modelling or deep learning techniques to predict and assess crash-prone blackspot road facilities. Subsequent analysis and improvement planning can therefore be informed by collecting multi-dimensional roadway traffic data, investigating crash affecting causal factors, identifying crash occurrence hotspot locations, analysing drawbacks of current management strategies, and building prediction models to validate improvement effects.

## 9.7 Summary

This chapter explores challenges in making short-term crash predictions and compares the pros and cons of different crash and conflict prediction models. The hourly crash prediction model emphasizes capturing longer-term crash patterns with temporal series data. Semi-hourly crash prediction model prioritizes capturing near future crash characteristics which are spatially and temporally correlated. The real-time conflict prediction model serves as a surrogate for real-time crashes, focusing on immediate driving maneuvers and vehicle-to-vehicle interactions. The stacked ensemble model (SEM) is determined to be the best-performing model in varying environments. SEM conflict prediction model utilises real-time traffic data that is extracted by video processing of UAV drones to achieve relatively high prediction accuracy. This chapter discusses the advantages and disadvantages of different initiated models in various environmental conditions, the innovation and contribution of this thesis, and the future development of the current study.

This chapter also describes other potential factors overlooked in traffic crash prediction modelling as well as how to implement pertinent interventions to prevent and alleviate traffic collisions. Pertinent interventions to prevent traffic accidents should be another hot topic that needs to be thoroughly discussed in further studies. Preventing traffic crashes and reducing crash rate is the main responsibility of traffic police. However, there are many types of traffic accidents, such as freeway traffic accidents, drunk driving accidents, fatigue driving accidents, urban city junction accidents, etc. Pertinent intervention strategies should be designed for different purposes. For example, speed limit and lane control are beneficial for preventing freeway accidents. The driver monitoring system is a more appropriate way to reduce fatigue driving. Police inspection at specific locations to check drunk driving is the most popular way to seize drunk drivers. Besides pertinent interventions, policy making should also be studied in future research in order to better regulate traffic order and driver behaviours.

# Chapter 10 Conclusion

This chapter concludes the whole thesis. It briefly retrospects thesis outlines, research background and purposes, proposed statistical machine learning methods, data collection procedures, result analysis, pertinent interventions, and policy implications according to research findings, real application of this study, and future research development. In addition, this chapter summarizes the importance, innovation, and contribution of this thesis. On the contrary, it also discusses the limitations of this research and the future improvement of the current study.

Unsafe traffic conditions consist of traffic crashes and traffic conflicts. The main purpose of this thesis is to improve traffic safety with utilisation of modern statistical, machine learning, and deep learning techniques to capture unsafe traffic conditions characteristics, investigate crash causation, and predict unsafe traffic conditions in the near future. The findings of this thesis are beneficial and conducive for stakeholders such as roadway management companies, traffic police, research institutes, and traveler, not only in crash prevention and prediction but also for pertinent intervention strategies and policy implementation.

## 10.1 Summary

This research focuses on near future traffic crash analysis and real-time traffic conflict prediction. Throughout the paper, it analyses traffic characteristics, traffic crash causal factors, traffic crash prediction intervals, crash influences, traffic management intervention strategies, traffic conflict characteristics, conflict prevention and analysis, and, most importantly, traffic crash prediction and conflict classification methods. The entire content can be divided into five parts:

1) Data collection and preparation

To conduct traffic crash analysis, sufficient traffic data is essential for modeling and interpretation. Various data sensors are necessary to collect multifaceted data from freeways, urban city junctions, and vehicle-based sources. These sensors include roadside surveillance cameras, UAV drones, Inducted Loop Detectors (ILD), and various in-vehicle cameras. After evaluating factors such as availability, complexity, time allocation, and expenses, the Sutong Bridge freeway, London M1 motorway, and urban city junctions in Shanghai were chosen for data collection. Traffic data are primarily collected using UAV drones, roadside surveillance cameras, ILDs, and in-vehicle cameras. Hourly and semi-hourly crash prediction models were built using traffic data collected from the Sutong Bridge freeway and London M1 motorway, respectively. Collecting data from two different countries increases sample diversity and provides validation testing to ensure model robustness and transferability. The real-time conflict prediction model utilises different road segments of the Sutong Bridge freeway and urban junctions in Shanghai. Collecting data from these two scenarios not only validates the model's effectiveness in both freeway and urban junction conflict prediction but also provides a larger sample size to interpret variable importance and investigate contributing factors.

2) Dynamic traffic data extraction:

This part discusses how to apply deep learning computer vision techniques to detect abnormal traffic scenarios, extract dynamic traffic data, derive traffic variables, and convert image coordinates to spatial coordinates. It provides variables for traffic crash analysis and integrated dynamic traffic parameterss from raw data processed by video analytics from surveillance cameras, drones, and in-vehicle cameras. Video processing techniques introduced in this research include YOLO-v8 for object detection and re-ID tracking and a modified FairMOT model for simultaneous detection and re-ID tracking. Affine spatial matrix transformation is used to calculate world space coordinates from image coordinates. Traffic abnormal scenarios are detected and classified into different use cases: congestion detection, pedestrian detection, emergency lane taking over detection, wrong way driving detection, stopped vehicle detection, fire detection, etc. The thesis puts forward an optimised FairMOT neural network model to conduct detection and tracking in the same stage. Other deep learning neural network models have been newly developed and adapted for our

application by modifying their original structures.

3) Crash prediction modelling and model interpretation:

Various methods can be used for crash prediction, but crash data are different from typical datasets—they do not follow a normal distribution and are extremely imbalanced with highly skewed distributions. Therefore, many prediction models are not suitable for crash prediction. In this research, a Zero-Inflated Log Count Data Time Series Seasonal INGARCH (ZILT) model is developed for hourly crash prediction in freeway management. Additionally, a Time Series generalised Regression Neural Network and a Weighted Convolutional Neural Network (TGRCN) model are built for semi-hourly crash prediction. The ZILT model captures temporal features in crash series, while the TGRCN model, a deep learning model, captures both temporal and spatial features, making it suitable for near-future crash prediction. For real-time crash prediction, conflicts are treated as surrogates for crashes in the analysis. A Stacked Ensemble model with Support Vector Machine, Random Forest, and Deep Neural Network as the first layer and Gradient Boosting Machine as the second layer is built for real-time traffic conflict detection. For crash prediction models, operational dynamic data such as speed, speed variances, traffic volumes, and vehicle types are analysed for variable importance using Intermediate Convnet Activations Visualization (ICAV) and Local Interpretable Model-agnostic Explanations (LIME) models, which apply to deep learning neural networks. For traffic conflict prediction models, the Recursive Feature Elimination method is applied to investigate variable contribution. A Weighted Summation Algorithm is also designed to integrate variable rankings returned by different models and layers to obtain the final variable contribution, representing the importance of each variable.

4) Traffic conflict prediction

Traffic conflicts are surrogate measures of traffic crashes. Traffic conflicts provide information regarding pre-crash conditions. Utilising pre-crash conditions can build a proactive safety model to predict hazardous traffic conditions in advance and prevent actual traffic crashes. Conflict prediction is also an indispensable component of the ADAS system to make warnings ahead of time before crashes.. This thesis gathers data from a variety of

infrastructure and vehicle-based sensors, including drones, lidars, radars, and cameras, across different settings in China and the UK, such as urban junctions, motorway segments, and vehicle-based data from instrumented vehicles. It introduces an innovative stacked ensemble learning model, with base learners including a Random Forest (RF), a three-layer Deep Neural Network (DNN), a Support Vector Machine with a Radial kernel (SVM-R), and a Gradient Boosting Model (GBM) meta-layer, aimed at improving prediction accuracy. The Recursive Feature Elimination (RFE) algorithm is then applied to identify the most influential SSMs for conflict prediction in each scenario. The results demonstrate the effectiveness of the stacked ensemble model, achieving accuracy rates of 88% for junctions, 87.5% for motorway segments, and 99% for vehicle-based conflicts. Additionally, the study emphasizes the importance of using different SSMs for conflict detection across various scenarios. These findings are valuable for roadway operators and vehicle manufacturers, providing insights for developing strategies to detect both infrastructure- and vehicle-related traffic conflicts.

Results show that Gap time, CAI, and DRAC are the three most significant SSMs for infrastructure-based motorway and urban junction scenarios. Conversely, significant variables for vehicles differ considerably, with TTC, MTTC, PET, CIF, and PSD being the five most significant.

5) Pertinent interventions to prevent traffic crashes and conflicts in advance

In the discussion chapter, pertinent interventions to prevent traffic crashes are also discussed. It should be an open question for further research to address the effective interventions to reduce crash rates and prevent accidents. Formulating pertinent interventions demands current traffic information such as traffic volume, speed, vehicle types, accident types, detected abnormal scenarios, and predictive information such as predicted crashes, detected conflicts, and predicted traffic flow conditions. This information needs to be displayed and processed properly in data visualization platform that has built-in functions to make recommendations for pertinent interventions. Modern big data and artificial intelligence systems provide the possibility to build real-time prediction, alert, intervention, and management platforms for traffic police stations with built-in deep learning and statistics algorithms. This ITS freeway

management platform can help road management centres and traffic police to keep track of real-time traffic environmental information on the roadway system. The understanding of current roadway status ensures effective freeway management by meeting goals of security, safety, and reliability. It also contributes to implications for policy making and crash prevention strategies for traffic management. The crash blackspot identification method is essential for making crash prevention strategies. By analysing crash causation, crash affecting factors, crash-prone segment conditions, and crash characteristics through the algorithm of blackspot identifications, pertinent interventions, and policies can then be initiated to handle instant traffic incidents and mitigate crash risk in crash-prone segments. Pertinent interventions are conducive to instant crash prevention, but adaptable policy implications are more strategic and beneficial for long-run traffic safety promotion. More in general policy implementation implications for freeway safety promotion include:

- ✓ Increase investment in Infrastructure: Enhance road capacity and maintain existing infrastructure to reduce congestion and improve safety;
- ✓ Real-Time Data Utilisation: Implement advanced traffic ITS systems to collect real-time data and then leverage real-time data for dynamic routing and crash/conflict response.
- ✓ Integrated Communication Systems: Establish protocols for inter-agency communication to coordinate responses to incidents effectively.
- ✓ Incident Management Programs: Develop and enforce policies for rapid incident reaction and clearance to minimize the impact on traffic flow with utilisation of intelligent transportation systems (ITS) incident detection and prediction modules.
- ✓ Safety Regulations: Enforce stricter regulations and penalties for unsafe driving practices such as drunk driving, fatigue driving, road rage, and distraction driving, to reduce crashes.
- ✓ Public Awareness Campaigns: Enhance education to the high risk public (truck drivers, bus drivers, a special purpose vehicle drivers, taxi drivers, etc) on safe driving practices.

Successfully implementing these policies can significantly improve traffic management and enhance overall road safety.

## 10.2 Research Contribution and Innovation

Traditional traffic analysis focuses on reactive approach in analysing countermeasures of pertinent intervention and association between contributing factors and crash occurrences. Although a reactive approach can investigate crash related factors and may help formulate traffic management and intervention strategies, reactive traffic analysis cannot prevent crashes in realistic. A proactive approach such as an active conflict detection and prevention system and further predictive safety approach such as a near future crash prediction model can prevent crash occurrences. In contrast with reactive traffic analysis, the predictive safety approach aims to detect unsafe traffic conditions in advance, predict when and where crash collisions and incidents are likely to happen, and then formulate effective intervention strategies to prevent them. The research conducted in this thesis is pioneering in the field of transportation engineering field by using computer vision techniques to extract dynamic traffic parameterss, predicting traffic crashes across different time spans, detecting abnormal scenarios, predicting traffic conflicts in real-time, and report dynamic influencing factors to inform traffic police for timely interventions to prevent traffic crashes.

This thesis focuses extensively on the quantitative modelling of traffic parameters extraction, crash prediction and conflict classification. The research lays the foundation for short-term crash prediction analysis and traffic conflict prediction. The methodologies proposed in this study can serve as references for successors aiming to build relevant crash or conflict prediction models in their own contexts. While future methodologies may differ due to varying application scenarios, the underlying logic and model structures from this study remain valuable. Key points that warrant attention include:

1) The consideration of the zero-inflated count data structure for building crash prediction models, effectively handles excessive zeros.

2) The unsuitability of ARIMA models for crash prediction due to errors not following a normal distribution. INGARCH models, adept at handling heterogeneity, offer a better time series structure for crash prediction.

3) The innovative approach of the TGRCN model, predicts independent variables from time t to time t+1 before predicting traffic crashes within the same time dimension. This idea can guide successors in developing crash prediction models.

4) CNN, typically an image classification model, proves to be a robust predictor when applied to crash prediction. Its application involves projecting crash series data onto a spectrogram image and extracting features through image processing.

5) While various methods exist for conducting traffic conflict prediction, this study innovatively outputs variable importance as part of the model results, addressed by the Stacked Ensemble model.

6) The flexibility of Stacked Ensemble model structures, which allow for different sub-models to be integrated into the first, second, and even third layers. However, such integration must be validated for model robustness and prediction accuracy.

Traffic conflicts as early detection of traffic incidents, providing additional insights into crash causation processes (Arun et al., 2021). In addition to crash prediction methods, this study introduces traffic conflict classification models for detecting real-time traffic conflicts between vehicles. Traffic crash data is extremely rare and difficult to collect. Compared to crash data that lagged behind hazardous conditions, traffic conflicts serve as crash surrogate measures to provide an instant indication of unsafe traffic conditions. Traffic conflict prevention transits traffic safety analysis from a reactive approach of passive safety to proactive safety management. Traffic conflict prediction moves one step forward by evolving proactive safety management to predictive traffic analysis. Without effective intervention, traffic incidents can lead to crashes.

Application of conflict prediction model can provide pre-crash alerts to reduce the likelihood of crash risk and prevent crashes in advance, including:

1) predict the location of crash hotspots and take instant intervention to prevent incidents from happening, which as a result, prevent crash to take place in the end.

2) use conflict data to measure the effectiveness of intervention. Traffic crash data usually takes long time to collect, but incident and conflict data are easier to acquire.

3) transfer safety promotion from infrastructure base to vehicle base. To prevent vehicle based incident so as to provide instant driver protection.

This thesis conducts research in traffic conflict prediction and analysis. It introduces a stacked ensemble model to capture conflict features, investigate conflict contributory factors, and analyse utility of different safety surrogate measures in various situations: infrastructure based freeway, urban city junctions, .and vehicle based scenarios.

Key contributions and innovations of this thesis include:

- Designing a spatial transformation matrix to convert image coordinates to world coordinates for calculating vehicle speed without recalibration for each video.

- Using video analytics to extract dynamic traffic data such as speed, acceleration, trajectory, traffic flow, and vehicle types from roadside surveillance cameras.

- Comparing different structures and approaches of crash prediction methods: Time Series generalised Weighted Convolutional Neural Network, Spatio-Temporal Convolutional Graph Neural Network, Long Short-Term Memory model, Multilayer Perceptron, Zero-Inflated Count Data Negative Binomial model, etc.

- Developing a new time series regression crash prediction model considering spatio-temporal, zero-inflated, and short-window crash characteristics.

- Introducing a stacked ensemble learning model for effective real-time traffic conflict

prediction in various scenarios.

- utilising the Recursive Feature Elimination method for real-time variable importance scores, identifying critical variables contributing to traffic conflicts, and suggesting interventions to prevent accidents based on these contributing factors.

- Conducting contributory factor analysis and model-based interpretation to analyse explanatory variable importance on crash occurrences using spatio-temporal generalised Regression Convolutional Neural Network.

- Initiating suitable pertinent interventions for traffic management according to different abnormal scenarios and severity of crashes. Implications for policy making is also discussed for future policy improvements.

Effective computer vision techniques are also put forward in this thesis for extracting dynamic traffic parameterss. The deep learning and conventional image processing methods proposed herein offer valuable insights for researchers considering similar technical approaches to obtain traffic operational data. Noteworthy aspects highlighted in this research include:

1) The introduction of a new affine matrix transformation for converting coordinates from image space to world space. Future studies can devise new transformation matrices for enhanced performance.

2) Speed detection remains a challenging aspect of computer vision recognition. The proposed model attempts to estimate passing vehicle speeds without calibration, relying only on lane width and default camera height. For more accurate speed estimates, pre-calibration involving sensitive zones (with known length and width) is recommended.

3) UAV drones demonstrate superior accuracy in calculating traffic parameterss compared to

surveillance cameras. In practical applications, video angle significantly influences dynamic traffic parameters estimation. Most calibrations are aimed at correcting angle distortions. Therefore, time-efficient options involve selecting segments equipped with built-in ETC cameras, positioned atop the road in the middle of lanes, providing optimal angles for estimating traffic parameterss.

4) The utilization of mFariMOT and YOLO-v8 models for object detection and tracking. Given the rapid advancements in image recognition, future researchers can explore more advanced models for real-time object detection and tracking.

5) The accuracy of detection models hinges on the quantity of labeled images. Researchers should prioritize labeling as many objects as possible to ensure detection accuracy in diverse real-world applications.

6) This thesis introduces a stacked ensemble model to predict conflicts in both urban junction and freeway scenarios. The proposed model can be used as a strong classifier in predicting conflicts in general cases. However, the stacked ensemble model is the integration of base learner and meta learner. Different sub model combinations bring different prediction results. The structure of the stacked ensemble model can be adjusted which is subject to specific use cases in different roadway scenarios.

Furthermore, this research proposes pertinent intervention strategies aimed at preventing crashes once predicted outcomes are received. While real-world scenarios require more tailored and pragmatic intervention strategies, the proposed interventions can serve as empirical recommendations, reflecting their application in real situations. Key intervention strategies deserving attention include:

1) Installing traffic signal boards on roadsides to instantly update traffic information and alert incoming drivers, thereby preventing traffic accidents.

2) Consider the use of hard shoulders as changeable lanes during traffic congestion to enhance traffic flow and avoid crashes or subsequent collisions.

3) Implementing ramp closures for freeway management to deter vehicles from entering, thus reducing the likelihood of crashes.

4) Installing strobe lights on roadsides to alert following vehicles in the event of a crash ahead, prompting caution and diversion.

5) Setting dynamic lane-specific speed limits for different road segments to facilitate traffic efficiency.

6) Installing severe weather warning system to alleviate environmental impact on traffic operation. Measures such as information release, traffic diversion, vehicle induction, speed and lane control, entrance and exit control, and safety facility activation are suitable candidates for dealing with various weather conditions. .

The effectiveness of certain pertinent interventions can be assessed and measured by building a traffic conflict analysis model to see before and after improvements. For example, by utilising a hard shoulder emergency lane as a temporary access lane in rush hours, the traffic conflict prediction model can be built to calculate the risk of real-time incidents to assess countermeasure effects within a short time period. Crash prediction model can also be built to assess the drop in crash rate after the collection of sufficient crash data.

The reactive road network is based on an association analysis of factors affecting crashes. Proactive in-vehicle safety systems are the development of active safety rather than passive safety via airbags and seat belts to reduce the severity of a collision. Predictive traffic safety management is through causal factor analysis, crash and conflict prediction methods to transit reactive and proactive safety management by preventing crashes from occurring in the very beginning. Conflict prediction model, crash prediction model, and pertinent interventions, all

together, form proactive and predictive safety analysis. In this thesis, the initiated conflict prediction model provides instant pre-crash information and acts as crash causation process. The put forwarded crash prediction model in near future short time period informs traffic police station and road control centre to take pertinent interventions according to crash prediction results to prevent actual crash from occurring. By doing so, both crash collision and conflict prediction modelling procedures are now predictive in essence. The transition from reactive road network to proactive in-vehicle safety systems, and eventually to predictive traffic safety management (crash/conflict prediction) has been realised.

## 10.3 Limitations of this Research

This research mainly introduces computer vision methods for extracting dynamic traffic data from surveillance camera and UAV drones, statistical machine learning models for one hour crash prediction, semi-hourly crash prediction, real-time traffic conflict prediction, and model interpretation including variable importance. However, there are some limitations to this research.

### 10.3.1 Regarding computer vision techniques for traffic parameters extraction:

This study mainly utilises YOLOv8 and a modified FairMOT model to detect, track and classify different objects. With the ongoing development of computer vision and deep learning, future models will likely be more robust, lighter, and accurate. Readers can replace the current used models with more effective ones. While advanced detection models can reduce missed detections, speed calculation is significantly affected by image coordinate conversion. This study proposes a statistical spatial matrix to infer world coordinates from image coordinates, but heavily influenced by the distance between detected objects and the camera, as well as the correctness of angles. Thus, speed calculation from UAV drones is more accurate than surveillance cameras, which are typically roadside and not at the correct

angle relative to passing vehicles. Speed measurement from side angles is inaccurate due to errors in inferred world coordinates. UAV drones capture videos from above roads where the distance to passing vehicles is fixed and there is no angle distortion. For practical applications, using ETC cameras in the middle of the road and front of vehicles is recommended over roadside surveillance cameras for better accuracy.

### 10.3.2 Regarding crash prediction modelling:

This thesis examines hourly and semi-hourly crash prediction. However, crash prediction is a complex problem in statistics and transportation engineering influenced by factors such as weather conditions, driver status, traffic dynamics, and interactions with other vehicles. This study primarily uses traffic dynamic data—such as speed, acceleration, speed variances, vehicle types, traffic volumes, and vehicle types—for crash prediction. However, research indicates that weather conditions and driver status are more critical than vehicle kinematic and operational data in crash prediction. Drawing on six years of experience with traffic police stations and crash prediction model construction, the author finds that weather conditions and driver status significantly influence crash occurrences but are challenging to integrate into crash modeling. The author previously developed a driver monitoring system using in-vehicle cameras to record real-time driver facial expressions and behaviours, aiming to link driver status with traffic crashes. Past experience shows that real-time traffic conflict decreased with the implementation of a driver monitoring system, which alerts drivers to abnormal behaviours such as fatigue, anger, and distraction. Weather conditions are typically obtained from weather stations, but real-time updates are often delayed. Hence, computer vision techniques can also recognise weather conditions and integrate them into crash prediction models as indicator variables, assigning different weights to different weather conditions. Incorporating weather conditions enhances the sensitivity of crash prediction models to sudden weather changes, which are common in real-world applications.

Including more factors in forecasting models improves crash prediction accuracy. More

variables and sufficient data improve model accuracy, illustrating why autonomous and intelligent connected vehicles experience fewer crashes, aside from algorithm failures, compared to human drivers.

### 10.3.2 Regarding traffic conflict prediction modelling:

Conflicts are indicators of crash occurrences and are part of the same sequence of events that produce crashes (Arun et al., 2021). Safety surrogate measures (SSMs) as conflict measures are used to quantify how close a conflict event is to evolve into an observable crash event (Arun et al., 2021). SSMs as conflict measures preclude other driver related factors such as drunk driving, drowsiness, road rage, distraction, phone use, and violation behaviours (Arun et al., 2021). These factors are not treated as conflict measures by definition (Arun et al., 2021). However, they are closely related to crash occurrences and also influence the severity of traffic conflicts. Although SSMs such as TET, and TTC can reflect driver factors to some extent, driver factors and violation behaviours should not be neglected and should be involved in the research concerning crash or conflict prediction to improve overall model performances. Future studies will take human factors and violation behaviours into modelling process. A more comprehensive model will be built to detect conflict by utilising multi-facet input variables.

In addition, the effectiveness of the stacked ensemble model can be improved by involving none or low correlated base models. The ensemble of diverse models can increase model diversity, average out noise from different models, and as a result, optimise model classifying performances. Future study will conduct preliminary analysis on base model correlation and optimise base model selection procedure by introducing recursive selection optimisation algorithms.

## 10.4 Recommendations for Future Research

Future research will aim to collect more extensive crash data covering diverse road environments, varying periods, and longer durations to validate model effectiveness. This will involve incorporating different types of cameras and sensors for data collection. Advanced statistical models will be applied and tested to enhance crash prediction analysis.

The model will include multifaceted data such as driver status (fatigue, anger, distraction) collected from driver monitoring systems, real-time weather conditions identified through computer vision recognition of surrounding weather conditions, and sensor data beyond cameras. By integrating these elements, a more robust and effective model can be developed. Once the model is built, it will be deployed in instrumented vehicles or traffic police station control centres to issue alerts for impending crashes. Real-time deployment will allow validation of prediction accuracy, detection of issues, and identification of improvement opportunities to optimize the crash prediction system.

Future research will also incorporate causal inference methods to better study variable importance and model interpretation. Causation theory explores various accident-related factors such as human behaviour, environmental conditions, and their interconnected causal relationships and influences. Current methods used for studying accident causes in China include neural network analysis, hierarchical correlation analysis, and gray correlation analysis. However, these methods often focus on isolated, superficial, single-factor analyses, overlooking the multidimensional and correlated nature of accident causes. Some scholars have begun exploring complex systems theory but have not yet comprehensively applied it to the entire road traffic system or established a systematic theoretical framework and supporting technologies.

Future studies will consider applying Bayesian Neural Network and Reinforcement Learning

methods for causal inference in crash occurrence analysis. These methods offer systematic insights into the impact of various factors on events and their interrelationships. The research will establish Bayesian networks for analysing traffic accident causality, incorporating insights into how traffic control optimization affects the severity of accidents.

In terms of real-time traffic conflict prediction, this thesis integrates a Random Forest (RF), three-layer Deep Neural Networks (DNN), Support Vector Machine Radial (SVM-R), and a Gradient Boosting Model (GBM) meta layer to enhance prediction accuracy. The Recursive Feature Elimination (RFE) algorithm is then employed to identify the most influential SSMs for conflict prediction in each scenario. The stacked ensemble model prediction accuracy is subject to individual model performance and combinations of different models. Future improvements for this study include splitting training data and constructing a weighted hierarchical stacked ensemble model to capture various aspects of traffic conflicts and assign different weights to individual models based on their respective performances. On the other hand, improving data quality and sufficiency will largely promote model performance. Future studies will expand the data pool in different roadway scenarios by recording more videos and identifying additional conflicts to validate model transferrability, enhance model robustness, and increase prediction and classification accuracy.

Aside from the above mentioned improvements on prediction models, further improvements to current study can be explored in the following two aspects: multi-faceted data collection and improvement of prediction algorithms.

Data Collection: Various multi-facet data in different aspects from diverse data sources will be collected in the future study, such as driver facial recognition and behaviour analysis from in-vehicle driver cameras, vehicle scenario detection from front cameras, and traffic data extraction from UAV drones, to form a holistic study of crash prediction analysis with multi-sourced traffic dynamic data processing.

Prediction Algorithm: The application of LLM (Large Language Model) will be explored in

unsafe traffic conditions (crash and conflict) prediction to improve the accuracy and interpretability of prediction. By redefining the traffic unsafe condition prediction task as a language modeling problem, LLM is able to use its powerful language modeling and reasoning capabilities to improve the accuracy of prediction, and enhance the interpretability of prediction by generating more intuitive and interpretable prediction results.

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# Bibliography

## Bowen Cai

## Research Interests

Traffic Safety, Driving behaviour, Traffic Engineering, Deep Learning, Computer Vision, Data Mining, Statistics.

## Education

| | |
|---|---|
| Imperial College London | 03/2022-Present |
| Ph.D Student, Civil and Environmental Engineering | |
| Loughborough University | 12/2020-02/2022 |
| Ph.D Student, Civil and Building Engineering | |
| University of Notre Dame | 8/2016-08/2017 |
| Ph.D Student, Applied Mathematics and Statistics | |
| University of Pennsylvania | 08/2016-08/2017 |
| Master of Science, Statistics, Measurement & Research | |
| University of Michigan, Ann Arbor | 08/2012-05/2016 |
| Bachelor of Science in Statistics, Minor in Mathematics | |

## Work Experience

| | |
|---|---|
| Research Assistant | 09/2023-04/2024 |
| Civil and Environmental Engineering, Imperial College London | |
| Research Associate Professor | 04/2021-03/2023 |
| College of Transportation Engineering, Tongji University, | |
| Research Assistant Professor | 08/2017-07/2018 |
| College of Transportation Engineering, Tongji University | |
| Leading Teaching Assistant | 8/2016-08/2017 |
| Department of Statistics, University of Notre Dame | |
| Marketing Analyst Assistant | 05/2017-08/2017 |
| The Wharton School, University of Pennsylvania | |

# Appendix

# Publications related to this research

A number of publications have been published in peer-reviews journals or presented at conferences as a result of this research. These are the following:

**Journal papers:**

1. **Cai, B.**, Feng, Y., Wang, X., Quddus, M. (2024). Highly Accurate Deep Learning Models for Estimating Traffic Characteristics from Video Data. Applied Sciences, 14(19), 8664. https://doi.org/10.3390/app14198664

2. **Cai, B.**, Camarcat, L., Shang, W., Quddus, M. (2024). A new spatiotemporal convolutional neural network model for short-term crash prediction. Frontiers of Engineering Management. 10.1007/s42524-024-4040-8.

3. **Cai, B.**, Wang, X. (2024). Estimation of the Smallest Acceptable Sample Size in Bilateral Approaches to Coefficient Estimation and Accuracy Prediction. Transportation Research Record, 2678, 8. https://doi.org/10.1177/03611981231220632

4. **Cai, B.**, Quddus, M., Wang, X., & Miao, Y. (2023). New Modeling Approach for Predicting Disaggregated Time-Series Traffic Crashes. Transportation Research Record, https://doi.org/10.1177/03611981231182703

5. Wang, X., Azati, Y., Quddus, M., **Cai, B.**, & Zhang, X. (2023). Statistical Analysis of Traffic Crashes on Mountainous Freeway Tunnel Sections. Transportation Research Record, https://doi.org/10.1177/03611981231172751

6. **Cai, B.**, Camarcat, L., Formosa, N., Quddus, M. (2024). A stacked ensemble model for traffic conflict prediction in different road environments with multi-modal sensor data. Minor Revision of Transportation Research Interdisciplinary Perspectives.

**Conference Papers:**

1. **Cai, B.**, Camarcat, L., Formosa, N., Quddus, M. (2024). A stacked ensemble model for traffic conflict prediction in different road environments with multi-modal sensor data. Presented in Conference in Emerging Technologies in Transportation Systems (TRC-30), Crete, Greece. (TRC-30 Conference)

2. **Cai, B.**, Quddus, M., Miao, Y., A New Modelling Approach for Predicting Disaggregated Time-Series Traffic Crashes, Presented at the 102nd Transportation Research Board Annual Meeting in Washington D.C., 2023. (TRB Conference)

3. **Cai, B.**, Quddus, M., Ma, L., Highly Accurate Deep Learning Models for Estimating Traffic Characteristics from Video Data, Presented at the 102nd Transportation Research Board Annual Meeting in Washington D.C., 2023. (TRB Conference)

4. **Cai, B.**, Camarcat, L., Shang, W., Quddus, M. (2024). A new spatiotemporal convolutional neural network model for short-term crash prediction, Presented at the 103rd Transportation Research Board Annual Meeting in Washington D.C., 2024. (TRB Conference)