

EEG Ensemble Learning Framework for Prognostic Prediction of Post-rTMS Motor Recovery in Stroke

Tianyu Jia, Haiyang Long, Diantong Xie, Yixu Zhao, Yifan Wu, Yifeng Li, Linhong Mo, Xinyu Guan, Dario Farina, *Fellow, IEEE*

Abstract—Repetitive transcranial magnetic stimulation (rTMS) is a promising neuromodulatory therapy for post-stroke rehabilitation, offering the potential to modulate brain network dynamics. However, its clinical effectiveness remains debated due to the high inter-individual variability in patient responses, largely attributed to heterogeneous patterns of neural reorganization after stroke. In this study, we proposed an EEG ensemble learning framework (EEG-ELF) to predict motor recovery outcomes following rTMS therapy in stroke patients. The framework was evaluated on EEG recordings acquired during a motor imagery task from 20 individuals with subcortical stroke, collected both before and after a four-week rTMS intervention, along with the upper-limb Fugl-Meyer Assessment (FMA) scores. EEG-ELF's prediction performance was assessed through both regression and classification tasks using leave-one-subject-out cross-validation. The results demonstrated a strong correlation between predicted and actual recovery rates (Pearson's $R = 0.92$, $p < 0.001$), and the framework achieved 95% accuracy in classifying patients into good and poor prognosis groups. These findings suggest that EEG-ELF can accurately predict individual motor outcomes from pre-treatment EEG features, highlighting its potential to guide personalized rTMS interventions through data-driven stratification of stroke patients.

Index Terms—Electroencephalogram, Ensemble learning, Stroke prognosis, Transcranial magnetic stimulation.

This work was supported in part by the National Natural Science Foundation of China under Grant 52305315, and in part by the China Postdoctoral Science Foundation under Grant 2023M731938. (Tianyu Jia and Haiyang Long contributed equally to this work.) (Corresponding author: Dario Farina, Xinyu Guan, and Linhong Mo.)

Tianyu Jia is with the Department of Bioengineering, Imperial College London, London W12 0BZ, U.K., and also with the Department of Mechanical Engineering, Tsinghua University, Beijing 100084, China (t.jia21@imperial.ac.uk).

Haiyang Long is with the School of Life Sciences, Tsinghua University, Beijing 100084, China.

Diantong Xie, Yixu Zhao, and Yifan Wu are with the School of Biological Science and Medical Engineering, Beihang University, Beijing 100191, China.

Linhong Mo is with the Beijing Rehabilitation Hospital of Capital Medical University, Capital Medical University, Beijing 100144, China (molinhong@163.com).

Xinyu Guan is with the Beijing Advanced Innovation Center for Biomedical Engineering, School of Engineering Medicine, Beihang University, Beijing 100191, China (guanxinyu@buaa.edu.cn).

Yifeng Li, and Dario Farina are with the Department of Bioengineering, Imperial College London, London W12 0BZ, U.K. (d.farina@imperial.ac.uk).

I. INTRODUCTION

STROKE is the third leading cause of death and disability worldwide, affecting approximately 94 million people globally [1]. Non-invasive neuromodulation techniques, such as repetitive transcranial magnetic stimulation (rTMS), have shown promise in promoting motor recovery following stroke by modulating brain network dynamics and enhancing neuroplasticity. However, clinical outcomes remain highly variable across individuals [2], [3]. This substantial heterogeneity in treatment response currently limits rTMS's widespread clinical adoption, underscoring the critical need for developing personalized neuromodulation strategies tailored to individual patients' neurophysiological profiles [4], [5].

rTMS promotes neuroplasticity and rebalances brain networks in stroke patients by modulating cortical excitability through targeted activation or inhibition of specific brain regions. However, post-stroke neural reorganization varies substantially across individuals, manifesting as patterns such as ipsilesional focusing or contralesional recruitment [6]. This heterogeneity has contributed to ongoing debate over the optimal rTMS intervention strategy. Some studies, grounded in the interhemispheric competition model [7], emphasize restoring activity in the ipsilesional hemisphere [8], whereas others support the vicariation model [9], suggesting that contralesional compensation may also support motor recovery [10]. The inconsistent clinical effectiveness and highly variable individual responses to rTMS may, in part, stem from the failure to account for this variability through patient stratification [3]. Predicting therapeutic outcomes based on individual neural signatures could enable more personalized and effective rTMS protocols.

Electroencephalography (EEG) has been increasingly utilized to investigate cortical reorganization following stroke [11]. EEG-derived features, such as spectral power and functional connectivity, have emerged as promising biomarkers for predicting motor recovery, offering insights into neuroplastic changes and individual recovery potential [12]. EEG spectral power has been shown to correlate with cortical responses to stroke. In particular, increased power in the delta and theta bands, with decreased power in the alpha and beta bands, reflects perturbations in brain oscillatory activity that may serve as early indicators of ischemic stroke [13]. Moreover, a

higher post-stroke baseline EEG theta/alpha ratio is associated with poorer motor recovery [14]. Symmetrical beta-band EEG power-spectral density between hemispheres is significantly correlated with paralysed hand motor function at the chronic stroke stage [15]. Furthermore, Saes *et al.* reported that inter-hemispheric theta-band symmetry is a strong EEG predictor of post-stroke motor recovery, with greater asymmetry correlating with more severe upper limb impairment [16].

Abnormalities in brain connectivity are common across a range of neurological disorders [17]. In the context of stroke, functional connectivity within the lesioned hemisphere and across hemispheres has emerged as a potential biomarker for predicting recovery outcomes. Specifically, reduced intra-hemispheric functional connectivity in the alpha and beta bands within the ipsilesional hemisphere has been associated with higher Fugl-Meyer Assessment (FMA) scores, suggesting a negative correlation between local connectivity and motor impairment [18]. Additionally, increased connectivity between the ipsilesional primary motor cortex (M1) and premotor area (PM) has been positively correlated with motor recovery, indicating that enhanced M1-PM communication supports functional gains [19]. Wu *et al.* also reported that stroke patients exhibiting lower inter-hemispheric synchrony tended to experience better motor recovery, further highlighting the complex role of connectivity dynamics in post-stroke outcomes [20].

Previous research explored the potential of various types of EEG features as biomarkers for rehabilitation outcomes, which is the neurophysiological basis for developing a prognostic prediction model of post-rTMS motor recovery [21]. Various prognostic prediction models for both classification and regression tasks have been proposed based on a single type of EEG features. Zhang *et al.* achieved an R^2 of 0.79 using a multiple linear regression model with alpha band phase synchronization index [21]. Jang *et al.* designed a power spectral density (PSD)-based deep learning architecture, attaining a root mean square error (RMSE) of 0.07 [22]. Cacciotti *et al.* employed functional connectivity features with support vector machine (SVM), achieving 94.75% accuracy [23]. Despite the promising performance of single-type EEG feature models, the predictive potential of approaches based on multi-type EEG features remains under-explored. For example, Lin *et al.* combined PSD and functional connectivity features in a deep learning model, achieving 91.84% accuracy [24]. In addition to feature diversification, ensemble learning strategies can also enhance performance. Shi *et al.* proposed an ensemble model ShuffleNet-LSTM that reached an AUC of 0.87 and 80.31% accuracy [25]. Moreover, previous studies overlooked the need to stratify stroke patients while developing prognostic prediction models, despite the likelihood that EEG biomarkers are influenced by individual differences in neural reorganization. As a result, in clinical practice, the relation between post-stroke neural dynamics and optimal rTMS protocols remains poorly understood. Developing a generalizable prediction framework for post-rTMS motor recovery is therefore essential. Such a framework could serve as a valuable tool for guiding the personalization of rTMS therapy in subacute stroke rehabilitation.

In this study, we enrolled ischemic subacute stroke patients with subcortical lesions. Previous research has indicated that these patients primarily exhibit ipsilesional neural reorganization [3], [6]. We aim to investigate the neural signatures and prediction models for treatment outcomes following high-frequency rTMS applied to the lesioned hemisphere. For this purpose, we developed a novel EEG-based prognostic framework, named the EEG ensemble learning framework (EEG-ELF), to predict post-rTMS motor recovery in stroke patients. In this way, an EEG dataset, along with upper-limb FMA scores, was collected from 20 stroke patients before and after a 4-week rTMS therapy to evaluate the framework's performance.

II. MATERIALS AND METHODS

A. Data recording

This study was approved by the Ethical Committee of Tsinghua University (No. 20220215; Date: December 6, 2022) and registered at the Chinese Clinical Trial Registry (No. ChiCTR2300070848). All participants provided written informed consent before participation. Stroke participants were recruited following a standardized screening process. Eligibility criteria included: (1) a diagnosis of first-onset ischemic stroke in the subacute phase, (2) absence of severe spasticity or joint contractures, and (3) preserved cognitive function (MMSE score ≥ 24). Twenty eligible individuals completed all study procedures and were included in the final dataset. The clinical characteristics of the participants are shown in Table I.

TABLE I. Characteristics of the participants

Variable	Subjects (n=20)
Age (yr)	64 $\pm$ 11.1
Sex (male:female)	10:10
Stroke type (Ischemic:hemorrhagic)	20:0
Side of lesion (Right:left)	7:13
Cortical lesion involvement	No
Baseline FMA	10.4 $\pm$ 9.6
Post-treatment FMA	19.1 $\pm$ 12.5
TFO (days)	34.3 $\pm$ 21.2

Note: Values are presented as mean $\pm$ standard deviation or number. FMA indicates the upper-limb Fugl-Meyer Assessment. TFO is the time from the onset of the first stroke.

The recruited stroke patients underwent 10-Hz rTMS treatment consisting of 20 sessions (5 sessions per week over 4 weeks). Stimulation was delivered using a Magstim stimulator with a figure-of-eight coil (Magstim Company, UK) positioned over the sensorimotor cortex. The resting motor threshold (RMT) was determined for each participant as the minimum intensity required to evoke motor-evoked potentials (MEPs) exceeding 50 μ V in at least five out of ten consecutive trials. rTMS was applied at 100% RMT intensity with 600 pulses per session. In cases where MEPs could not be elicited from the contralateral sensorimotor cortex, RMT measurements were instead performed on the ipsilateral hemisphere [3].

The recorded data include EEG and upper-limb FMA scores measured immediately before and after the 4-week rTMS

therapy. Two clinicians independently assessed patients using FMA, with any discrepancies in scoring resolved through consensus discussion. The recovery rate was used to measure the patient's recovery quantified as the change in the upper-limb FMA normalized by the patient's potential for recovery [26]. In this study, this was defined as the difference between the upper-limb FMA score after the 4-week rTMS intervention and the baseline score, normalized by the difference between the maximum possible score (66) and the baseline score. This measure of recovery was chosen in order to compensate for the differences in baseline scores among patients [27], [28]. Patients were allocated into good and poor recovery groups based on the recovery rate. Using the distribution peak of 16.17% (Shapiro-Wilk test, $p > 0.05$) as a cutoff, patients were categorized into poor recovery ($< 16.17\%$) and good recovery ($\geq 16.17\%$) subgroups. As shown in Fig. 1, EEG data were collected using a motor imagery (MI) paradigm consisting of two tasks: resting state and imagined flexion of the paralyzed arm. Each task included 40 trials presented in a randomized order. Visual cues instructed participants to either perform motor imagery or remain at rest. Stroke patients participated in preparatory training sessions to familiarize themselves with the MI protocol and improve task performance. During the experiment, 64-channel EEG recordings were obtained using an ANT eegoTM amplifier with AFz as a ground electrode and CPz as a reference electrode. Data were sampled at 500 Hz, and electrode impedance was maintained below 10 k Ω .

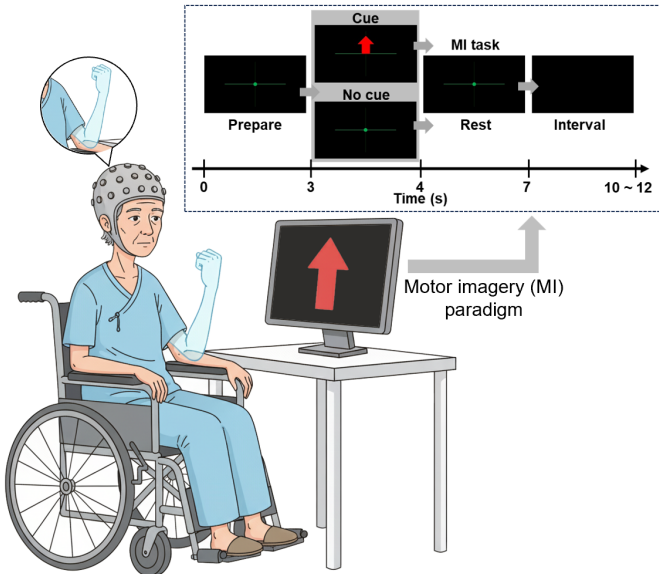


Fig. 1. Motor imagery (MI) experiment setup. The MI test involved two kinds of tasks: rest and imagined flexion of the paralyzed arm. Each trial began with a horizontal line. After 3 s, a red arrow cue was displayed for 1 s to initiate the MI task until the line disappeared; otherwise, the rest state was maintained.

B. EEG Ensemble Learning Framework

Figure 2 illustrates the architecture of EEG-ELF, outlining the systematic workflow from raw EEG signals to prognostic predictions. The following sections describe six key processing

stages of EEG-ELF: data preprocessing, feature extraction, feature selection, data normalization, cross-validation model training, and ensemble learning. Each stage plays a critical role in enabling robust and clinically interpretable predictions of post-rTMS motor recovery.

1) Data Preprocessing: An EEG dataset was collected based on a motor-imagery paradigm. To mitigate the potential confounding effects of lesion lateralization on EEG analysis, the EEG spatial distribution patterns of stroke patients with left-hemisphere lesions were horizontally mirrored. EEG pre-processing was conducted based on custom routines using MATLAB R2021a (MathWorks Inc., USA) and EEGLAB V2024.0 according to the following steps: (1) common average reference, (2) 48–52 Hz notch filtering and 1–45 Hz band-pass filtering using finite impulse response (FIR), (3) artifact removal using independent component analysis by an expert practitioner based on the commonly used criteria [29], including abnormal kurtosis, identifiable EOG and muscle artifacts, and (4) segmentation into rest-state and task-state epochs.

2) Feature Extraction: Five comprehensive categories of EEG features depicting brain activation dynamics and functional connectivity were extracted as input to the prognostic model, including: EEG power, motor-related spectral shift (MRSS), brain connectivity, hemispheric asymmetry patterns, and statistical features.

EEG Power: Motor-related channels $M = \{C3, C4, Cz, FC3, FC4, CP3, CP4\}$ [30], [31] were selected for EEG power feature extraction with the following equation:

$$P_c^{(b)} = \frac{1}{T} \sum_{t=1}^T |x_c^{(b)}(t)|^2 \quad (1)$$

where $x_c^{(b)}(t)$ represents the EEG signal for channel c within frequency band b . Three kinds of EEG power features, including power in rest and task state, power changes ($\Delta P = P^{\text{task}} - P^{\text{rest}}$), and power ratios ($P^{\text{task}}/P^{\text{rest}}$), were extracted.

MRSS: Motor-related cortical dynamics are quantified using MRSS features defined as:

$$\text{MRSS}_c^{(b)} = \frac{P_c^{\text{rest},(b)} - P_c^{\text{task},(b)}}{P_c^{\text{rest},(b)}} \times 100\% \quad (2)$$

where positive values indicate motor-related power spectral desynchronization, while negative values represent motor-related synchronization, capturing task-induced modulation of cortical rhythms. Additional temporal dynamics features were computed by analyzing MRSS variations across 1-second sliding windows, yielding mean and standard deviation of MRSS dynamics for enhanced characterization of motor-related changes.

Brain Connectivity: Eight key electrode pairs were symmetrically selected from bilateral brain regions to assess motor-related brain connectivity, covering the motor cortex (C3-C4, FC3-FC4, CP3-CP4), frontal regions (F1-F2, F3-F4, AF3-AF4), and parietal areas (P1-P2, P3-P4) [32]. Two common methods for estimating brain connectivity were applied: phase slope index (PSI) [33] and phase locking value (PLV) [34]. PSI-based brain connectivity quantifies directional information

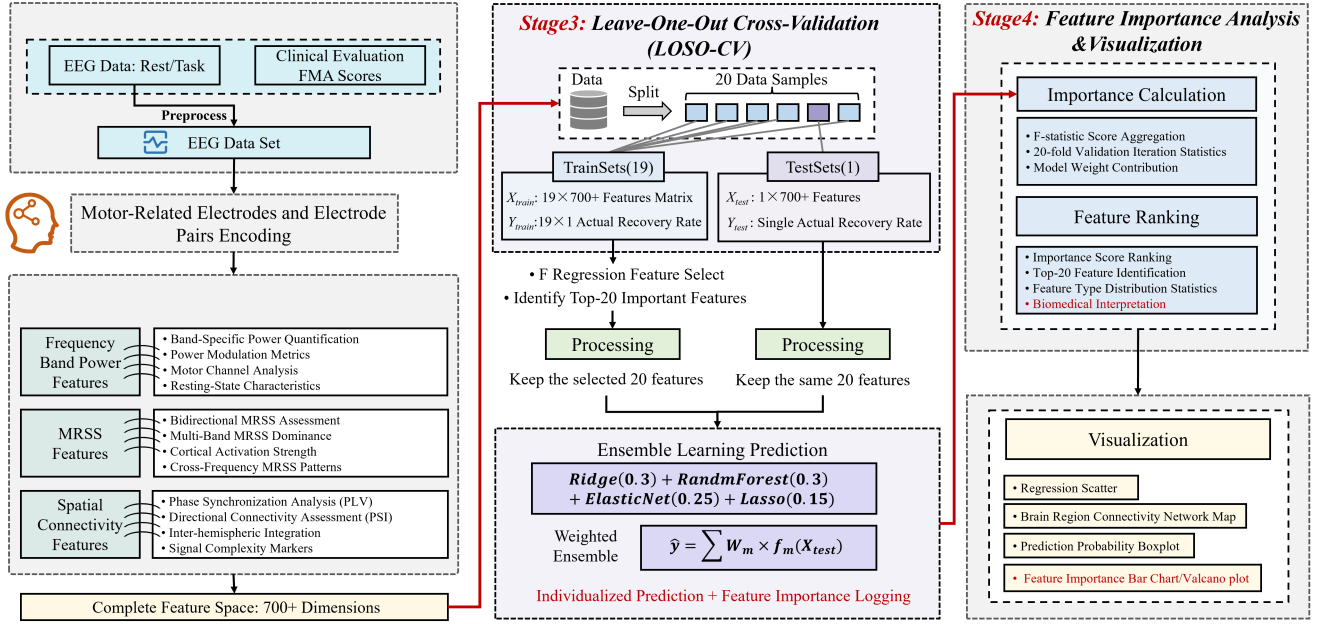


Fig. 2. The architecture of the EEG ensemble learning framework (EEG-ELF). This framework consists of four parts: (1) data collection and preprocessing, (2) feature extraction, (3) cross-validation with ensemble learning, and (4) feature importance analysis and visualization.

flow between brain regions through phase slope analysis of cross-spectral density:

$$\text{PSI}_{ij} = \frac{1}{2\pi} \cdot \frac{d\phi_{ij}(f)}{df} \quad (3)$$

where $\phi_{ij}(f)$ represents the cross-spectral phase between channels i and j , and $\frac{d\phi_{ij}(f)}{df}$ denotes the phase slope indicating the rate of phase change across frequencies. Hilbert transform-based PSI and cross-spectral density-based PSI were both extracted with the following approaches:

$$S_{ij}^{(H)}(f) = \text{FFT}(H_i(t)) \cdot \text{FFT}^*(H_j(t)) \quad (4a)$$

$$\text{PSI}_{ij}^{(H)} = \frac{1}{2\pi} \cdot \text{slope}(\text{unwrap}[\angle(S_{ij}^{(H)}(f))], f) \quad (4b)$$

$$\text{PSI}_{ij}^{(C)} = \frac{1}{2\pi} \cdot \text{slope}(\text{unwrap}[\angle(C_{ij}(f))], f) \quad (5)$$

where $H_i(t)$ denotes the Hilbert transform of signal i , FFT represents fast Fourier transform, FFT^* denotes the complex conjugate, $S_{ij}^{(H)}(f)$ is the cross-spectrum derived from Hilbert transforms, and $C_{ij}(f)$ represents the cross-spectral density between channels i and j , computed using Welch's method with 250-point segments and 50% overlap. For each channel pair and frequency band, PSI features were calculated as follows: direct values, changes ($\Delta\text{PSI}_{ij}^{(b)} = \text{PSI}_{ij}^{\text{task},(b)} - \text{PSI}_{ij}^{\text{rest},(b)}$), and ratios ($\text{PSI}_{ij}^{\text{ratio},(b)} = \text{PSI}_{ij}^{\text{task},(b)} / (\text{PSI}_{ij}^{\text{rest},(b)} + \epsilon)$), where $\epsilon = 10^{-8}$ prevents division by zero.

PLV-based brain connectivity quantifies phase synchronization strength:

$$\text{PLV}_{ij}^{(b)} = \left| \frac{1}{N} \sum_{n=1}^N e^{i(\phi_i^{(b)}(n) - \phi_j^{(b)}(n))} \right| \quad (6)$$

where $\phi_i^{(b)}(n)$ and $\phi_j^{(b)}(n)$ represent instantaneous phases derived from Hilbert transform of band-pass filtered signals,

and N denotes the number of time points. Analogous features were also calculated based on PLV, including direct values, changes ($\Delta\text{PLV}_{ij}^{(b)}$), and ratios ($\text{PLV}_{ij}^{\text{ratio},(b)}$).

Hemispheric Asymmetry Patterns: Hemispheric asymmetry features were computed to capture spatial organization of motor-related brain networks. For each frequency band, signals from left hemisphere channels $L = \{F3, FC3, C3, CP3, P3\}$ and right hemisphere channels $R = \{F4, FC4, C4, CP4, P4\}$ were analyzed. The hemispheric asymmetry index (HAI) was calculated as:

$$\text{HAI}^{(b)} = \frac{P_R^{(b)} - P_L^{(b)}}{P_R^{(b)} + P_L^{(b)}} \quad (7)$$

where $P_L^{(b)}$ and $P_R^{(b)}$ represent the average power of left and right hemisphere channels in the frequency band b . Asymmetry features were computed for both rest and task states, along with asymmetry changes.

Statistical Features: To capture signal characteristics beyond spectral properties, statistical features were extracted from key motor channels (C3, C4, Cz) for both rest and task states. These included first-order statistics (mean, standard deviation), higher-order statistics (skewness, kurtosis), and signal complexity measures. Signal complexity was quantified using zero-crossing rate, defined through the following steps:

$$\text{ZC}_c(t) = 1[\text{sign}(x_c(t+1)) \neq \text{sign}(x_c(t))] \quad (8)$$

$$\text{Complexity}_c = \frac{1}{T-1} \sum_{t=1}^{T-1} \text{ZC}_c(t) \quad (9)$$

where $\text{ZC}_c(t)$ represents the zero-crossing detection at time t for channel c , $1[\cdot]$ is the indicator function, and T is the signal length.

3) *Feature Selection Strategy*: F-regression feature selection was employed to identify features with significant linear relationships to the recovery rate. For each feature, a linear regression model was fitted independently, and the F-statistic quantified feature-target dependency:

$$F_k = \frac{(TSS - RSS)/1}{RSS/(n - 2)} \quad (10)$$

where TSS (total sum of squares) and RSS (residual sum of squares) denote total and residual sum of squares respectively, n is the number of observations, and the degrees of freedom are 1 and $(n - 2)$ for the numerator and denominator respectively. Features are ranked by F-statistic magnitude, with the top 20 features selected as the input of the model, ensuring consistency with the leave-one-subject-out cross-validation (LOSO-CV) protocol.

4) *Data Normalization*: Standard scaling ensured comparability across features with heterogeneous units and scales:

$$z = \frac{x - \mu}{\sigma} \quad (11)$$

where μ and σ represent feature-specific mean and standard deviation. This z-score normalization yields zero-centered, unit-variance distributions across all features. Feature normalization was performed first on the training set. These parameters were then used to normalize the test sets, ensuring that no information from the test set leaked into the training process.

5) *Cross-Validation and Model Training*: LOSO-CV was employed to ensure rigorous, subject-independent evaluation. In each iteration, the top 20 features were selected from the training set (19 subjects) based on F-regression scores. The model was then evaluated on the held-out subject using these selected features. This procedure prevents data leakage and provides a robust assessment of the model's generalizability.

6) *Ensemble Learning*: The EEG-ELF integrates four complementary regression models, Ridge Regression ($\alpha = 1.0$), Lasso Regression ($\alpha = 0.1$), ElasticNet ($\alpha = 0.1, \rho = 0.5$), and Random Forest (100 trees, maximum depth = 10), chosen to span distinct inductive biases: stable L2-regularized shrinkage, L1-induced sparsity, grouped-feature preservation, and nonlinear tree-based interaction capture, respectively. The ensemble combines predictions with empirically optimized weights $w = [0.30, 0.15, 0.25, 0.30]$.

C. Prognostic Prediction Performance Evaluation

The performance evaluation of EEG-ELF was based on both regression and classification tasks, employing multiple metrics to ensure robust characterization of prognostic predictive capabilities. For regression performance evaluation, the continuous prediction of recovery rates was evaluated through the Pearson correlation coefficient $R = \frac{\text{cov}(y, \hat{y})}{\sigma_y \sigma_{\hat{y}}}$, which quantifies the linear relationship between the predicted and the true recovery rate. The coefficient of determination R^2 indicated the proportion of variance in recovery rates, while the mean absolute error $\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$ and $\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$ provided complementary measures of prediction accuracy, with RMSE particularly sensitive to large

prediction errors. For classification performance evaluation, EEG-ELF was tested on its ability to accurately predict post-treatment outcomes, classifying patients into good or poor recovery groups. Prediction confidence was quantified through probability estimates derived by transforming the predicted recovery rate values through a sigmoid function: first converting to z-scores using $(\text{predicted}_{\text{recovery rate}} - 16.17)/10.0$, then applying the logistic transformation $1/(1 + e^{-z})$ to obtain probability estimates. This transformation maps the continuous recovery rate predictions to a probability scale, providing an interpretable measure of prediction confidence.

Feature importance analysis was conducted through LOSO-CV across the 20 subjects, computing statistical measures for each feature based on the true recovery rate. Statistical significance was assessed by testing the null hypothesis of absence of difference between good and poor prognosis groups. Cohen's d effect size provided a standardized measure of the magnitude of differences between groups, calculated as $d = \frac{\mu_1 - \mu_2}{s_p}$, where μ_1 and μ_2 represent the group means and s_p denotes the pooled standard deviation. This statistical approach enabled identification of features that were both statistically significant ($p < 0.05$) and clinically meaningful ($|d| > 0.5$), facilitating neurophysiological interpretation of the prognostic biomarkers underlying differential treatment responses.

III. RESULTS

A. Regression and Classification

Figure 3 illustrates the regression performance of EEG-ELF in predicting recovery rate values. The scatter plot demonstrates a remarkably strong linear relationship between the predicted and the true recovery rate. The model achieved a Pearson correlation coefficient of $R = 0.92$ ($p < 0.001$), indicating highly significant predictive capability. MAE of 3.3% and RMSE of 5.6% further confirmed the model's precision in continuous outcome prediction. The distribution of data points reveals effective stratification between the good recovery (red dots) and the poor recovery (blue dots) groups. The fitted regression line (solid) closely followed the ideal prediction line (dashed), with $R^2 = 0.85$. Individual subject analysis revealed exceptional prediction accuracy for some patients, with absolute errors as low as 0.003% and 0. The model demonstrated consistent performance across both prognosis groups, with slightly lower prediction errors observed in the poor prognosis group (mean error = 2.4%) compared to the good prognosis group (mean error = 4.3%). This model achieved an overall classification accuracy of 0.95 with perfect specificity (1.00), and all 10 patients with poor recovery were correctly identified (true negatives = 10, false positives = 0). The sensitivity reached 0.90, with 9 out of 10 patients with good recovery correctly classified (true positives = 9, false negatives = 1). The single misclassification occurred for one stroke patient who had a true recovery rate of 30.65% but was predicted as 15.48%, representing the largest prediction error (15.17%) in the dataset. As shown in Table II, ablation analysis further confirmed that the four-model design outperforms all smaller subsets: single-model oracle accuracy was 0.80, two-model 0.85, three-model 0.85, whereas the

full four-model ensemble achieved 0.95. The comparison of performance between the existing models and EEG-ELF is shown in Table III. The proposed model outperforms other models in both classification tasks and regression tasks.

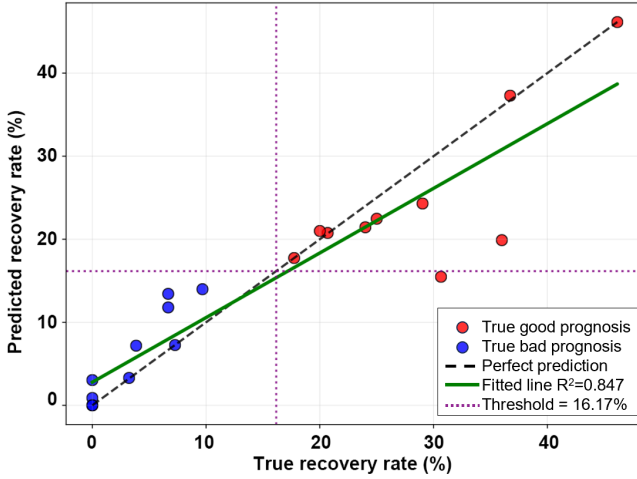


Fig. 3. Regression performance of the EEG ensemble learning framework (EEG-ELF) in predicting recovery rate. Red dots represent patients with good prognosis, while blue dots represent those patients with poor prognosis. The dashed line indicates perfect prediction accuracy (predicted recovery rate = true recovery rate), whereas the solid line is the fitted regression of model predictions against true values.

B. Prediction Confidence Analysis

Figure 4 presents the distribution of prediction confidence scores for both prognosis groups. The clear separation between the two distributions, with minimal overlap, confirms the model’s ability to make accurate predictions with high confidence levels. All predictions for the poor recovery group fell well below the 0.5 decision threshold, while predictions for the good recovery group mostly exceeded this threshold. The minimal overlap between distributions suggests that EEG-ELF successfully learned discriminative features that robustly differentiated between recovery trajectories. The confidence distribution patterns align with the perfect AUC score, confirming that the probability estimates were well-calibrated and reliable. This clear probabilistic separation enables confidence-based clinical decisions.

C. Key Feature Visualization

To further validate the discriminative power of the extracted features, we conducted statistical comparisons between the good and poor recovery groups. We visualized the significance levels of features extracted during the model computation through the joint evaluation of effect values and p-values. Figure 5 visualizes the distribution of feature significance between the two prognosis groups based on Cohen’s d effect size and $-\log_{10}(p\text{-value})$. Gray points ($|d| < 0.5$) indicate negligible effects, while green points ($|d| \geq 0.5, p\text{-value} \geq 0.05$) represent features with large but statistically marginal effects. The minority of orange points ($|d| \geq 0.5, p\text{-value} < 0.05$)

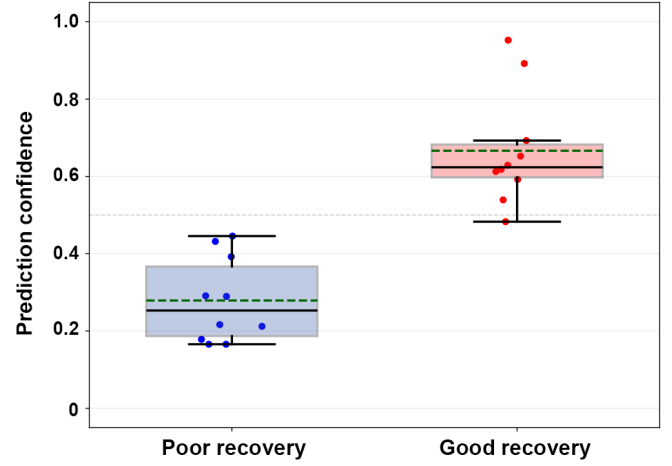


Fig. 4. Distribution of prediction confidence scores for both the poor and the good recovery group.

highlight key features with both strong effects and statistical significance. Overall, the vast majority of features are gray and green dots, indicating that most features are not statistically significant, even though they have large effects; orange dots, as a minority group, represent those key features that have both large effects and are statistically significant. These significant features are marked with an asterisk in Fig. 6.

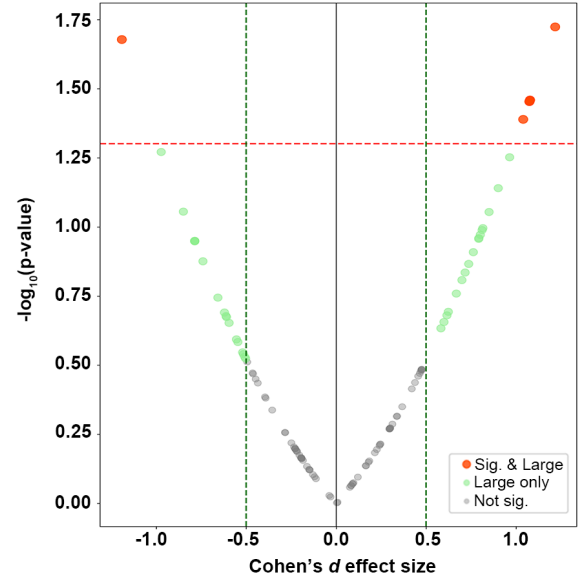


Fig. 5. Volcano plot of the distribution of feature significance based on Cohen’s d effect size and $-\log_{10}(p\text{-value})$.

Figure 6 shows the top 25 most influential features ranked by Cohen’s d effect size in LOSO-CV, sorted from smallest to largest. The names of the features in Fig. 6 follow a systematic naming convention. The prefixes indicate the type of feature being measured: “PLV” reflects PLV-based brain connectivity; “power” indicates EEG power within a specific frequency band; “MRSS” represents motor-related cortical dynamics; “kurt” denotes kurtosis, describing the sharpness of the peak in the probability density distribution; and “complexity” quantifies the variability and intensity of fluctuations in the EEG signal (e.g., zero-crossing rate). The suffix “_diff” indicates

TABLE II. Model-count ablation study

Subset Size	Best Subset	Accuracy	AUC	Pearson R	MAE (%)
1 model	RF	0.80	0.91	0.680	7.00
2 models	Lasso + RF	0.85	0.95	0.738	5.51
3 models	Ridge + Lasso + RF	0.85	0.95	0.742	5.32
4 models	Ridge + Lasso + ElasticNet + RF	0.95	1.00	0.920	3.31

TABLE III. Performance comparison of different models

Models	Accuracy	AUC	Pearson R	R ²
Linear regression [16]	\	\	\	0.68
Multiple linear regression [21]	\	\	\	0.79
EEG-PLS + RBF-SVR [27]	\	0.80	0.53	\
A supervised deep learning architecture [24]	0.92	0.96	\	\
Quadratic support vector machines [23]	0.95	0.95	\	\
ShuffleNet-LSTM [25]	0.80	0.87	\	\
EEG-ELF (this study)	0.95	1.00	0.92	0.85

the difference between the task and resting states (task - rest), while “_ratio” refers to the ratio between them (task/rest). Figure 6 shows that the absolute value of Cohen’s d of all the 25 selected features was greater than 0.5, indicating that these features have more than moderate effect sizes for distinguishing good and bad prognosis. The red columns represent the good prognosis group with positive Cohen’s d values, reflecting that this feature was more significant in patients with good prognosis (17 in total), while the blue columns represent the poor prognosis group with negative Cohen’s d values, indicating that the feature prevailed in patients with poor prognosis (8 in total). There were 10 features with Cohen’s d values greater than 1.0, showing excellent discriminatory effects.

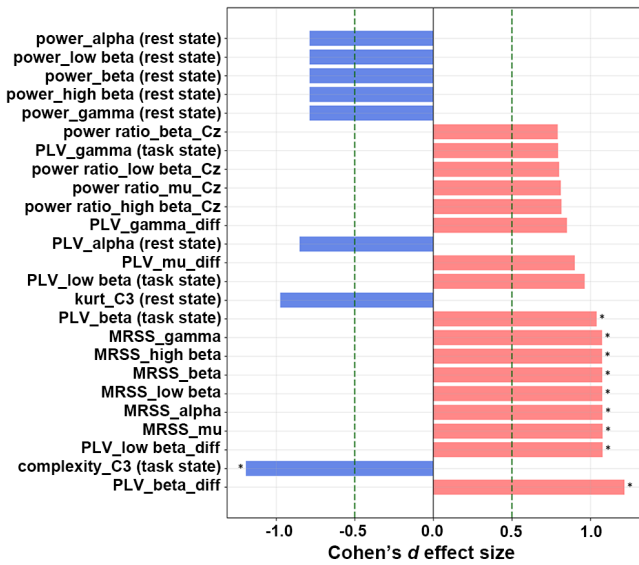


Fig. 6. Top 25 most influential features ranked by Cohen’s d effect size in leave-one-subject-out cross-validation (LOSO-CV) analysis. * indicates those key features that had both large effects and were statistically significant.

IV. DISCUSSION

We proposed an EEG ensemble learning framework for prognostic prediction of post-rTMS motor recovery in stroke patients. By combining comprehensive EEG features with F-regression feature selection and weighted ensemble learning, EEG-ELF achieved near-optimal classification accuracy and strong discriminative ability within the dataset. The consistently low prediction errors and high coefficient of determination indicate that EEG-ELF can stratify stroke patients according to pre-treatment EEG biomarkers predictive of functional recovery. These results emphasize that interpretable machine-learning architectures grounded in neurophysiological knowledge can provide practical precision tools for individualized neuromodulation.

While demographic and baseline clinical variables are frequently used to model stroke outcomes, their prognostic value for rTMS response remains uncertain. Reviews and cohort studies have shown that age, sex, and time post-stroke are not reliable predictors of rTMS efficacy [35], [36], [37]. The predictive role of baseline motor impairment is even more controversial: Hamaguchi *et al.* [38] reported that patients with severe or moderate impairments benefited most from contralesional 1 Hz stimulation, whereas Tatsuno *et al.* [39] found no relationship between baseline impairment and treatment response under identical conditions. Several studies and expert consensus reports reached similarly divergent conclusions [40], [41], [42], reinforcing the concept that conventional clinical metrics capture only a fraction of the neurophysiological mechanisms driving recovery. Quantitative EEG research has shown that neural indices, such as power ratio or connectivity, outperform baseline FMA scores in forecasting rehabilitation outcomes [43], and critical reassessments of the proportional-recovery rule further argue that baseline severity should not be overemphasized as a deterministic factor [44]. Consequently, we excluded baseline FMA from EEG-ELF inputs and focused on EEG biomarkers that directly reflect cortical excitability, connectivity, and plasticity.

During model development, deep-learning architectures were also tested but failed to generalize, largely due to the small sample size ($n = 20$) and the high dimensionality of

EEG data, which created unfavorable bias–variance trade-offs and susceptibility to overfitting. Ensemble learning provides a principled approach for combining complementary regressors with distinct inductive biases. Our ablation analysis confirms that all four base models contribute to the final performance: classification accuracy improved from 0.80 (single model) to 0.95 (four models), and Pearson R from 0.680 to 0.920. By combining stable linear shrinkage with nonlinear tree interactions, the framework improves robustness to data heterogeneity and small sample sizes. This observation aligns with Fang *et al.* [45], who reported that an ensemble architecture improved stroke-outcome prediction accuracy by over 10% compared with single learners and maintained performance under noisy data. Our results therefore suggest that for clinical datasets where sample expansion is constrained, combining domain-informed feature engineering with ensemble integration yields higher reliability and interpretability than end-to-end deep models. Beyond numerical performance, interpretability is crucial: EEG-ELF allows the physiological meaning of each EEG feature to be explicitly examined, a requirement for clinical translation where understanding the neural basis of prediction is as important as accuracy itself.

Functional connectivity features, particularly beta-band PLV, emerged as dominant predictors of recovery. Beta synchrony has long been recognized as a key mechanism supporting motor preparation, inhibition, and steady-state maintenance [46]. Preserved beta coherence enables efficient coordination of neuronal firing across distributed motor regions, while pathological synchronization impairs flexibility. In motor imagery paradigms, Benzy *et al.* [47] demonstrated that PLV features accurately decode movement intentions, underscoring their role as functional markers of motor-network engagement. Similarly, Shim *et al.* [48] showed that network efficiency and clustering in alpha and low-beta bands correlate strongly with FMA scores, linking organized connectivity with better motor function. Conversely, excessive and prolonged beta synchronization, as observed in Parkinsonian cortico-basal ganglia networks [49], disrupts timing precision and movement initiation. These converging results suggest that adaptive, flexible beta synchrony, rather than absolute power, is critical for rTMS responsiveness, as it reflects the brain’s capacity to reconfigure network states in response to external stimulation.

MRSS features further captured dynamic changes in oscillatory activity associated with movement. Stronger mu- and low-beta-band event-related desynchronization (ERD) over the lesioned hemisphere correlated with better residual motor function and smaller lesion volumes [50]. Longitudinal analyses indicate that successful recovery is accompanied by a progressive increase in ipsilesional ERD strength and reduced contralesional dependence [51]. Mechanistically, ERD magnitude reflects a transient increase in cortical excitability and reduction in short-interval intracortical inhibition (SICI) mediated by GABA_A disinhibition [52]. These excitability states are particularly favorable for neuromodulation: closed-loop TMS systems that trigger stimulation during beta-ERD epochs produce significantly greater corticospinal potentiation than stimulation delivered at random times [53]. Enhanced

gamma-band MRSS observed in our good-outcome patients may further indicate stronger local processing and engagement of inhibitory interneurons, consistent with Nowak *et al.* [54], who found that driving gamma oscillations in M1 reduces GABA_A inhibition and facilitates motor learning. Together, these results establish MRSS as a mechanistic biomarker of cortical readiness, linking frequency-specific desynchronization to increased excitability and neuroplastic capacity.

Hemispheric asymmetry patterns provided complementary evidence of hemispheric cooperation. Good-prognosis patients exhibited symmetric activation across motor and premotor cortices, suggesting balanced interhemispheric recruitment and efficient network integration, while poor-prognosis patients showed fragmented or lateralized activation dominated by contralesional compensatory circuits. Such spatial disorganization likely limits the brain’s ability to redistribute functional load, reducing responsiveness to rTMS. The spatial topology of activation therefore provides macroscopic confirmation of the connectivity findings, suggesting that recovery depends not only on the strength of oscillatory coupling but also on the coordinated spatial organization of sensorimotor networks.

Statistical and complexity-based features yielded additional insight into cortical state dynamics. For movement of healthy people, EEG signals become more regular and predictable, reflecting a transition to an ordered state optimized for stable motor command generation [55]. Poor-prognosis patients in our study displayed elevated signal complexity within ipsilesional M1 during motor tasks, implying inefficient network stabilization and a “noisy” cortical environment that may hinder effective communication among neuronal populations. Such disorganized activity could explain reduced susceptibility to rTMS-induced plasticity, which depends critically on stimulation being delivered during high-excitability, low-entropy phases. Indeed, state-dependent TMS experiments have shown that the timing of stimulation relative to the endogenous oscillatory phase determines whether LTP- or LTD-like effects occur: stimulation at high-excitability phases enhances potentiation, while stimulation at low-excitability phases promotes inhibition [56], [57]. These findings integrate well with our complexity observations, suggesting that cortical entropy indices may serve as indirect markers of instantaneous excitability and predict individual sensitivity to rTMS.

The strong performance of EEG-ELF also underscores methodological implications for data-limited clinical research. Ensemble learning mitigates the variance inherent to small samples by averaging over multiple learners, producing stable and generalizable models [45]. This hybrid approach combines interpretable, neurophysiology-based features with ensemble integration to balance domain expertise and data-driven modelling. Importantly, the framework preserves transparency: each feature maps onto a specific physiological process, allowing clinicians to interpret model outputs in mechanistic rather than purely statistical terms. Such interpretability is essential for integration into clinical decision-support systems, where transparent evidence underpins trust and adoption.

A key limitation of this study is the relatively small sample size. The necessity for large-scale cohorts in prognostic prediction research is due to the substantial inter-individual

heterogeneity among stroke patients. This variability complicates the model's ability to learn generalizable features in a robust way. Based on our previous clinical studies examining the influence of neural reorganization on rTMS treatment outcomes [3], we specifically enrolled stroke patients with subcortical lesions. This helps mitigate the confounding effects of contralateral compensatory reorganization, while focusing on a population whose favorable recovery is largely associated with ipsilesional reorganization. Furthermore, the present study employed ensemble learning, which integrates multiple classical machine learning algorithms. This approach, to some extent, alleviates the dependency of large-scale models on extensive datasets. Although the current sample size is comparable to those reported in clinical studies on prognosis prediction, future efforts should aim to incorporate multi-center datasets to further fine-tune and validate the proposed model.

V. CONCLUSION

We proposed an EEG ensemble learning framework to predict motor recovery following rTMS therapy in stroke patients. This work demonstrates that EEG biomarkers spanning power, spectral, connectivity, spatial, and statistical domains can predict post-rTMS motor recovery by capturing cortical organization and excitability. The EEG-ELF, grounded in ensemble learning and interpretable, domain-informed feature design, offers a mechanistically guided, data-driven approach to patient stratification. By moving beyond demographic and baseline assessments toward dynamic neural-state characterization, this study establishes a foundation for precision neuromodulation in stroke rehabilitation, where interventions are tailored not only to the individual but also to the optimal neural state for promoting plasticity and functional recovery.

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