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A Deep Learning-Based Prognostic Classification Model for Patients with Prolonged Disorders of Consciousness

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Abstract: ***Accurate prognostic assessment of patients with prolonged disorders of consciousness is critical for clinical decision-making. However, traditional behavioral scales and neuroimaging techniques are limited by subjective interpretation and low temporal resolution, which impede the dynamic characterization of consciousness fluctuations. To address these challenges, this study proposes a deep learning-based prognostic classification model integrating multiscale electroencephalogram features. First, geometric features including maximum radius, regional density, and dispersion were extracted from power spectrum-Poincaré scatter plots, while nonlinear dynamic features were constructed using sample entropy and multiscale entropy. Second, a temporal hybrid network enhanced by cross-attention mechanisms was designed to strengthen the modeling of feature interdependencies. Experimental validation on 8-channel electroencephalogram data from 15 patients demonstrated a classification accuracy of 90.83 percent and sensitivity of 94.73 percent, with significant performance improvements compared to random forest and support vector machine baselines.***

Keywords: Prolonged Disorders of Consciousness, Multiscale, Deep Learning, Classification Model**.**

1. Introduction

The accuracy of prognostic assessment in patients with prolonged disorders of consciousness (pDoC) directly impacts clinical decision-making and rehabilitation resource allocation [1]. Current mainstream methods rely on behavioral scales [2,3] and neuroimaging techniques [4,5]; however, the former is susceptible to subjective biases, while the latter suffers from low temporal resolution, both failing to capture dynamic fluctuations in consciousness [6]. Electroencephalography (EEG), with its millisecond-level temporal resolution [7], offers unique insights into pDoC pathophysiology, such as gamma oscillation attenuation and theta-band synchrony abnormalities [8,9]. Nevertheless, traditional EEG analysis depends on manual feature engineering, which cannot resolve high-dimensional nonlinear brain network interactions, limiting prognostic stratification accuracy. Deep learning provides a novel pathway to overcome these bottlenecks through end-to-end feature learning: convolutional neural networks automatically identify local oscillatory abnormalities in EEG signals, while graph neural networks model dynamic topological evolution of cross-regional connectivity [10]. Transfer learning leverages EEG big data from epilepsy [11] and Alzheimer's disease [12] to pretrain models, which are then fine-tuned for pDoC data, mitigating sample scarcity. Cross-disease studies validate the transfer potential of deep learning in neurological disorders—for example, CNN-LSTM models precisely detect epileptiform discharges in epilepsy [13], and graph networks improve Alzheimer's subtyping accuracy through multimodal data fusion [14,15]. These findings demonstrate that deep learning exhibits strong generalization capabilities for shared pathological features like functional network dissociation and oscillatory rhythm abnormalities, establishing a theoretical foundation for pDoC prognostic modeling. This study proposes a deep learning model integrating multiscale EEG features to address the feature representation limitations of traditional methods and the overfitting risks in small-sample scenarios, aiming to provide an objective and interpretable intelligent tool for pDoC prognosis evaluation.

2. Method

2.1 EEG Signal Preprocessing

2.1.1 EEG Denoising

EEG signals are often contaminated by powerline interference (50/60 Hz) and baseline drift (<1 Hz), which require preprocessing to enhance analytical reliability [16]. This study implemented a two-stage denoising protocol: Powerline Interference Removal: A notch filter (stopband: 49–51 Hz) was applied to attenuate alternating current artifacts. Baseline Drift Correction: A 0.5 Hz high-pass filter eliminated low-frequency fluctuations.

2.1.2 EEG Normalization

Signal normalization mitigates systemic biases introduced by cross-subject, cross-experimental, and cross-device variability, ensuring inter-individual comparability. We adopted Z-score normalization to align voltage distributions across channels through zero-meaning and unit-variance standardization. Crucially, signal quality verification and prior denoising were mandatory before normalization to prevent noise amplitude from distorting standard deviation calculations. This method eliminated dimensional discrepancies, enabling population-level statistical analysis of brain network features.

2.2 EEG Signal Feature Extraction

2.2.1 Power Spectrum-Based Feature Extraction

EEG power spectral features effectively characterize cognitive states in patients with prolonged disorders of consciousness (pDoC) [17]. Power spectrum analysis, a standard method for spectral decomposition of time-series signals, quantifies energy distribution across frequency bands. For instance, heightened energy in theta (4–8 Hz) and alpha (8–12 Hz) bands, coupled with suppressed high-frequency (>30 Hz) activity, reflects rhythmic alterations in neural oscillations. Investigating time-frequency properties of pDoC EEG signals holds significant prognostic value.

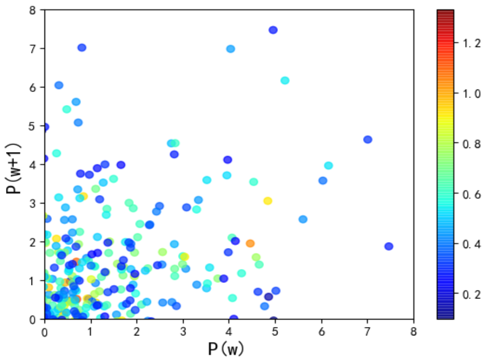
Given an EEG signal sequence {x(1),x(2),…,x(N)} with N sampling points, the power spectrum is computed follows1:

$$P(\omega)=\frac{|X(\omega)|^2}{N}=\frac{1}{N}\left|\sum_{n=0}^{N-1}x_n e^{\frac{-2R\pi\omega n}{N}}\right|^2,\ \omega=\frac{2\pi f_s}{N}\times n,\ n=1,2,\cdots,N$$

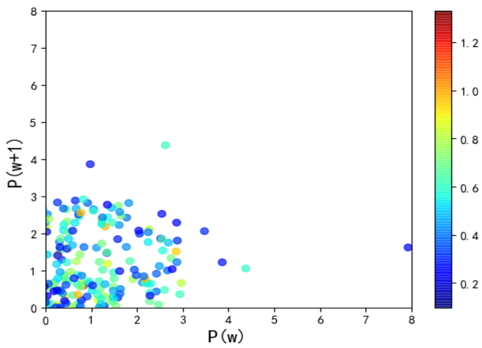
The complete power spectrum of the EEG signal was calculated according to Formula 1. To facilitate data visualization and further investigate EEG disparities between chronic disorders of consciousness patients with favorable and poor prognoses, Poincaré scatter plots were employed for characterization. The formula is defined as follows, where T denotes the time interval period:

$$PP(\omega)=\{(P(\omega),P(\omega+T)),\ \omega=\frac{2\pi f_s}{N}\times n,\ n=1,2,\cdots,N-1\}$$

Based on Formula 2, gamma-band power spectrum-Poincaré scatter plots were generated. Figures 1 and 2 respectively display the power spectrum-Poincaré scatter plots of chronic disorders of consciousness patients with favorable and poor prognoses. The figures distinctly reveal significant differences between the two groups: patients with favorable prognoses exhibit dispersed scatter plot distributions and larger coverage areas, whereas those with poor prognoses show clustered distributions and smaller coverage areas. This observation aligns with human neural activity patterns, where normal brain activity demonstrates higher complexity, stronger connectivity, and more dynamic neural interactions.



Figures 1: Power spectrum-Poincaré scatter plots of patients with favorable prognosis



Figures 2: Power spectrum-Poincaré scatter plots of patients with poor prognosis

To further characterize the prognostic EEG feature disparities in patients with prolonged disorders of consciousness based on power spectrum-Poincaré scatter plots, this paper proposes three metrics: maximum radius, regional density, and dispersion, constructing power spectrum-based prognostic EEG features for these patients, denoted as F1.

2.2.2 Nonlinear Characteristics of EEG Signals

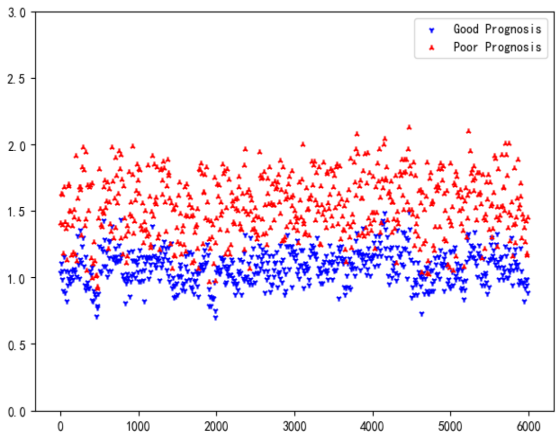
EEG signals exhibit complex nonlinear dynamical properties. In EEG analysis, entropy quantifies signal irregularity and complexity, serving as a parameter to describe system complexity. This study extracts EEG features based on nonlinear dynamic theory to identify disparities in patients with prolonged disorders of consciousness. Li et al. extracted features such as approximate entropy and sample entropy from a nonlinear dynamics perspective for EEG analysis [18]. Among these, sample entropy and multiscale entropy demonstrate superior classification performance in distinguishing prognostic outcomes for these patients [19].

Multiscale entropy extends sample entropy to multiple temporal scales, providing additional observational perspectives when temporal scales are indeterminate. To quantify signal complexity across temporal scales, Costa et al. proposed multiscale entropy [20]. The implementation procedure is detailed below:

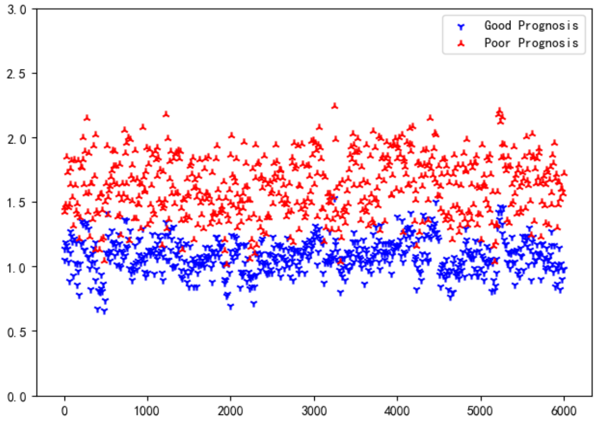
For a time series of length N, divide it into multiple non-overlapping segments of length τ (scale factor). Compute the arithmetic mean for each segment to generate a new time series. The multiscale entropy of the signal is obtained by calculating the sample entropy of this new series, where the elements of the new series are defined as in Formula.

$$y_j^{(\tau)}=\frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau}x_i,\ 1\leqslant j\leqslant N/\tau$$

Figures 3 and 4 demonstrate the distributions of sample entropy and multiscale entropy feature values across EEG segments. Blue points represent feature values from patients with favorable prognosis, while red points correspond to those with poor prognosis. The figures reveal that the sample entropy and multiscale entropy values of patients with favorable prognosis are proportionally lower than those of patients with poor prognosis.



Figures 3: Sample Entropy



Figures 4: Multiscale Entropy

Fusion of sample entropy and multi-scale entropy as two feature indices to construct electroencephalographic characteristics for the prognosis of patients with chronic consciousness disorders based on nonlinear features, referred to as F2.

2.3 Algorithm Design for EEG Signal Feature Classification

After extracting the electroencephalographic (EEG) features of patients with chronic consciousness disorders, five EEG features are obtained: based on power spectrum-Poincaré scatter plot: maximum radius, regional density, and discreteness; based on nonlinear features: sample entropy and multi-scale entropy. Due to the complexity of the EEG signals in chronic consciousness disorder patients, this study proposes a lightweight deep learning model—Cross-Attention Enhanced Temporal Hybrid Network. First, the original features are mapped to a high-dimensional space through an embedding layer, and layer normalization is applied to eliminate dimensional differences. Then, a cross-attention mechanism is introduced to analyze the correlation weights between Poincaré geometric features and nonlinear entropy features, enhancing the synergistic expression of pathological key features. Next, a bidirectional gated recurrent unit (GRU) is used to model the temporal evolution patterns of multi-time-window features, capturing the dynamic compensatory trajectory of the brain network. Finally, an adaptive pooling strategy is employed to integrate temporal information, and a multi-layer perceptron is used to output prognostic classification probabilities. To improve the classification model's accuracy and generalization, this paper proposes the fusion of all features to obtain the electroencephalographic feature fusion of patients with chronic consciousness disorders, referred to as F3.

$$F_3 = [F_1, F_2]$$

3. Result

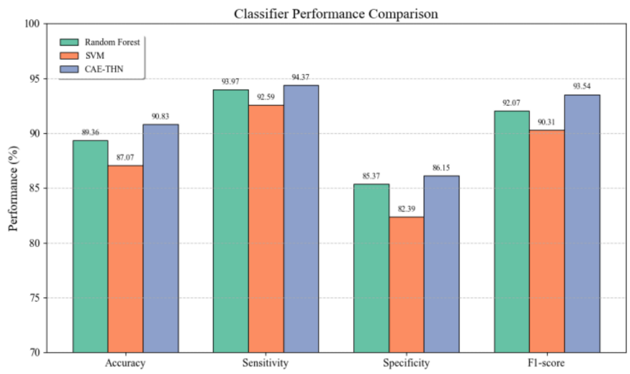
3.1 DATA

The electroencephalographic (EEG) dataset used in this study was collected from the neurosurgery department of a hospital in Sichuan Province. All EEG data were collected under the supervision of professional physicians. This EEG dataset records data from 15 patients with chronic consciousness disorders, with each patient having 4 sets of 8-channel EEG data (2 sets recorded at admission and 2 sets recorded at discharge). Each EEG data set was recorded for 2 hours, with a sampling frequency of 2048Hz. Neurosurgeons conducted a comprehensive clinical assessment of the patients' consciousness states using both EEG and the CRS-R scale, and classified the EEG data based on the corresponding time points into two groups: poor prognosis and good prognosis.

3.2 Experimental Results

To validate the classification performance of the extracted features for prognostic assessment of patients with chronic consciousness disorders, the features were input into classifiers after EEG signal preprocessing to verify the classification accuracy. Based on the fusion of EEG features from patients with chronic consciousness disorders, three classifiers were tested: Random Forest Classifier, Support Vector Machine Classifier, and Cross-Attention Enhanced Temporal Hybrid Network. The performance of these three classifiers was compared. Before discussing the classification performance metrics, four classification situations need to be defined, as shown in Table 1: Positive class (correctly predicting good prognosis), False negative (predicting good prognosis as poor prognosis), False positive (predicting poor prognosis as good prognosis), and Negative class (correctly predicting poor prognosis). The performance metrics used for evaluation in this study include Accuracy, Sensitivity, Specificity, and F1 score (H-mean).

Figure 5 shows the classification performance of feature fusion based on EEG signals from patients with chronic consciousness disorders, input into the Random Forest Classifier, Support Vector Machine Classifier, and Cross-Attention Enhanced Temporal Hybrid Network. The comparison of feature fusion across the three classifiers is presented. From the chart, it can be observed that, compared to the Random Forest Classifier and Support Vector Machine Classifier, the Cross-Attention Enhanced Temporal Hybrid Network achieves better classification performance, with an accuracy of 90.12% and sensitivity of 94.37%.



Figures 5: Performance evaluation of feature fusion in each classifier

4. Conclude

A feature extraction scheme based on power spectrum-Poincaré scatter plot is designed, and three measurement indicators are proposed: maximum radius, regional density, and discreteness, which are fused into feature F1. Nonlinear EEG features, sample entropy and multiscale entropy, are designed and fused into feature F2. Finally, features F1 and F2 are fused into feature F3. A classification algorithm for prognostic assessment of patients with chronic consciousness disorders is designed based on Random Forest. The proposed method is validated using EEG data collected from the Neurosurgery Department of a hospital in Sichuan Province. The method successfully assists clinical doctors in diagnosis in clinical applications.

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