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Deep Learning-Based EEG Frequency Domain Analysis for Classification of Disorders of Consciousness

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Abstract: Disorders of Consciousness (DOC), including Minimally Conscious State (MCS) and Unresponsive Wakefulness Syndrome (UWS), are neurological conditions characterized by severe impairment in cognition and perception due to brain injury or degeneration. Traditional behavioral and imaging-based diagnosis methods are costly, subjective, and dependent on expert interpretation. To address these limitations, this study proposes a deep learning-based method that leverages EEG frequency domain features for objective DOC classification. Power Spectral Density (PSD) is extracted from EEG signals using the Welch method to capture multi-band neural oscillation characteristics. A two-dimensional Convolutional Neural Network (CNN) is then employed to automatically learn discriminative representations from the spectral maps. Dropout regularization and ReLU activation functions are integrated to enhance generalization and nonlinear feature extraction. Experimental evaluation on EEG datasets from MCS and UWS patients demonstrates that the proposed method achieves an average classification accuracy of 86.22%, significantly outperforming traditional machine learning approaches. The results confirm that PSD-based spectral encoding enhances robustness and interpretability by emphasizing frequency bands most associated with consciousness states. This framework provides an efficient, scalable, and objective solution for DOC classification, offering valuable support for clinical prognosis assessment and intelligent diagnosis.

Keywords: EEG classification; Disorders of Consciousness (DOC); Power Spectral Density (PSD); Convolutional Neural Network (CNN)

1. Introduction

Laser Disorders of Consciousness (DOC) are neurological diseases caused by damage to systems such as the cerebral cortex, resulting in severe cognitive and language impairments. Depending on the level of consciousness, DOC can be classified into Minimally Conscious State (MCS) and Unresponsive Wakefulness Syndrome (UWS). DOC is typically caused by brain damage or degeneration, presenting symptoms such as aphasia and comprehension difficulties. Traditional prognosis assessment methods involve clinicians evaluating patient behavior along with physiological images obtained through brain imaging techniques and neuroplasticity technologies, combined with the Coma Recovery Scale-Revised (CSR-R) for scoring[1]. However, these methods require specialized personnel to operate professional equipment, are costly and inefficient, and demand high clinical expertise from physicians. Therefore, there is an urgent need for effective, objective, and quantitative methods to classify and diagnose DOC.

Electroencephalogram (EEG) is a technique that records brain electrical activity by placing multiple electrodes on the scalp to capture the electrical activity of the brain neurons. During the treatment of DOC patients, EEG can be used to assess the recovery of neurological functions such as cognition, emotional state, and language abilities. It is also employed for diagnosing and monitoring patients' consciousness and sleep states, becoming an essential tool for objective evaluation of DOC[2-3]. However, EEG signals, although rich in information, are characterized by high dimensionality and low signal-to-noise ratio, posing challenges in their analysis and processing. With technological advancements, research combining EEG and machine learning is rapidly advancing human understanding of the brain. Machine learning has gained significant attention in EEG-based prognosis assessment of DOC[4-5], such as feature extraction for prognosis classification and the development of DOC-Forest algorithm to differentiate UWS and MCS patients.

The integration of machine learning with EEG features greatly enhances the efficiency of DOC diagnosis and treatment. In recent years, deep learning has demonstrated stronger classification and prediction capabilities in brain function and cognition recognition based on EEG. Studies have utilized Convolutional Neural Networks (CNN) with convolutional kernels to classify EEG data, achieving high accuracy. However, despite the widespread application of deep learning in brain cognition recognition, its application in the field of prognosis classification of DOC is relatively limited. Most studies focus on electrode-level features for classification, neglecting source-level features and the quantitative analysis of relevant feature key parameters[6-7].

Therefore, based on the current research status, this article proposes a deep learning method for classifying disorders of consciousness based on EEG frequency domain features. This approach utilizes a two-dimensional Convolutional Neural Network for classification and conducts in-depth analysis of the impact of key parameters in feature extraction on classification effectiveness..

2. DataSection Headings

The sample data includes 15 patients in Unresponsive Wakefulness Syndrome (UWS) state and 15 patients in Minimally Conscious State (MCS). Approximately 40% of the patients have chronic disorders of consciousness caused by traumatic brain injury, while the rest suffer from chronic disorders of consciousness due to ischemic causes. In order to assess patient consciousness levels more accurately, we conducted clinical behavioral assessments on each patient more than three times, with psychologists using the CSR-R scale to score the patients.

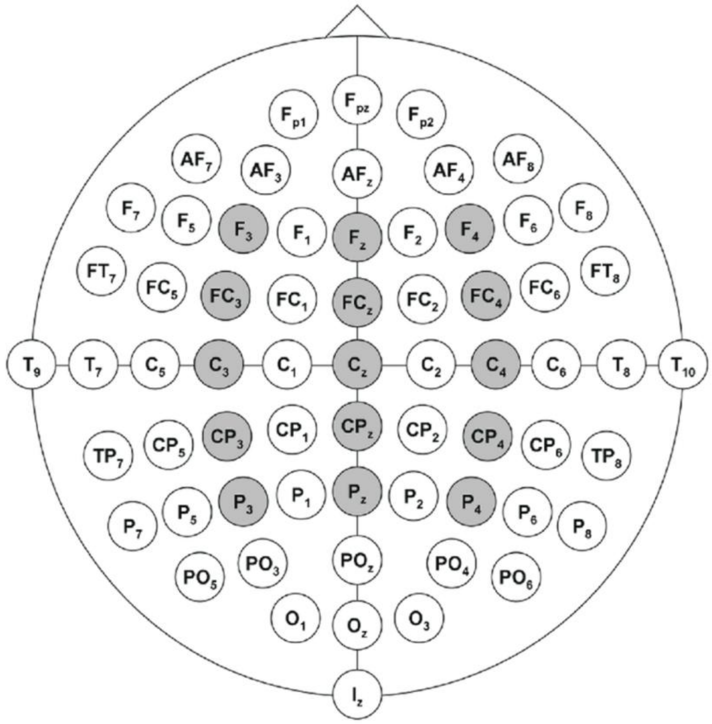

Figure 1. Illustration of EEG sampling points.

3. Feature extraction and deep learning classification methods.

3.1 Power Spectral Density

In the field of EEG data analysis, Power Spectral Density (PSD) is a typical feature of EEG frequency domain characteristics. PSD represents the distribution of power within a specified frequency range. Analysis of PSD can help researchers determine the energy distribution of different frequency bands, thereby gaining a better understanding of brain activity patterns. It helps extract power information from different frequency bands such as theta, alpha, beta, gamma, etc., aiding in understanding the activation or inhibition of the brain in different frequency ranges.

Comparing PSD from different time periods or conditions can reveal spectrum feature differences between different brain regions or individuals, aiding in the study of changes in cognition, emotion, diseases, and other aspects. It can be used to monitor the spectral characteristics of brain electrical signals, helping assess an individual's attention, relaxation, wakefulness, etc., which is significant for studying areas such as sleep, concentration, mental activity, and so on. The Welch method is a commonly used spectral estimation technique that divides the signal into multiple overlapping segments, applies window functions and Fourier transform to estimate the power spectral density (PSD). Its advantages include reducing variance, decreasing spectral leakage, enhancing flexibility to meet different requirements, and having high computational efficiency. These combined advantages have made the Welch method widely used in fields such as signal processing and communication system analysis. In this experiment, all collected EEG signals will be processed using Welch to extract PSD.

$$\hat{P}_{PER}(w) = \frac{1}{MUL} \sum_{i=1}^{L} \left| \sum_{n=0}^{M-1} x_N^i(i) w(n) e^{-iwn} \right|^2 \tag{1}$$

For a random signal ɟ(ε) of length ΰ́, it is segmented into ΰ́ segments of length ΰ̏ using a window function, where the window length is ΰ̏ and the normalization factor is Ɇ. This is done to reduce the mutual interference between different spectral peaks in the actual Power Spectral Density (PSD)..

3.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have many significant advantages in EEG analysis. Firstly, CNNs are able to effectively learn spatial and temporal features in EEG signals, thus better capturing complex patterns in brain activity. Secondly, CNNs have good generalization capabilities, enabling them to handle EEG data from different sources and types, providing broader application possibilities in neuroscientific research. Additionally, convolutional networks can automatically extract discriminative features, reducing the burden of manual feature design for researchers and improving the efficiency and accuracy of the analysis. As shown in Figure 2:

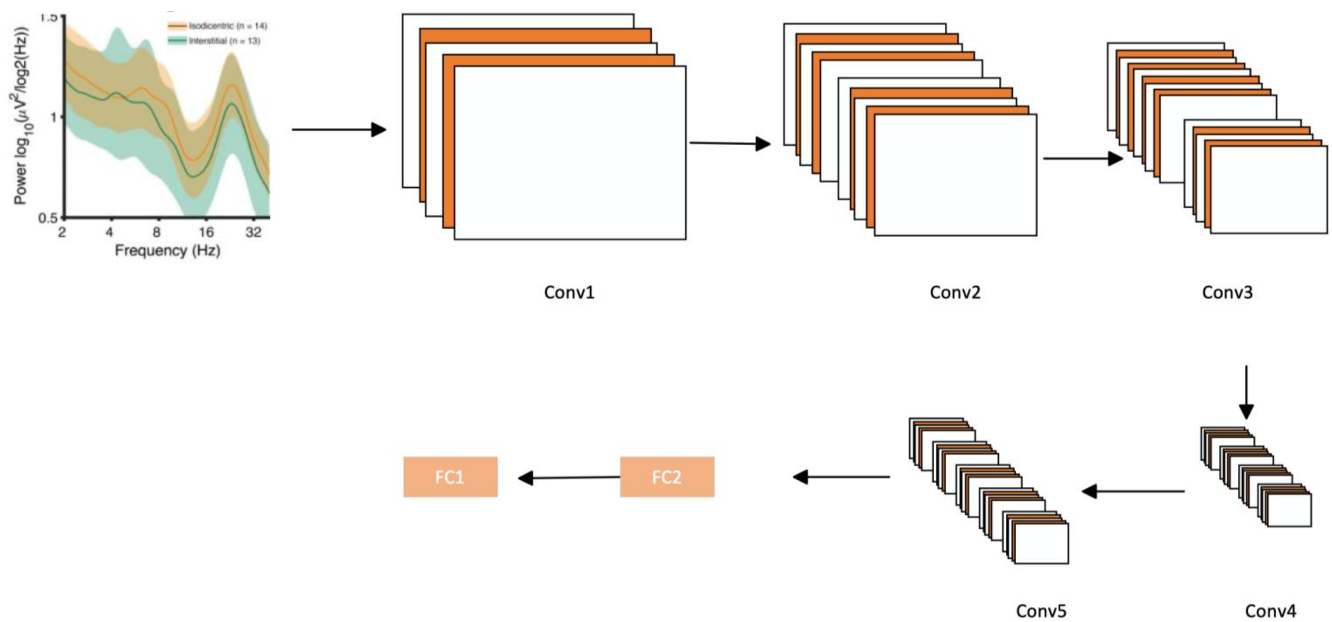

Figure 2. CNN Network Architecture Model

Although we segmented the experimental dataset into multiple files using the sliding window method, the overall data volume is still relatively limited. To effectively avoid overfitting, we introduced Dropout layers in the first convolutional layer and fully connected layer, randomly dropping about 10% of the nodes. Furthermore, the Relu activation function was used after each pooling layer to enhance the network's ability to extract nonlinear features.

4. Experiment and evaluation

4.1 Model training and validation.

To prevent overfitting, we chose to use 10% of the data as the test set and performed 5-fold cross-validation on the remaining data. During the training phase, we set the learning rate to 0.001, employed backpropagation with cross-entropy as the loss function, and used the Adam optimizer for gradient descent. After multiple parameter tuning experiments, we set the batch size to 64 and the number of training epochs to 100. These optimization measures help improve the model's generalization ability and performance.

To ensure the effective utilization of data and enhance the model accuracy, this study conducted performance evaluation using 5-fold cross-validation experiments and utilized the mean value as the evaluation metric for model performance. Additionally, accuracy was used as the comprehensive evaluation metric for model performance. The calculation formulas for these metrics are as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{2}$$

The meaning of TP is true positives, which represents positive samples predicted as positive. TN stands for true negatives, indicating negative samples predicted as negative. FP represents false positives, representing negative samples predicted as positive. FN stands for false negatives, representing positive samples predicted as negative.

4.2 Result

Based on the results obtained, extracting PSD features from the original data can effectively enhance the classification performance of consciousness disorders. As shown in Figure 3, classifying based on PSD features achieves a classification accuracy of 86.22%, indicating a significant improvement compared to conventional machine learning approaches..

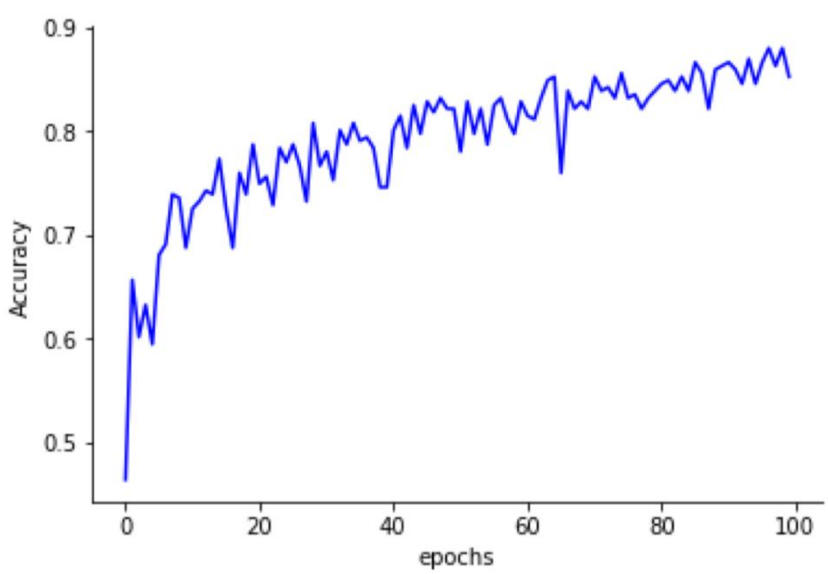

Figure 3. CNN Training Results

5. Conclusion

The research results indicate that compared to using the original EEG data directly as input, the classification efficiency of the network based on PSD features has been greatly improved. This demonstrates that the extraction and utilization of power spectral density (PSD) information can effectively enhance the discriminative capability of EEG signals by emphasizing the frequency-domain characteristics most relevant to different states of consciousness. Through this transformation, the model not only reduces noise interference and redundant temporal information but also captures the intrinsic oscillatory patterns associated with neural activity. Consequently, the proposed method achieves higher accuracy, robustness, and generalization performance in distinguishing various consciousness levels. Overall, this study provides an important research foundation for the subsequent prognosis assessment of disorders of consciousness (DOC) using EEG data and offers valuable insights for developing intelligent diagnostic systems capable of supporting clinical decision-making and long-term patient monitoring.

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