Automatic classification of EEG signals via deep learning

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***Abstract*—Electroencephalogram (EEG) is widely used to diagnose many neurological and psychiatric brain disorders. The correct interpretation of EEG data is critical to avoid misdiagnosis. However, the analysis of EEG data requires trained specialists and may vary from expert to expert. Meanwhile, it can be challenging and time-consuming to assess the EEG data since these signals may last several hours or days. Therefore, rapid and accurate classification of EEG data may be a key step towards interpreting EEG records. In this study, a novel deep learning model with an end-to-end structure is proposed to distinguish normal and abnormal EEG signals automatically. For this purpose, we investigate the possibility of combining the core ideas of inception and residual architectures into a hybrid model to improve classification performance. We evaluated the proposed method through extensive experiments on a real-world dataset, and it shows feasibility and effectiveness. Compared to previous studies on the same data, our method outperforms other existing EEG signal methods. Thus, the proposed method can aid clinicians to automatically detect brain activity.**

Keywords*—*electroencephalogram, convolutional neural network, inception, residual architecture, EEG signal classification

I. INTRODUCTION

Electroencephalogram (EEG), which records brain electrical activity generated by an electric volume conductor placed on the scalp [1], is a valuable tool for detecting many neurological diseases [2]–[5], such as epilepsy, stroke, sleep disorders, etc. Nowadays, the EEG has been widely used in the clinical environment because of its non-invasiveness and relatively low cost [6]. However, neurologists still require to evaluate these signals by manual visual inspection in practice, which is time-consuming [1]. Moreover, EEG interpretation process has relatively low inter-observer agreement [7], which may result in the misdiagnosis of brain disorders. Therefore, the development of the automatic assessment of EEG signals is of great significance in this research field.

With the recent development of machine learning technology, researchers have suggested numerous methods to classify EEG signals. Most of the methods in the literature are to extract hand-crafted features from the EEG signals by using traditional feature extraction technology or domain expert knowledge [8], [9]. The extracted features are then fed into a classification model to detect or classify the EEG signals. This means that the feature quality has an important impact on the reliability and accuracy of the methods. However, EEG signals are highly subject-dependent, the effective feature extraction often requires deep domain knowledge and expertise [10]. Moreover, the extracted features are not generally robust with respect to many variations, e.g., translation, noise, scaling. In addition, some researchers have proposed automatic classification of the EEG signals using signal processing techniques such as wavelet transform [11]. As there are generally significant differences between patients with EEG signals, these methods do not perform well in practice [4].

Recently, deep learning methods have been successfully applied in a variety of areas such as speech recognition, information retrieval, image recognition [12]–[14]. As one of the popular deep learning techniques, convolutional neural network (CNN) has attracted great attention in various fields, including EEG signal processing. CNN-based methods can combine both feature extraction and classification into a single body, unlike conventional machine learning methods. Meanwhile, they can automatically extract the representative features from the raw data and use these features for detection or classification. To date, various CNN-based methods have been proposed and used in different domains. For instance, Acharya et al. [2] presented a method for automated identification of seizure and non-seizure EEG signals using deep CNN; Oh et al. [15] proposed a CNN-based method for the detection of Parkinson's disease. Li et al. [16] introduced a new classification method based on a one-dimensional convolution neural network (1D-CNN) to classify and diagnose arrhythmia signals directly.

Despite the performance of these CNN algorithms have greatly improved, there are still some shortcomings. For example, it is difficult to find the most suitable CNN architecture. Hence, researchers have carried out a lot of research on this subject and proposed many greater effectiveness learning frameworks, such as GoogLeNet [17], residual networks (ResNet) [18]. By analyzing network structure, we can find that there are two representative structures to significantly improve the performance of deep learning in literature: inception structure and residual structure. Specifically, the inception structure can extract more abundant features by broadening the width of the network and increasing the adaptability of the network to the scale of the convolution kernel; the residual structure can increase the depth of the network without increasing system errors.

Inspired by the excellent performance of these CNN architectures in various applications, in this paper, we combine the core principles of inception and residual structure into a deep learning model to classify EEG signals. Based on this, we present a novel, fully automated 1D-CNN for the classification of normal and abnormal EEG signals, called IRCNN. As stated earlier, the proposed method does not require any manual intervention or user-assisted feature extraction. The new algorithm is evaluated on an actual data set. The experimental results show that the IRCNN is robust in performing the identification of abnormal EEG signals. In summary, the main contributions of this paper are as follows:

1. To the best of our knowledge, there are no prior studies combining the core ideas of inception and residual architectures into a one-dimensional CNN model to classify EEG signals.

2. The proposed model operates directly on the raw EEG signals without any manual feature extraction. Moreover, our method achieves state-of-the-art performance on the EEG classification task.

The rest of the paper is organized as follows. Section 2 includes a short review of the related work of CNN. The details of the proposed deep learning model are described in section 3. Section 4 presents the experimental design and evaluates the performance of the real-world data set. Finally, we conclude the paper and discuss future work in section 5.

II. Related Work

In this section, we briefly review the related work regarding the existing methods of CNN.

A. CNN

In recent years, deep learning is already being extensively used to automate feature extraction procedures, and many achievements can be found in the literature [19]. As a subset of deep learning, CNN has attracted great interest because of its performance similar to or even better than humans in many domains [15]–[18], [20], especially in computer vision. The CNN generally consists of different types of basic layers, including convolutional, pooling, and fully connected layers. The convolutional layers are designed with various kernels to convolute the whole input, and one or more feature maps are generated for the next layer after the convolution operation. Then, the convolutional layer is typically followed by a non-learnable layer called pooling layer, which purpose is to further downsample the feature maps to enhance invariance of the features and reduce the computational complexity of the neural network considerably, without increasing the number of parameters [21]. This means pooling layers, such as mean pooling, max pooling, etc., can resize the feature maps whilst retain their distinctive features. After several convolution and pooling layers in the neural network, the obtained feature maps may be flattened into a feature vector and injected as input to one or more fully connected layers. For the classification task, usually, a softmax layer is attached behind the fully connected layer as the final output, it is possible to output the predictive outcome of input data. Here, this layer is a dense layer with a softmax activation function. Meanwhile, the number of its neurons is equal to the number of classes in the dataset. In addition, the network parameters are optimized by minimizing the loss using the gradient descent method and backpropagation of the error [22].

Nowadays, as the recent variants of conventional CNN, 1D-CNN has been actively developed and used in numerous applications, e.g., damage detection in bearings [23], [24], early arrhythmia detection in EEG beats [4], [25]. The infrastructure is similar to that of the conventional CNN. The major difference is the dimension of the input data and convolution kernels. In the 1D-CNN, the convolution kernel exhibit only one dimension [21]. Meanwhile, it slides in only one direction for extracting meaningful features. Thus, 1D-CNN is a type of neural network well-suited to time series data such as EEG data. Recently, 1D-CNN has successfully been used for the classification of automatic sleep stage [5], achieving state-of-the-art performance in terms of accuracy. Furthermore, in a recent study [26], 1D-CNN has achieved high accuracy and recall for detecting the suspect of anomalies in the electrocardiogram.

B. Inception Module

The traditional deep learning networks (e.g., AlexNet [12], VGGNet [14]) commonly obtain better performance by increasing the depth of the network (number of layers). With an increase in the number of layers, however, these CNN models are much more difficult to optimize. This is because the increase of layers usually causes a series of problems such as slow convergence and gradient vanishing. To solve this problem, Szegedy et al. proposed a deeper and wider convolutional neural network in [17], called GoogleNet. The GoogleNet contains 22 layers, which introduces a new building block known as the inception module. Compared with the traditional deep learning architectures, the inception module does not follow the typical sequential process but concatenates multiple convolution kernels into a new filter. More specifically, the inception module stacks convolution kernels of different scales (1×1, 3×3, 5×5) and pooling operations (3×3) in parallel. To further reduce the dimension, 1×1 convolution kernels are added before each expensive convolution. The design of this architecture enhances both the network's width and the adaptability of the network to multiple scales. On the other hand, it significantly reduces the number of parameters to be optimized and thus efficiently saves computational cost.

C. Residual Module

As mentioned above, the excessive depth of a neural network can result in a degradation problem in the training of deep CNN. Therefore, He et al. [18] proposed a deep residual network to alleviate this issue in 2015. Its core architecture is to present the basic deep learning network unit called the residual block. Each residual block is added a shortcut connection to enable the gradient flow directly through the bottom layers. A typical residual block consists of convolutional, batch normalization, and nonlinear activation function layers. Fig. 1 shows a schematic diagram of the original residual block. Let the input of the l-th residual block is x_l, then the residual block can be shown below:

$$y_l = h(x_l) + F(x_l, W_l) \quad (1)$$

$$x_{l+1} = f(y_l) \quad (2)$$

Here, $F(x_l, W_l)$ is the residual function, W_l is the weight parameter corresponding to the residual function, $f(*)$ is the rectified linear unit (Relu) activation function, x_{l+1} is the output of the l-th residual block. In [18], $h(x_l) = x_l$ is an identity mapping.

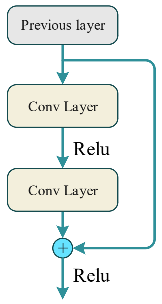

Fig. 1. The structure diagram of the original residual block.

The ResNet that is formed by stacking multiple residual blocks achieves state-of-the-art performance for object detection and other recognition tasks on ImageNet [18]. Obviously, the network architecture in ResNet is more compact than other CNN methods, e.g., VGGNet.

III. Methodology and Material

In this section, a novel CNN-based model is proposed for detecting normal and abnormal EEG signals. This model that uses an end-to-end network architecture can automatically learn the features without any crafting in feature engineering. The model is individually trained and tested on a real-world dataset. A flow diagram of the automated system for the automatic detection of EEG developed from this paper is given in Fig. 2. Specifically, our proposed automation detecting system involves the following steps in this work. First, the raw EEG data is converted to obtain more quality data by adopting some solutions. Then, to improve the generalization capabilities of the classifier, a data augmentation technique is used to increase the amount of training data. Next, the training data is used to train our proposed model, and the testing data is used to evaluate the model obtained in the training phase, making sure that it performs well. Finally, the optimal model can be applied to the new, unseen EEG signals to make predictions. Note that when the new raw data is predicted by using our trained model, it is only necessary to transform and extract the first minute of the data as input.

A. Public EEG Dataset

In this study, the Temple University Hospital Abnormal EEG Corpus (TUAB) [8] is used. The data comprise EEG records that have been manually labeled as either clinically abnormal or normal EEG sessions. It is derived from the Temple University Hospital EEG Corpus (TUEG), which is the largest publicly available database of clinical EEGs [27]. The TUEG currently contains over 25000 clinical recordings of more than 18000 unique patients since 2002. In the whole database, approximately 75% of the data are classified as abnormal EEGs. As an important corpus, the TUAB is formed by selecting a demographically balanced subset of the TUEG. Currently, the dataset consists of 1472 abnormal and 1521 normal EEG sessions, respectively. These sets are further divided into two parts: training set (1346 abnormal/1371 normal samples) and testing set (126 abnormal/150 normal samples). Besides, in the majority of the approaches to automatic abnormal EEG identification so far, the TUAB has been extensively used [7], [28].

B. Pre-Processing

In TUAB, each of the EEG sessions contains at least 21 channels of signal data. For accentuating spike activity, we first convert the raw EEG signals into a set of standard montages according to the very popular transverse central parietal (TCP) montage system [7], which is proposed by the American Clinical Neurophysiology Society [8]. In addition, to reduce the influence of strong artifacts and speed up computations, we clip the amplitude values to within ±100μV, and resample the data to 100 Hz. It is obvious that we do not extract any hand-crafted features from the raw EEG data in this work. This is because we believe that the proposed method can automatically extract and learn relevant features from the raw data.

In previous studies [8], [28], the authors noted that neurologists generally classify an EEG session as either abnormal or normal by only examining the initial portion. Moreover, once the EEG electrodes are placed on the scalp to start recording data, the change of brain electrical impedance will cause the signal to gradually deviate from the first minute [29]. This indicates that the first-minute EEG signals may be the most representative of the test data. Therefore, researchers use the first-minute data of EEG signals to detect whether an EEG session is abnormal or normal [6], [7], [28]. To compare fairly with other related algorithms, we extract only the first-minute data from the source dataset as input.

Unfortunately, the above method has greatly limited the amount of labeled training data obtained from the TUAB. This may result in one problem. The superior performance of deep CNN relies heavily on huge amounts of well-annotated training data. Meanwhile, training a deep neural network on a small amount of training data can easily overfit, which

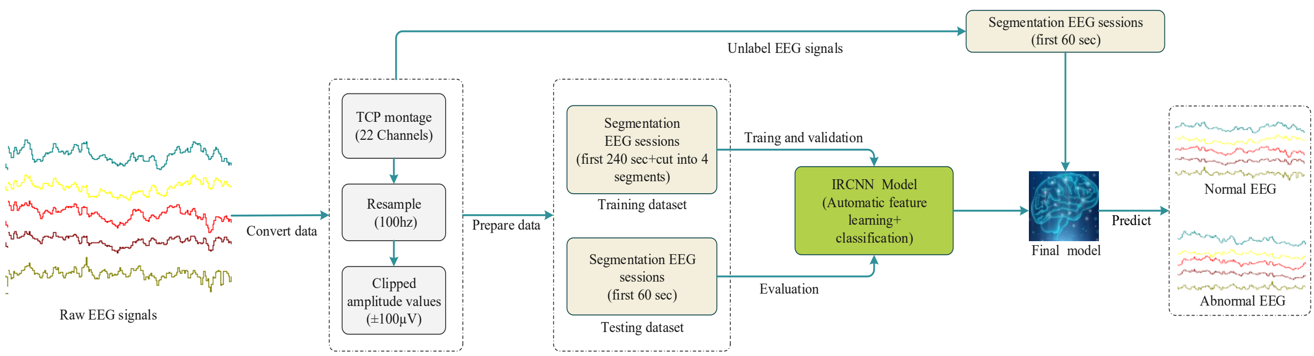

Fig. 2. Flow diagram of the proposed automated system for abnormal EEG identification.

decreases prediction performance in classification. To solve the problem of insufficient training data, an effective solution is data augmentation that improves the scale and quality of the training set. According to the literature [7], we can extract the signal data except for the first minute from the original training data to increase more label data in the training phase. Note that each extracted data has the same category label as the original data. The experimental results show that we only require to take four-minute duration data from the original training data to obtain good performance. Compared to training with no data augmentation, the amount of training data has a 4-fold increase. Finally, the relevant information of the training and testing dataset is shown in Table I.

TABLE I. DISTRIBUTIONS OF TRAINING AND TESTING SET

Description	Normal	Abnormal
Train	5484	5384
Test	150	126

C. The Proposed CNN Model

The EEG recordings are typically obtained from multiple electrodes over a specific time period, which indicates that EEG data can be seen as multivariate time series. As described previously, a CNN-based method has been greatly used to analyze various data types, including time series. Motivated by the success of various CNN methods in many different domains, we would investigate using deep learning techniques based on CNN for the analysis of EEG signals.

As the most important part of CNN architecture, convolutional layers are generally devised with many convolution kernels and a suitable stride to automatically learn relevant features. Considering the input data based on EEG signals are multiple one-dimensional sequences, the convolution kernel slides in one direction from the beginning of sequences towards its end, performing convolution. In other words, a convolution kernel can be regarded as applying and sliding a filter over the time series [21]. For multi-channel EEG signals, using multiple one-dimensional convolution layers with different strides can extract various discriminative features useful for the classification task. Thus, by stacking multiple one-dimensional convolution layers and one or more pooling layers, we can build the basic framework of deep learning for EEG signal classification.

Recent studies [12], [17] have shown that higher quality CNN model can be obtained by increasing both the depth and the width of the network. Here, the width of the network refers to the number of units at each level. However, this simple solution comes with two main issues: the model tends to be more prone to overfitting due to a larger number of parameters, the computation is more complicated. On the other hand, it is difficult to determine the size of convolutional kernels and the stride on the CNN classification tasks. Taking inspiration from the core idea of inception and residual structure, we carefully optimize part of the convolutional layers to alleviate the problem, namely reducing the network's depth and increasing the network's width. Fig. 3 shows our final proposed deep learning network architecture. The architecture contains one residual block and one inception block. Here, the formats for describing Conv1D, MaxPool, Dropout, and Dense layers are (layer name, kernel size, activation name, stride size), (layer name, pool size, stride size), (layer name, rate value), and (layer name, activation name), respectively. The right side of each layer in Fig. 3 represents the output of that layer. All the parameters are tuned accordingly to the training dataset provided that gives the optimum training accuracy.

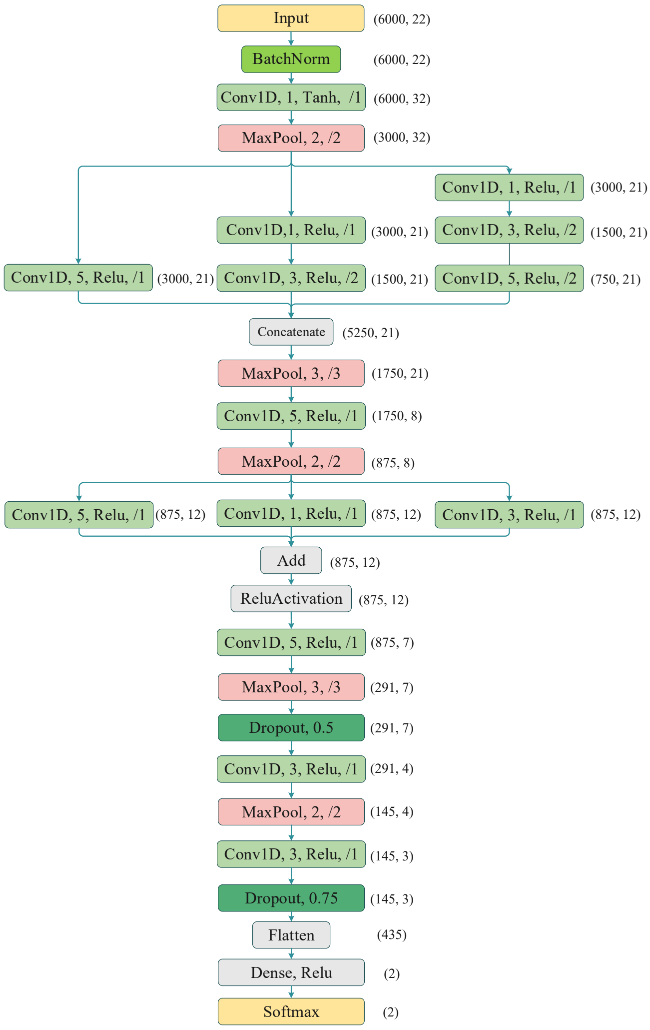

Fig. 3. The network structure of the proposed deep 1D-CNN model.

The distribution of each batch of EEG data that feeds into the neural network is actually different, which may result in the internal covariate shift problem. A standard solution is to add a batch normalization layer to normalize the input data of the neural network. In our proposed model, the maxpooling layers are added in various positions to reduce the size of feature maps. Then, we use a dropout layer to weaken the joint adaptability between neuron nodes. The last layer of the model is the softmax layer, where the output predicts the result (normal or abnormal) of the input signal.

IV. EXPERIMENTS

Now we move forward to evaluate the performance of the proposed IRCNN model for classifying normal and abnormal EEG signals. We compare our method with some of the previous models in the experiments. All experiments are conducted on a computer with an Intel Core (TM) i7-10700 CPU @2.90GHz, NVIDIA GeForce RTX 3070 8GB graphics card, 32.0 GB RAM, and a 64-bit Windows 10 operating system.

A. Experimental Setup

In this study, our deep learning method was implemented with Keras deep learning library. We trained the proposed model with the Adam optimizer [30] for gradient descent optimization and used an initial learning rate of 0.0006. Additionally, 22 batch size and 50 epochs were used for each training phase. Categorical cross entropy loss function was selected.

After that, in order to verify the classification ability of the IRCNN algorithm for EEG signals, we compared IRCNN with three deep learning algorithms based on the considerations that these methods are representatives for adopting different strategies to classify EEG signals and that they also achieve good results. The three algorithms are ChronoNet [7], DeepCNN [6], and CNN-MLP [28]. Here, CNN-MLP and DeepCNN are based on CNN, and ChronoNet is based on recurrent neural networks. The authors of CNN-MLP used this data set to explore various machine learning and deep learning methods and found that the best performance is achieved when CNN is adopted to classify frequency features extracted from the raw input signals. In the reference [6], the authors obtained better classification effect by building a CNN based on the automatic hyperparameter optimization method. In addition, ChronoNet proposed a deep gated recurrent neural network, which broadened the width of the network to extract more information by using the inception structure, it reported the best classification accuracy so far.

Finally, in order to further assess the classification performance of the proposed model, some common performance criteria are used. These criteria are accuracy, recall, and F1-score.

B. Results

In this work, our first experiment is to evaluate the proposed model performance on the test data. We split the training dataset into 80% for training and 20% for validation. Fig. 4 shows the training accuracy and validation accuracy results during the 50-epoch period. It can be noted that the proposed model finished the training process without overfitting data. Table II presents the summary of classification performance for both the training and testing datasets. Table III shows the confusion matrix obtained after the trained CNN model is applied to the testing dataset.

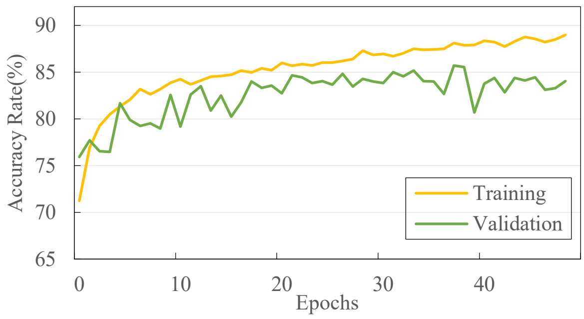

Fig. 4. Performance graphs of the IRCNN model at the training stage

TABLE II. SUMMARY OF THE ACCURACY, RECALL, F1-SCORE OBTAINED USING TRAINING AND TESTING DATABASES

Task	Accuracy (%)	Recall (%)	F1-score (%)
Train	88.65	88.62	88.23
Test	87.68	87.39	86.17

As can be seen from Table II and III, the proposed method gained good test accuracy for normal and abnormal EEG signals. Our proposed model detects 88% of all normal EEG signals truly and does not detect 12% of all normal EEGs. In case of EEG abnormalities, 87.3% of all abnormal records are detected truly, 12.7% of them are detected wrongly. It indicates that the CNN-based approach can directly extract the effective features for classification by way of the convolution and subsampling operations.

TABLE III. CONFUSION MATRIX OF THE PROPOSED IRCNN CLASSIFICATION ON THE TESTING DATASET

Original	Predicted	
	Normal EEG	*Abnormal EEG*
Normal EEG	132	18
Abnormal EEG	16	110

In the next experiments, we compared the classification results with other state-of-the-art methods. For IRCNN, we report the mean accuracies over five independent experiments with different random seeds in Table IV. Meanwhile, the results of the other three classification methods to date on this dataset are included for comparative analysis, and results reported in [6] (see DeepCNN), [7] (see ChronoNet) and [28] (see CNN-MLP).

TABLE IV. PERFORMANCE COMPARISON OF THE IRCNN WITH OTHER WORKS USING THE SAME DATASET

Method	Training accuracy (%)	Testing accuracy (%)
CNN-MLP	N/A	78.80
DeepCNN	N/A	85.40
ChronoNet	**90.60**	86.57
IRCNN	87.92	**87.10**

As is shown in Table IV, by adopting the core idea of inception and residual structure, the accuracy of our proposed method with the testing dataset is obtained as 87.10%, which is far greater than the result of CNN-MLP that is achieved by combining a CNN and a multilayer perceptron. It is noteworthy that compared with CNN-MLP, our method does not need to manually extract the features from the raw data with hand-crafted techniques or use the features learned by other methods. Moreover, we can see that IRCNN outperforms the best accuracy reported in [6] by 1.7%. Furthermore, compared with the most advanced method recently published [7], IRCNN can obtain better testing accuracy performance. According to previous studies [31], [32], the deep learning model is considered to overfit the training data when the accuracy of the training data is much better than that of the testing data. As we can see, our proposed model is that its performance on testing data is not different from the performance observed during training. In other words, compared to ChronoNet, our model does not overfit the data on the training set and has better generalization performance on EEG classification tasks.

V. CONCLUSIONS

In this study, a novel, fully automatic method for EEG signal identification has been proposed, which deals with binary classification problems (normal vs. abnormal). The proposed method is based on deep learning techniques, which employ an end-to-end deep learning structure and is straightforward to implement. For this method, we propose a combination of the main ideas of two structures into one model to accurately classify EEG signals. Simultaneously, our proposed method does not need to rely on any hand-crafted features. Overall, the method in this work is designed to be flexible and adaptable, and it is well-suited for the analysis of EEG data. To show the effectiveness of the new method, we have evaluated our method on the real-world dataset. The obtained results show that the novel method can provide outstanding performance on the classification task. These results indicate that our method has excellent potential for EEG analysis. In the future, we plan to use CNN technology to automatically eliminate EEG noise signals.

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