An Attention-Based Wavelet Convolution Neural Network for Epilepsy EEG Classification

Qi Xin, Shaohai Hu, Shuaiqi Liu, Ling Zhao, and Yu-Dong Zhang, *Senior Member, IEEE*

***Abstract*— As a kind of non-invasive, low-cost, and readily available brain examination, EEG has attached significance to the means of clinical diagnosis of epilepsy. However, the reading of long-term EEG records has brought a heavy burden to neurologists and experts. Therefore, automatic EEG classification for epileptic patients plays an essential role in epilepsy diagnosis and treatment. This paper proposes an Attention Mechanism-based Wavelet Convolution Neural Network for epilepsy EEG classification. Attention Mechanism-based Wavelet Convolution Neural Network firstly uses multi-scale wavelet analysis to decompose the input EEGs to obtain their components in different frequency bands. Then, these decomposed multi-scale EEGs are input into the Convolution Neural Network with an attention mechanism for further feature extraction and classification. The proposed algorithm achieves 98.89% triple classification accuracy on the Bonn EEG database and 99.70% binary classification accuracy on the Bern-Barcelona EEG database. Our experiments prove that the proposed algorithm achieves a state-of-the-art classification effect on epilepsy EEG.**

***Index Terms*— Attention, convolution neural network, epilepsy EEG classification, wavelet.**

I. Introduction

As a chronic neurological syndrome, epilepsy may occur for all ages. It has the characteristics of repeatability and sudden onset. Seizures are characterized by the sudden loss of consciousness, convulsions and varying degrees of consciousness, and obvious thinking, perception, emotion, and psychomotor disorders. Epilepsy has a serious impact on brain function. It is the second-largest nervous system disease after cerebrovascular disease [1]–[3]. About 50,000,000 people worldwide suffer from the disease, of which nearly 80% are from low- and middle-income countries and regions [4], [5]. Therefore, the diagnosis and treatment of epilepsy have paramount significance.

Clinical detect and diagnose epilepsy with Electroencephalography (EEG), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Magnetoencephalography (MEG), and other imaging modalities [6]. MRI, CT, and MEG are primarily used to detect secondary epilepsy caused by intracranial lesions or injuries and have no auxiliary effect on primary epilepsy without solid lesions in the intracranial. As a non-invasive, readily available, and low-cost brain examination, EEG stands out among many clinical examinations and has become the main tool of clinical diagnosis of epilepsy. However, mass data of EEG brings a heavy burden to the diagnosis of neurologists and experts. Relevant experts need to read many EEG data to diagnose patients with epilepsy, and the diagnosis is very subjective. The necessity of EEG classification and detection on epilepsy and the shortage of artificial detection make the adaptive automatic EEG classification algorithm a new research hotspot.

The research on EEG analysis algorithms and automatic detection for epilepsy began in the 1970s [7]. With the development of signal processing and pattern recognition, more and more automatic detection algorithms of epileptic EEG have been proposed. The existing EEG classification algorithms mainly include the following categories: algorithms based on time-domain analysis, frequency domain analysis, time-frequency analysis, nonlinear dynamics analysis, and deep learning. Template matching is a typical time-domain analysis algorithm. Vijayalakshmi and Appaji [8] proposed an algorithm based on template matching for EEG peak detection in epilepsy patients in 2011. However, the integrity and universality of the template set are required due to the complexity of EEG and the diversity of epileptic discharges. The complex EEG, which is difficult to analyze in the time domain, can be transformed into the frequency domain for analysis. The frequency-domain analysis based on the Fourier transform is an efficient algorithm for analyzing and classifying epileptic EEG signals. The commonly used methods include power spectrum analysis, autoregression (AR), correlation analysis,

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and EEG topography. Kim *et al.* [9] proposed a multi-variable EEG time series prediction algorithm for epilepsy based on a coercively adjusted autoregression model (CA-AR). In [10], Wulandari *et al.* proposed an EEG visualization method based on Fourier spectrum analysis by using the genetic algorithm, which can analyze the brain state of epilepsy patients through visualization. Although frequency domain analysis can extract the relevant features of epileptic EEGs, the advantage of Fourier transform is to process the stationary linear signal. EEG is nonlinear, non-normal, and non-periodic, whose features are difficult to extract completely only by Fourier transform.

With the help of the advantages of analysis in time and frequency domains, the time-frequency analysis can extract the time-domain features of EEG effectively and extract its frequency-domain features well. Therefore, the time-frequency analysis of EEG can describe the relationship of EEG frequency with time more clearly. The commonly used time-frequency domain analysis tools mainly are several transforms, which are short-time Fourier transform (STFT), Wavelet transform (WT) and Hilbert-Huang transform, etc. Since epileptic discharges are various and EEGs are quite complicated, its time series is nonnormality, nonlinearity, and aperiodicity. Consequently, it attaches great significance to extract these special features appropriately. As a multi-scale and multi-resolution time-frequency domain analysis algorithm, the wavelet can decompose the signal into multi-scale subspace, which can extract features of EEG in either time-domain or frequency-domain, making it more convenient to analyze the time-frequency features of signals. Omidvar *et al.* [11] proposed a seizure detection algorithm combining biorthogonal wavelet, genetic algorithm, and support vector machine. Tang *et al.* [12] proposed an epilepsy EEG classification algorithm by combining wavelet transform and detrended fluctuation analysis in the local area. Firstly, the original EEG is decomposed by wavelet. Then, the dynamic fractal structure of wavelet packet sub-bands is described by detrended fluctuation analysis. Finally, EEG is classified by combing fractal spectrum features and support vector machines.

Although the above time-frequency algorithms can classify epileptic EEG well, the nonlinear features of EEG greatly influence the time-frequency domain epilepsy detection algorithms. To better classify epileptic seizures, many scholars proposed classification algorithms of EEG for epilepsy based on nonlinear dynamics. For example, Kamath [13] used the nonlinear dynamics method and Hilbert scatter diagram to extract features of EEG, which achieves good result for the classification of epileptic seizure states. Craley *et al.* [14] proposed an EEG classification algorithm for epilepsy based on the hidden Markov model, and the algorithm achieved good result on public data sets. A classification algorithm based on fractal dimension for epileptic EEG is proposed by Banerjee [15], which can effectively classify epileptic EEG. Although fractal dimension is a mature theory in the analysis of nonlinear time series, it is difficult to estimate the chaotic features of EEG shape and has high computational complexity.

As a machine learning algorithm, deep learning has been applied in various fields in recent years, such as image denoising, image fusion, target detection, etc. [16]–[18]. Since it uses a multi-layer nonlinear processing unit to process different data, which can better extract the relevant features of EEG, it is more and more used in EEG processing. For example, a CNN-based EEG classification algorithm for epilepsy is proposed by Zhou *et al.* [19], which directly inputs the untreated epilepsy EEG into CNN for classification. Zhao *et al.* [20] proposed a classification algorithm of epilepsy EEG based on one-dimension CNN and data enhancement, which improved the classification accuracy by 3%. Xin *et al.* [21] proposed an EEG classification algorithm for epilepsy by combining convolutional support vector machine (CSVM) with principal component analysis (PCA) and achieved good classification results. Although the classification algorithm of epilepsy EEG based on the convolutional neural network can effectively improve the effect of classification, on the one hand, the feature extracted by the existing algorithm is single, which results in insufficient information extraction; On the other hand, since input signals are time series, their multi-scale information are not made full use by existing algorithm.

In recent years, there have been many improved algorithms in deep learning. Among them, the attention mechanism enables the network to focus on the most closely related information to the task. EEG is complex nonlinear, non-periodic, and non-stationary data with a large amount of information, which makes feature extraction difficult. However, assigning more weights to important features allows attention mechanisms to ignore the noise and other redundant information while focusing on important features. Accordingly, we propose an attention-based wavelet convolution neural network for epilepsy EEG classification to make full use of the multi-scale features of EEG. In experiments, the proposed novel AMWCNN yielded an impressive classification effect on epilepsy EEG.

To sum up, specific contributions of this work are to:

(1) Combining wavelet transform, AMWCNN is constructed for EEG classification.

(2) The constructed AMWCNN can fully maintain the multi-scale information in the EEG signal and make a preliminary estimate of the important information.

(3) The proposed end-to-end EEG classification algorithm achieves accurate and robust epilepsy detection on Bonn EEG Database [22] and the Bern-Barcelona Database [23] for EEG classification.

II. The Construction of AMWCNN

Aiming to facilitate the multi-scale features of EEG and focus on the critical features of EEG, an attention-based wavelet convolution neural network is constructed in this paper and applied to the classification of epilepsy EEG. The proposed flowchart can be seen in Fig. 1.

As can be seen from Fig. 1, after EEG is input into the network, multi-scale decomposition is firstly carried out through Wavelet transform. Then, feature extraction of the signal is carried out through the attention-based wavelet convolution

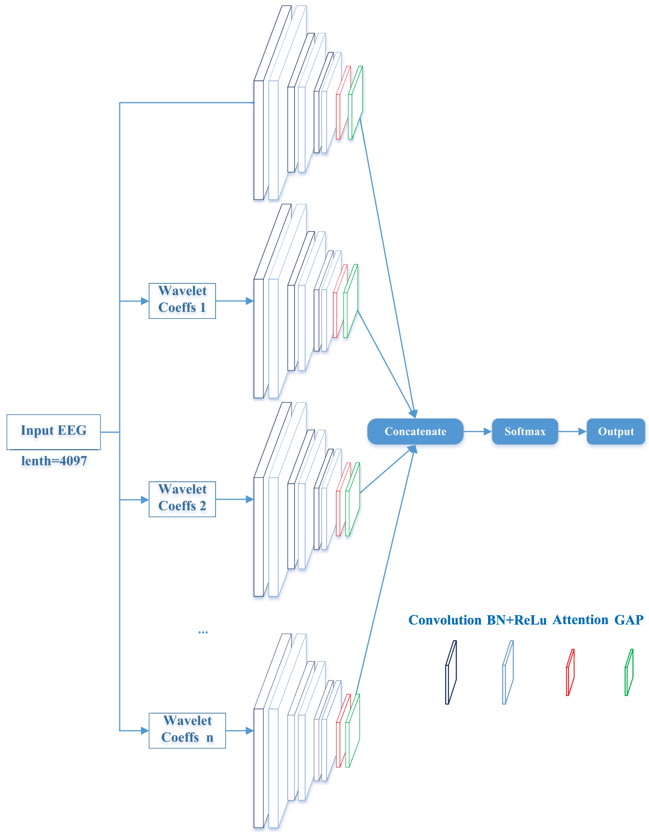


Fig. 1. AMWCNN flowchart.

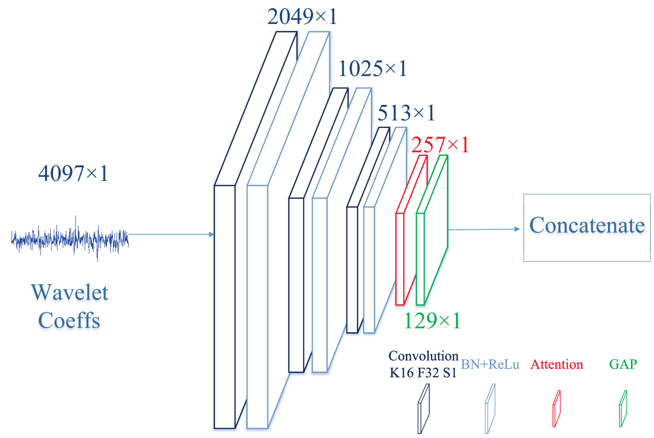


Fig. 2. Attention mechanism-based CNN.

neural network constructed in this paper. Finally, classification results are output through the Softmax function. In III-C Ablation experiments, the effect of Wavelet decomposition level on AWCNN based EEG classification for epilepsy is analyzed. The number of wavelet coefficients depends on the number of wavelet layers, so it is denoted as "Wavelet Coeffs n" in Fig. 1. Next, this section will describe the proposed algorithm in detail.

Firstly, the original input EEGs are turned into Wavelet coefficients by Wavelet transform, in which the features of signals are extracted. Wavelet transform has good local time-frequency characteristics and can describe the signal features well in both time and frequency domains. It is suitable for non-stationary, nonlinear and non-periodic EEGs. The basic principle of wavelet transform is as follows [24].

$\hat{\psi}(\omega)$ is the Fourier transform of $\psi(t) \in L^2(R)$ (where $L^2(R)$ represents the square-integrable real number space), which satisfies the admissible condition:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{\left|\hat{\psi}^2(\omega)\right|}{|\omega|} d\omega < \infty \tag{1}$$

Then $\psi(t)$ is called as the mother wavelet. $\psi(t)$ generates wavelet functions through scaling and translation, that is

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}} \psi(\frac{t-b}{a}) a, b \in R, a \neq 0 \tag{2}$$

where a denotes the scaling factor and b denotes the translation factor. Suppose EEG $e(t) \in L^2(R)$ and its continuous Wavelet transform can be defined as:

$$W_\psi e(a,b) = \int_{-\infty}^{+\infty} \bar{\psi}_{a,b}(t) e(t) dt \tag{3}$$

So, we can get the discrete Wavelet decomposition of EEG. At this time, discrete sampling of scaling factor a and translation factor b is required as follows:

$$a = a_0^p, b = q b_0 a_0^p (a_0 > 0, b_0 \in R, p \in Z, q \in Z) \tag{4}$$

Then the wavelet function $\psi_{a,b}(t)$ can be discretized into:

$$\psi_{p,q}(t) = a_0^{-\frac{p}{2}} \psi(a_0^{-p} t - q b_0) \tag{5}$$

Therefore, the discrete Wavelet transform (DWT) of $e(t)$ can be defined as:

$$DW_{p,q}(e) = \int_R e(t) \bar{\psi}_{p,q}(t) dt = \langle e, \psi_{p,q} \rangle \tag{6}$$

That is, the wavelet coefficient of each layer is

$$WC_n = DW_{p,q}(e) = \int_R e(t) \bar{\psi}_{p,q}(t) dt = \langle e, \psi_{p,q} \rangle \tag{7}$$

Next, the wavelet coefficients of epilepsy EEG are used as the input of the CNN. The wavelet coefficient of each layer is input into the proposed attention mechanism-based CNN. The structure of the proposed network is shown in Fig. 2.

As one of the most potent tools in deep learning, CNN has been widely used in signal processing. CNN consisted of convolution, pooling, and fully connected layer (FC), where the rectified linear unit (ReLU) is often used as the activation function. It has the characteristics of the local receptive field, weight sharing and down-sampling [25]. The proposed attention-based convolutional neural network is mainly composed of three modules: the convolutional block, which is composed of convolution, batch normalization, and rectified linear unit (BN+ReLU), the attention block, and the global averaging pooling (GAP) block.

The formula of convolution in the convolution block can be defined as:

$$WC_j^l = f\left(\sum_{i \in M_j} WC_i^{l-1} * k_{ij}^l + b_j^l\right) \tag{8}$$

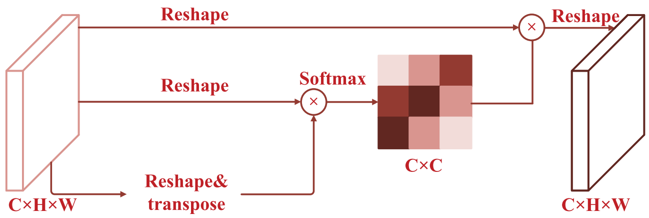


Fig. 3. Attention mechanism network.

where M_j are feature graphs of input signals; k_{ij}^l represents the convolution kernel connected by the i-th feature graph for upper layer; $*$ stands for convolution; b_j^l stands for bias; $f(\cdot)$ represents the activation function, which is ReLU in this paper.

The neural network normalized the data to a unified interval through batch normalization to reduce the data divergence and the difficulty of learning the network. The activation function of the proposed network is the nonlinear function ReLU, whose formula is:

$$f(x) = \max(0, x) \tag{9}$$

ReLU has sparsity, enabling the sparse model to better mine relevant features and fit training data. It avoids gradient disappearance and accelerates training speed. After three convolution blocks, the features of the Wavelet coefficients converted from epilepsy EEG are further extracted. The output of the third layer activation function is input into the attention block, whose structure is shown in Fig.3.

Attention model (AM) has become a vital research field in neural network research since it was proposed to solve the problem of machine translation. The attention model has been widely used in artificial intelligence-related fields. Attention mechanism allows a neural network to focus only on a portion of its input and select specific inputs.

From Fig. 3, in the attention block, Wavelet coefficients $WC_c \in \mathbb{R}^{C\times H\times W}$ output by convolution block are converted into channel attention maps $M \in \mathbb{R}^{C\times C}$. Firstly, WC_c is reshaped to $\mathbb{R}^{C\times N}$. Next, matrix multiplication is performed between WC_c and its transpose matrices. Finally, channel attention maps $M \in \mathbb{R}^{C\times C}$ is obtained by Softmax, which is

$$m_{ji} = \frac{\exp(WC_{ci} \cdot WC_{cj})}{\sum_{i=1}^{C} \exp(WC_{ci} \cdot WC_{cj})} \tag{10}$$

where m_{ji} is the impact of the channel i on the channel j.

Next, we perform matrix multiplication between M and the transposed matrices of WC_c. The product is reshaped to $M \in \mathbb{R}^{C\times W\times H}$. The reshaped product is multiplied by a scale parameter β. The final output $A \in \mathbb{R}^{C\times H\times W}$ can be obtained by summing the elements of WC_c, that is

$$A_j = \beta \sum_{i=1}^{C} (m_{ji} WC_{ci}) + WC_{cj} \tag{11}$$

where β is the learning weight starting from 0.

We use global averaging pooling instead of a fully connected layer at the end of each attention-based convolutional neural network. Fig. 4 gives the parallels of FC and GAP. If the fully connected layer is replaced by global average pooling, the number of parameters can be reduced since the GAP has no parameters. On the one hand, this block can avoid overfitting; On the other hand, it is more consistent with the work structure of CNN, associating each feature map with category output.

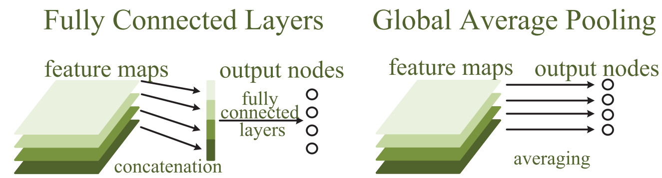


Fig. 4. Attention mechanism network.

Algorithm 1 AMWCNN

input : EEG time series $= e(t)$
output: Prediction

The detailed procedure of the proposed algorithm is discussed stepwise as follows:

Step 1: Calculate Wavelet coefficients of input EEG time series. $WC_n = DW_{p,q}(e) = \int_R e(t)\bar{\psi}_{p,q}(t)dt = \langle e, \psi_{p,q}\rangle$

Step 2: Calculate every Wavelet coefficient after convolution network.

$WC_j^l = f\left(\sum_{i\in M_j} WC_i^{l-1} * k_{ij}^l + b_j^l\right)$

Step 3: Calculate channel attention maps $M \in \mathbb{R}^{C\times C}$ of Wavelet coefficients.

$m_{ji} = \frac{\exp(WC_{ci}\cdot WC_{cj})}{\sum_{i=1}^{C}\exp(WC_{ci}\cdot WC_{cj})}$

Step 4: Output reshaped product $A \in \mathbb{R}^{C\times H\times W}$.

$A_j = \beta \sum_{i=1}^{C} (m_{ji} WC_{ci}) + WC_{cj}$

Step 5: Apply GAP to reshaped product

Step 6: Concatenate all of the output of attention mechanism-based CNN.

Step 7: Apply Softmax to the concatenated series.

Step 8: Output prediction.

Finally, an attention-based convolutional neural network concatenated all the Wavelet coefficients. The classification results are output after classifying by the Softmax function.

The AMWCNN proposed in this paper firstly uses Wavelet multi-scale analysis to decompose the input EEGs to obtain their components in different frequency bands. Then these multi-scale EEG coefficients are then fed into the attention mechanism based on CNN for feature extraction and classification. Feature extraction of epilepsy EEG from time domain and frequency domain is made full use of different feature extraction methods and achieves good classification effect. Algorithm 1 shows the detailed algorithm for the proposed AMWCNN.

III. Results and Analysis

A. Objective Evaluation Index

Experiments in this paper are implemented in a Python environment. The operating system is Windows 10. The memory size is 64GB, the CPU is Intel(R) Xeon(R) Silver 4110, and the GPU is GeForce RTX 2080Ti. Accuracy, specificity, and sensitivity are used to evaluate the EEG classification effect for epilepsy.

(1) Accuracy evaluates the performance of classification network, which is defined as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

(2) Specificity measures EEG features differences, which extracted from epileptic focal and non-focal areas or seizure and seizure-free, namely the ability to avoid misdiagnosis, which can be expressed as

$$Specificity = \frac{TN}{TN + FP} \tag{13}$$

(3) Sensitivity refers to the sensitivity of the network to EEG of focal area and seizure period, which is defined as

$$Sensitivity = \frac{TP}{TP + FN} \tag{14}$$

where TP represents true positive events, while TN represents true negative events, that is, correctly classify epilepsy EEG; FP represents false positive events, while FN represents false negative events, respectively.

B. Database Description

Utilizing Bonn EEG Database [22] and the Bern-Barcelona Database [23], the classification effect of the proposed AMWCNN is verified. Bonn EEG Database is a multi-category database consisting of five subsets, i.e., Datasets A, B, C, D, and E. Taking Dataset A as an example, firstly, electromyogram (EMG) and electrocardiogram (ECG) artifacts in EEG are deleted. And then, 100 single-channel EEG fragments of 23.6 seconds are extracted from continuous multichannel EEG. A 128-channel amplifier system performs 12-bit analog-to-digital conversion on the 100 EEG fragments at a sampling frequency of 173.61Hz. The EEG frequency is controlled between 0.53Hz and 40Hz (12Db/OCT) by using a bandpass filter. Similar methods generate other datasets. Datasets A and B are EEG data from five healthy volunteers. In Dataset A, subjects are awake with open eyes, while in Dataset B, subjects are awake with closed eyes. EEG samples from healthy volunteers are placed according to the standard EEG electrode placement scheme, shown in Fig. 5, and sample electroencephalogram in Fig. 6.

Datasets C, D, and E are preoperative EEG data of 5 epileptic patients. The seizures in all five patients are controlled after removing the hippocampus structure, and the removed brain area is considered the focal area. Fragments of Dataset D are from the focal areas, and fragments of Dataset C are from the hippocampus. The two datasets only include interictal EEG, and Datasets E only contained the EEG activity during the ictal phase. Table I gives the details of the mentioned database.

Bern-Barcelona Database is a binary-category database containing two sub-datasets, Dataset F and Dataset N, representing EEGs in focal areas and non-focal areas. Bern-Barcelona Database contains long-term EEG recordings from 5 patients

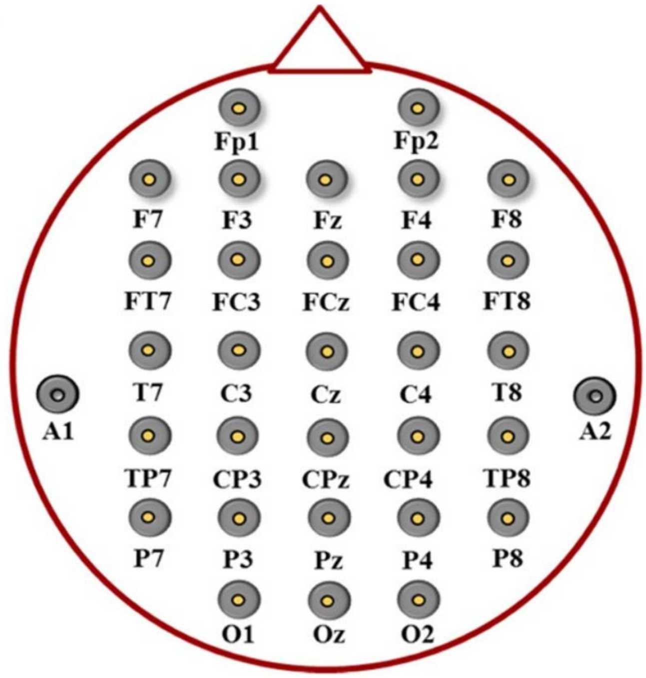


Fig. 5. The international 10-20 system.

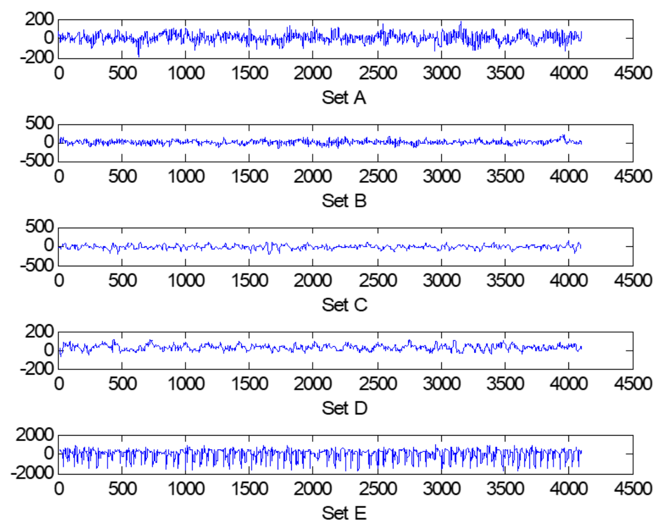


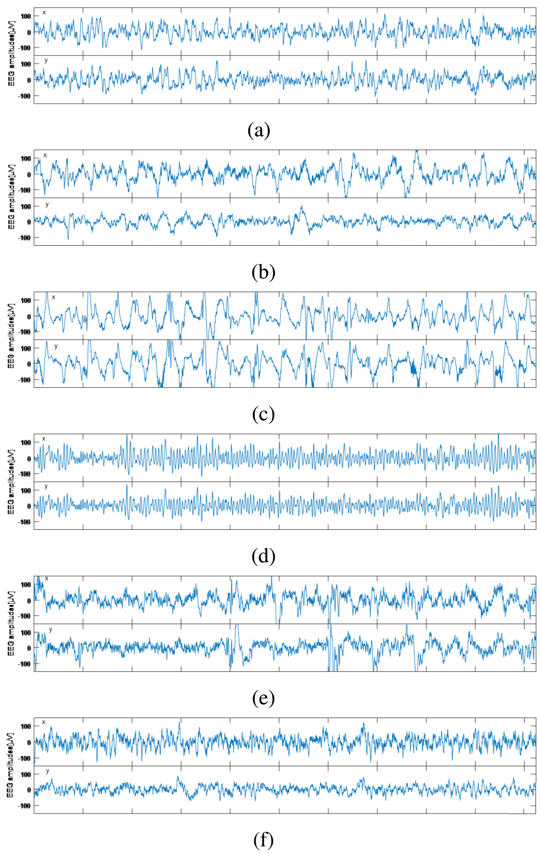
Fig. 6. Examples of Bonn EEG database.

with temporal lobe epilepsy. All electroencephalograms are intracranial EEG recordings. Due to long-term drug resistance, five epileptic patients undergo epileptic focal lesion excision, and all the database records are preoperative EEG records. Electrodes are depth electrodes and intracranial strip electrodes produced by AD-TECH (Racine, WI, USA). All EEG recordings are multichannel sampled at 512Hz, except at 1024Hz when EEG is less than 64 channels. The Kanton of Bonn ethics committee approved the EEG database for research purposes, and all patients have signed informed consent forms.

During the generation of the two datasets, 3750 pairs of EEG fragments (F for focal areas and N for non-focal areas) are randomly selected from the EEG of corresponding areas, except for the EEG signals during the seizure and 3 hours after the last seizure. Two signals x and y in the same signal pair (x, y) are recorded simultaneously. Each signal is

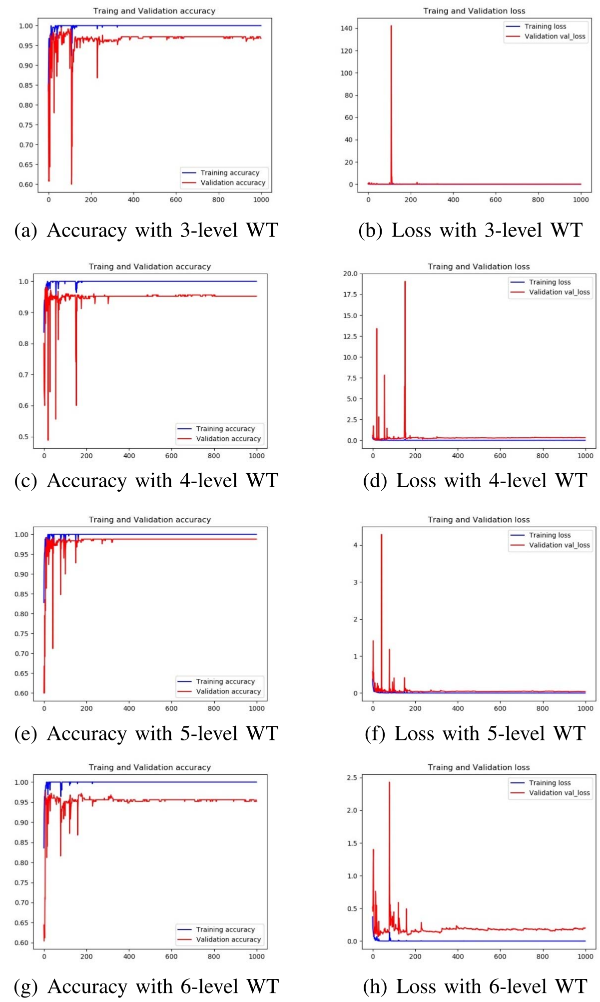
TABLE I
BONN EEG DATABASE

Dataset	Label	State	Subject	Electrpde type	Electrpde placement
A	Healthy	Awake and eyes open	Healthy subjects	Extra-cranial	International 10-20 system
B	Healthy	Awake and eyes closed	Healthy subjects	Extra-cranial	International 10-20 system
C	Inter-ictal	Seizure-free	epileptic patients	Intra-cranial	Opposite to focal area
D	Inter-ictal	Seizure-free	epileptic patients	Intra-cranial	Focal area
E	Ictal	Seizure activity	epileptic patients	Intra-cranial	Focal area



(a) (b) (c) (d) (e) (f)

Fig. 7. Sample signal pairs for Datasets F and N.



(a) Accuracy with 3-level WT (b) Loss with 3-level WT (c) Accuracy with 4-level WT (d) Loss with 4-level WT (e) Accuracy with 5-level WT (f) Loss with 5-level WT (g) Accuracy with 6-level WT (h) Loss with 6-level WT

Fig. 8. The effect of wavelet decomposition level on classification.

TABLE II
CLASSIFICATION RESULTS OF DIFFERENT WAVELET DECOMPOSITION LEVELS

Number of wavelet decomposition levels	Accuracy	Specificity	Sensitivity
3-level	95.20%	95.31%	95.31%
4-level	95.20%	95.31%	95.31%
5-level	**98.80%**	**98.82%**	**98.82%**
6-level	95.60%	95.70%	95.70%

10240 samples with a time window of 20 seconds. In random signal pair, the first five patients are randomly selected from a patient of EEG data, a random sample from the EEG data in patients with a focal area of brain electric signal, which is the signal x, then the signal selection within the neighborhood of a focal area of the brain electrical signal, that is the signal y, finally divided each signal for the length of the sample of 20 seconds. The uniform random number generator is used for segmentation without repetition.

In addition, each signal pair should be visually examined before Dataset F is generated. If the signal pair contains obvious artifacts, it cannot be included in the dataset. Finally, EEG pairs in focal areas were saved according to the sequence of extraction and segmentation. In contrast, the original information such as patient name, signal name, and window were not saved simultaneously. Similarly, the above process when generating Dataset N. Sample signal pairs for Datasets F and N are shown in Fig. 7.

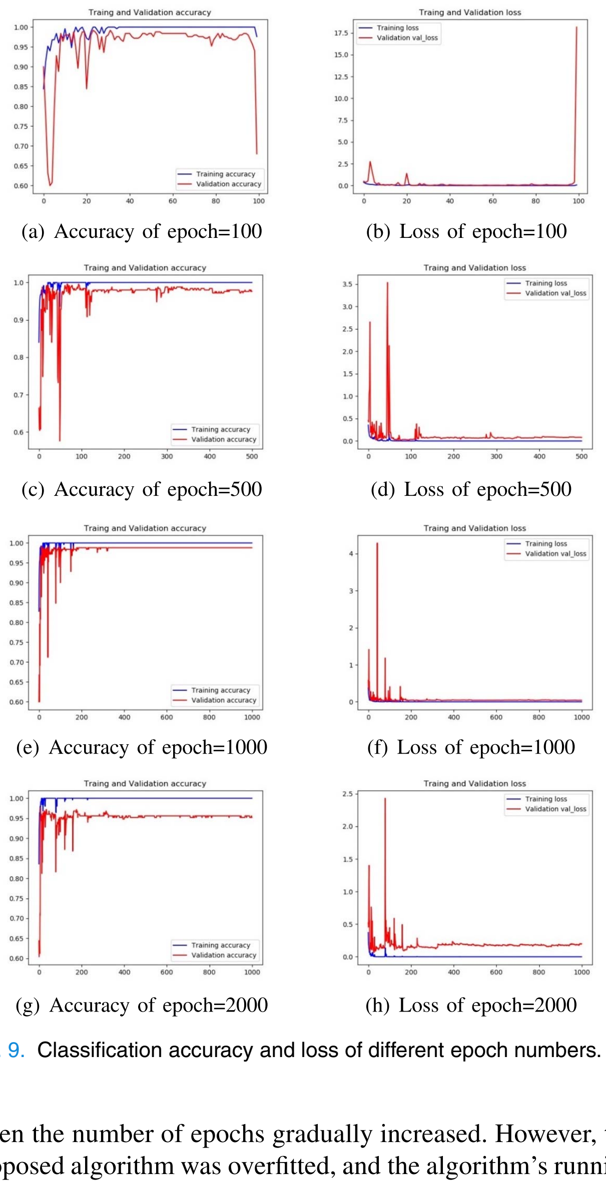
C. Ablation Experiments

In this section, Datasets A and B in Bonn EEG Database are labeled as normal EEG signals, and the Datasets C and D are labeled as interictal EEG signals that came from epileptic patients. Based on the hyper-parameters of the constructed network, the ablation experiments are conducted with the classification of the mentioned two kinds of EEG signals as an example. Firstly, the effect of Wavelet decomposition level on AWCNN based EEG classification for epilepsy is analyzed. In Fig. 8, we give the effect of epileptic signal classification obtained by signal decomposition with different Wavelet transform levels. What's more, the specific details are concluded in Table II. According to Fig. 8 and Table II, we find that the classification effect of the proposed algorithm is the best when the wavelet decomposition level is 5.

Next, the effect of epoch number on epilepsy EEG signal classification is analyzed. Fig. 9 and Table III show the accuracy and loss of epilepsy classification when epoch numbers are 100, 500, 1000, and 2000. Fig. 9 and Table III reveal that the classification accuracy, specificity, and sensitivity increased

TABLE III
CLASSIFICATION RESULTS OF DIFFERENT WAVELET DECOMPOSITION LEVELS

Epoch	Accuracy	Specificity	Sensitivity	Running time(s)
100	97.20%	97.27%	97.27%	**920.71**
500	98.40%	98.43%	98.43%	4543.58
1000	**98.80%**	**98.82%**	**98.82%**	12090.48
2000	98.40%	98.43%	98.43%	18270.12

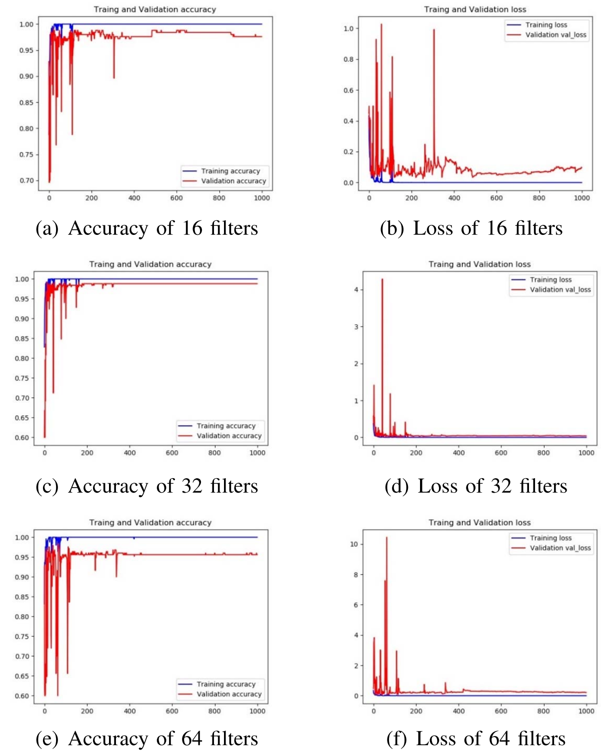


(a) Accuracy of epoch=100 (b) Loss of epoch=100
(c) Accuracy of epoch=500 (d) Loss of epoch=500
(e) Accuracy of epoch=1000 (f) Loss of epoch=1000
(g) Accuracy of epoch=2000 (h) Loss of epoch=2000

Fig. 9. Classification accuracy and loss of different epoch numbers.

when the number of epochs gradually increased. However, the proposed algorithm was overfitted, and the algorithm's running time significantly increased along with the increase of the epoch number. In Table III, the number of epochs is one of the influencing factors of algorithm performance and running time. The more epochs are, the more running time is. However, the algorithm performance reaches the best at 1000 epochs. For the purpose of algorithm performance, we choose 1000 epochs and the running time is relatively longer. Therefore, from two aspects of the algorithm running time and classification performance, the epoch number of the algorithm in this paper is set as 1000.

Finally, the effect of filter number in each convolutional layer on EEG classification of epilepsy is analyzed. Fig. 10 shows the accuracy and loss of classification under different filter numbers. Table IV gives further specific data in detail. From Fig. 10 and Table IV, we can conclude that the best classification effect can be achieved when the filter number is 32. Similarly, in Table IV, the number of filters is one of the influencing factors of algorithm performance and running time. The more filters are, the more running time is. However, the algorithm performance reaches the best at 32 filters. For the purpose of algorithm performance, we choose 32 filters and the running time is relatively longer.



(a) Accuracy of 16 filters (b) Loss of 16 filters
(c) Accuracy of 32 filters (d) Loss of 32 filters
(e) Accuracy of 64 filters (f) Loss of 64 filters

Fig. 10. Classification accuracy and loss of different filter numbers.

TABLE IV
CLASSIFICATION RESULTS OF DIFFERENT FILTER NUMBERS

Filter numbers	Accuracy	Specificity	Sensitivity	Running time(s)
16	97.60%	97.65%	97.65%	**5425.60**
32	**98.80%**	**98.82%**	**98.82%**	12090.48
64	95.60%	95.70%	95.70%	20501.63

TABLE V
EEG TYPES

Type	Subject	Database	Dataset
Healthy	Healthy volunteers	Bonn EEG Database	Dataset A and Dataset B
Seizure-free (Inter-ictal)	Epileptic patients	Bonn EEG Database	Dataset C and Dataset D
Seizure-activity (Ictal)	Epileptic patients	Bonn EEG Database	Dataset E
Focal	Epileptic patients	Bern-Barcelona Database	Dataset F
Non-focal	Epileptic patients	Bern-Barcelona Database	Dataset N

D. Comparison Results

To illustrate the superiority of our algorithm and making classification results more meaningful, epilepsy EEG data of two databases, Bonn EEG Dataset and Bernn-Barcelona

TABLE VI
EXPERIMENT DESCRIPTION OF HEALTHY VS. EPILEPTIC

Database	Classification task	Experiment Number	Dataset	Lable
Bonn EEG Database	Healthy vs. Epileptic	No. 1-1	AB vs. CDE	Datasets A and B are labeled as 0 and Datasets C, D, and E are labeled as 1.
Bonn EEG Database	Healthy vs. Epileptic	No. 1-2	AB vs. CD	Datasets A and B are labeled as 0 and Datasets C, D, and E are labeled as 1.

TABLE VII
CLASSIFICATION COMPARISON EXPERIMENTS BETWEEN HEALTHY AND EPILEPTIC EEGS

Experiment Number	Dataset	Method	Accuracy	Specificity	Sensitivity
No. 1-1	AB vs. CDE	TFFWT-FD	92.55%	92.08%	91.53%
		WTPRNet	98.75%	98.48%	95.33%
		AMWCNN	98.79%	98.82%	98.82%
No. 1-1	AB vs. CDE	TFFWT-FD	93.75	93.77%	91.08%
		WTPRNet	99.4%	99.21%	96.37%
		AMWCNN	99.50%	99.50%	96.50%

TABLE VIII
CLASSIFICATION COMPARISON RESULTS AMONG HEALTHY, SEIZURE-FREE, AND SEIZURE EEGS

Database	Classification task	Experiment Number	Dataset	Label
Bonn EEG Database	Healthy vs. Ictal	No. 2-1-1	A vs. E	Dataset A is labeled as 0 and Dataset E is labeled as 1.
		No. 2-1-2	B vs. E	Dataset B is labeled as 0 and Dataset E is labeled as 1.
		No. 2-1-3	AB vs. E	Datasets A and B are labeled as 0 and Dataset E is labeled as 1.
Bonn EEG Database	Inter-ictal vs. Ictal	No. 2-2-1	C vs. E	Dataset C is labeled as 0 and Dataset E is labeled as 1.
		No. 2-2-2	D vs. E	Dataset D is labeled as 0 and Dataset E is labeled as 1.
		No. 2-2-3	CD vs. E	Datasets C and D are labeled as 0 and Dataset E is labeled as 1.
Bonn EEG Database	Healthy vs. Inter-ictal vs. Ictal	No. 2-3	AB vs. CD vs. E	Datasets A and B are labeled as 0, Datasets C and D are labeled as 1 and Dataset E is labeled as 2.

Dataset, are labeled as the following five labels: (1) Healthy, including Dataset A and Dataset B in Bonn EEG Dataset; (2) Seizure-free (also known as Inter-ictal), including Bonn EEG Dataset C and D; (3) Seizure activity (also known as Ictal), including Bonn EEG Dataset E; (4) Focal, including Bern-Barcelona Dataset F; and (5) Non-focal, including Bern-Barcelona Dataset N. The specific EEG types are described in Table V.

Common epileptic EEG classification has the following three types:(1) Healthy vs. Epileptic; (2) Healthy vs. Seizure-free (Inter-ictal) vs. Seizure activity (Ictal); (3) Focal vs. Non-focal. According to the three common epileptic EEG classification types above, the following three experiments are designed in this paper.

1) Healthy vs. Epileptic: In this section, two experiments are designed based on EEG of healthy volunteers and epileptic seizure signals classification. Healthy signals include Dataset A and Dataset B, and epileptic EEGs include Dataset C and Dataset D. The specific description of experiments is shown in Table V.

In this paper, the above classification tasks are tested. Our AMWCNN algorithm is proceeded and compared with some commonly used methods. These algorithms include: (1) An epileptic seizures classification algorithm combined fractal dimension (FD) with time-frequency flexible WT (abbreviated to be TFFWT-FD) proposed by Sharma *et al.* [26]; (2) An explainable graph feature convolutional neural network for epileptic EEG classification (abbreviated as WTPRNet) proposed by Xin *et al.* [27]. The proposed algorithm is abbreviated as AMWCNN. Table VII has given the experiments.

As shown in Table VII, when classifying healthy EEG signals, including Datasets A and B, and epileptic EEG signals, including Datasets C, D, and E, the proposed algorithm achieves a better classification effect than traditional machine learning algorithm TFFWT-FD and deep learning algorithm WTPRNet. This is mainly attributed to the fact that our algorithm takes advantage of EEG multi-scale features while associating the important information of EEG signals through attention mechanisms while ignoring unimportant information.

2) Healthy vs. Seizure-Free (Inter-Ictal) vs. Seizure Activity (Ictal): Healthy, seizure-free, and seizure EEG signals are classified in this section. Using all datasets in Bonn EEG Database, three experiments are designed to achieve different classification tasks. The specific experiment descriptions can be seen in Table VIII.

The proposed algorithm is tested for the above classification tasks and compared with some commonly used algorithms. These algorithms include: (1) An epileptic seizure identify algorithm based on Fourier-Bessel series expansion (abbreviated as FBSE) proposed by Gupta [28]; (2) An automatic detection algorithm for epilepsy seizure based on orthogonal matching pursuit, entropy, and DWT (abbreviated as OMP-DWT) proposed by Zarei and Asl [29]; (3) An epileptic EEG brain seizure classification algorithm based on autonomous deep feature extraction (abbreviated as ACNN) proposed by Woodbright *et al.* [30]; (4) A general regression neural network for epileptic EEG classification based on dual complex WT (abbreviated as DTCWT-GRNN) proposed by Swami *et al.* [31]; (5) An explainable graph feature convolutional neural network for epileptic EEG classification (abbreviated as WTPRNet) proposed by Xin *et al.* [27]. Table IX has given the mentioned experimental results.

In the classification task of experiment No. 2, experiments No. 2-1-1, No. 2-1-2, and No. 2-1-3 are all aimed at classification between healthy EEG signals, including Dataset A and Dataset B, and seizure EEG signals, including Dataset E. Due to there are quite large differences in features of these two signals, almost all algorithms have achieved good classification results. In contrast, the classification effects between seizure-free EEG signals, including Dataset C and Dataset D, and seizure EEG signals, including Dataset E, are much worse

TABLE IX
CLASSIFICATION COMPARISON RESULTS AMONG COMMONLY USED ALGORITHMS AND OUR AMWCNN ALGORITHM FOR HEALTHY, SEIZURE-FREE, AND SEIZURE EEGS

Experiment Number	Dataset	Method	Accuracy	Specificity	Sensitivity
No. 2-1-1	A vs. E	FBSE	99.5%	-	-
		OMP-DWT	100%	100%	100%
		ACNN	98.17%	96.82%	98.49%
		DTCWT-GRNN	100%	100%	100%
		WTPRNet	100%	100%	100%
		AMWCNN	100%	100%	100%
No. 2-1-2	B vs. E	FBSE	99.5%	-	-
		OMP-DWT	98%	99.23%	96.79%
		DTCWT-GRNN	98.9%	98.75%	97.92%
		WTPRNet	100%	100%	100%
		AMWCNN	100%	100%	100%
No. 2-1-3	AB vs. E	DTCWT-GRNN	100%	100%	100%
		OMP-DWT	99%	100%	96.66%
		WTPRNet	100%	100%	100%
		AMWCNN	100%	100%	100%
No. 2-2-1	C vs. E	FBSE	99.5%	-	-
		OMP-DWT	98.5%	99.23%	96.79%
		DTCWT-GRNN	98.7%	98.56%	98.15%
		WTPRNet	99.2%	99.38%	97.17%
		AMWCNN	99.39%	99.23%	98.42%
No. 2-2-2	D vs. E	FBSE	97.5%	-	-
		OMP-DWT	93%	91.21%	94.46%
		DTCWT-GRNN	93.3%	93.21%	91.19%
		WTPRNet	99%	99.35%	98.82%
		AMWCNN	99.11%	99.43%	98.90%
No. 2-2-3	CD vs. E	FBSE	99%	-	-
		OMP-DWT	98.33%	98.41%	98.5%
		DTCWT-GRNN	90.4%	92.2%	94.2%
		WTPRNet	98%	98.17%	95.95%
		AMWCNN	98.12%	98.23%	97.66%
No. 2-3	AB vs. CD vs. E	DWT-BayKNN	98.6%	98.35%	97.75%
		WTPRNet	98.75%	98.9%	99.22%
		AMWCNN	98.89%	99.10%	99.22%

than experiment No. 2-2-1, No. 2-2-2, and No. 2-2-3. This is mainly because the feature differences between epilepsy patients' seizure activity and seizure-free EEG signals is relatively small. Therefore, the classification accuracy of experiments No. 2-2-1, No.2-2-2, No. 2-2-3 of all the classification algorithms is relatively low. However, compared with other epilepsy EEG classification algorithms, the proposed algorithm still achieves a good classification effect, which also shows the algorithm's effectiveness in this paper. In experiments No. 2-2-1 and No. 2-2-3, the specificity and sensitivity of the proposed algorithm are slightly lower than other algorithms, while the difference is not much, and it is the second-best among all the algorithms. The accuracy of this paper is the best among all algorithms, for which it can accurately classify EEG signals between seizure activity and seizure-free. Moreover, in experiments No. 2-3 can be seen in Table IX that the proposed algorithm can be well applied to the three-classification task, which can more accurately distinguish among inter-ictal, ictal and healthy EEGs. AMWCNN can achieve a superior classification effect.

3) Non-Focal vs. Focal: This section mainly focuses on EEG signals records in epileptogenic structures area and other brain areas. Two sets of experiments are designed with Dataset F and Dataset N of the Bern-Barcelona Database. The specific experiment descriptions are shown in Table X.

TABLE X
EXPERIMENT DESCRIPTIONS OF NON-FOCAL AND FOCAL EEG CLASSIFICATION

Database	Classification task	Experiment Number	Dataset	Label
Bern-Barcelona Dataset	Non-focal vs. Focal	No. 3-1	N vs. F	Dataset N is labeled as 0, and Dataset F is labeled as 1.

TABLE XI
UNITS FOR MAGNETIC PROPERTIES

Experiment number	Dataset	Method	Accuracy	Specificity	Sensitivity
No. 3-1	N vs. F	FBSE-WT	95.85%	95.47%	96.24%
		TOCF	99%	98.68%	99.32%
		PCA-CSVM	99.56%	99.72%	99.52%
		WTPRNet	99.67%	99.87%	99.57%
		WCNN	99.70%	99.79%	99.65%

Finally, a classification test is carried out on EEG signals recorded from the focal area and EEG signals recorded from the non-focal area. The proposed algorithm has been compared with some commonly used algorithms meanwhile. These algorithms include: (1) A flexible time-frequency coverage wavelet transform algorithm for focal EEG signal classification based on Fourier-Bessel series expansion (FBSE) (abbreviated as FBSE-WT) proposed by Gupta and Pachori [33]; (2) Automatic focal EEG signal detection based on third-order cumulant function (abbreviated as TOCF) proposed by Sharma *et al.* [34]; (3) A focal EEG signal classification algorithm on the principal component analysis and convolutional support vector machine (abbreviated as PCA-CSVM) proposed by Xin *et al.* [21]; (4) The WTPRNet algorithm proposed in [27]. Table XI has given the experimental results.

The fact that the specificity of the proposed algorithm is slightly lower than that of WTPRNet in experiment No. 3-1 can be seen in Table XI. But the difference is not significant and is the suboptimal value of all algorithms. In this paper, two kinds of signals in Dataset F and Dataset N, namely epileptic focal EEG and non-focal EEG, are classified with optimal accuracy. The accuracy is the highest among all comparison algorithms. It can be seen from the above that the proposed algorithm is robust and can achieve excellent classification effects for different types of epileptic EEG classification. EEG signals of healthy subjects, seizure-free EEG of epileptic patients, and EEG during the epileptic seizure of epileptic patients can be accurately classified. Furthermore, the focal EEG signals and non-focal EEG signals of epileptic patients can be accurately classified, too. It has a strong generalization ability and can adapt to a variety of epileptic EEG signal classification scenarios.

IV. CONCLUSION

A new attention-based wavelet convolution neural network for epilepsy EEG classification is proposed in this paper. Wavelet multi-scale analysis is first used to decompose the input EEG signals to obtain EEG signals of different frequency bands. Then these multi-scale EEG coefficients are then input into the AMWCNN network proceeding with feature extraction first and then classification. Our AMWCNN algorithm can classify three categories: EEGs of healthy volunteers, seizure-free EEGs of epileptic patients and seizure EEGs of epileptic patients, and two categories: focal area EEGs of epileptic patients and non-focal areas EEG of epileptic patients. Relevant details from neurophysiological signals have been extracted with the proposed algorithm, which is helpful for the localization of focal epilepsy regions. A three-class accuracy rate of 98.89% is obtained on Bonn EEG Database, and a two-class accuracy rate of 99.70% is obtained on Bern-Barcelona EEG Database. Although a good classification effect and strong generalization ability have been achieved by our method, the model training is relatively time-consuming. In the future, the network model can continue to be optimized to improve the efficiency of model training.

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