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RESEARCH ARTICLE

# Empirical Mode Decomposition for Deep Learning-Based Epileptic Seizure Detection in Few-Shot Scenario

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**ABSTRACT** The precise and automated detection of epileptic seizures has become a focal point of research due to its potential to alleviate the severe consequences experienced by patients. Recent advancements in deep learning-based detection techniques utilizing electroencephalogram (EEG) signals have yielded state-of-the-art performance. However, these methods typically require a large number of training samples to effectively train the deep neural networks. Consequently, their performance can be compromised in scenarios where only a limited number of samples are available. This paper presents two novel approaches that aim to improve seizure detection accuracy in situations with a scarcity of data by harnessing the power of empirical mode decomposition (EMD) applied to EEG signals. Specifically, in both methods, the EMD of EEG signals and the power spectral density (PSD) of the resulting EMD components are employed as inputs for subsequent neural networks. Multiple convolutional neural networks (CNNs) are purposefully designed to perform seizure detection using these inputs. Experimental results demonstrate that our proposed methods achieve superior detection accuracy compared to traditional deep learning-based detection methods that do not incorporate EMD in few-shot scenarios. In particular, when the number of training samples is reduced to 10%, our method shows an improvement of 23%, 19%, and 26% in accuracy, sensitivity, and specificity, respectively, compared to the original EEG input across different networks.

**INDEX TERMS** Seizure, electroencephalogram (EEG), empirical mode decomposition (EMD), deep learning, convolutional neural networks (CNNs).

## I. INTRODUCTION

### A. BACKGROUND

Epilepsy is a chronic nervous system disease [1], [2]. It is a transient brain dysfunction caused by the sudden super-synchronous abnormality of brain nerve cells. According to World Health Organization (WHO) [3], as of 2019, nearly 50 million people in the world suffered from epilepsy, accounting for about 1%-2% of the world's population. Repeated seizures directly lead to neurological dysfunction or degradation of thinking, perception and behavior, which not only causes irreversible brain damage to the cognitive function of the patient, but also makes the patient prone to physiological and psychological disorders. Therefore, early diagnosis helps to prevent seizures and brain damage, and plays a key role in improving the quality of life of epilepsy patients.

At present, electroencephalogram (EEG) sensors [4], [5] are used to record the electrophysiological activities of brain neurons from the scalp. EEG signals are recorded

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by placing several electrodes (scalp surface) or probes (intracranial) on the subject's head according to certain criteria. The EEG signals of epilepsy often show abnormal waves such as sharp wave, spike wave and spike slow complex wave. In clinical practice, neurosurgeons extract the shape, frequency, amplitude and other characteristics of EEG signals according to the status of epileptic activity, so as to infer whether the EEG has the characteristic waveform of epilepsy. However, it is obviously a time-consuming and tedious work for medical experts to diagnose whether there is epilepsy by visual examination based on clinical experience, and there will be a high misdiagnosis rate [6]. Therefore, it is necessary to study the automatic detection method of epilepsy based on EEG to improve the accuracy and efficiency of epilepsy detection, enabling accurate and timely detection of seizures in patients and improving treatment outcomes and patients' quality of life.

With the vigorous development of digital signal processing, machine learning and other technologies, people have made remarkable research achievements in the field of automatic detection of epilepsy. The proposed methods can be roughly divided into two categories: feature-based methods and deep learning-based methods. The feature-based methods are mainly based on artificial feature extraction and machine learning classifier. The extracted features usually consist of features form time-domain EEG [7], [8], [9], features from frequency transform of EEG [10] and features from time-frequency analysis of EEG [11], [12], [13], [14], [15]. In contrast, the deep learning-based methods are data-driven methods. They use deep neural networks such as long short-term memory networks (LSTMs) [16], [17] and convolutional neural networks (CNNs) [18], [19], [20] to automatically learn features from the input data. The learned features will support the detection of epilepsy. Due to the powerful feature automatic learning ability of deep learning, deep learning-based methods have achieved better detection performance than feature-based methods.

However, the method based on deep learning often needs a large number of training samples to support the learning and training of the network model. When the sample size is small, its performance will be affected to some extent. For epileptic EEG samples, building a large number of tagged samples means that a large number of EEG signals of epileptic patients need to be collected, which is often impractical. A more practical situation is that epilepsy detection needs to be implemented based on a small number of labeled samples, which is called a few-shot learning scenario. Meanwhile, epilepsy detection in few-shot scenarios helps to provide a deeper understanding of disease characteristics and individual differences, providing an accurate basis for personalized treatment plans. In the few-shot scenario, if the raw data is still used directly for training, the model is likely to fall into the local optimum and the phenomenon of over-fitting will occur, and the accuracy rate in the test stage will be greatly reduced. In few-shot scenarios, the performance of epilepsy detection may be improved if the EEG signals can be preprocessed in advance to extract richer and more detailed information, so that the subsequent neural networks can be more direct and easier to learn. In our prior work [21], we used multiple time-frequency inputs to feed into the CNN to improve the detection performance of seizure. However, only discrete Fourier transform (DFT) and wavelet transform are explored in this method. In this paper, we explore another time-frequency tool, empirical mode decomposition (EMD), to decompose the EEG signals to obtain the components containing more detailed information, and then implement deep learning on the decomposed components, so as to complete the epilepsy detection in few-shot scenarios.

### B. CONTRIBUTION

The contributions of the paper can be summarized as follows.

1) We propose two learning-based methods for epilepsy detection, termed EMD-EEG and EMD-PSD, both of which are empowered by EMD to enhance detection performance in few-shot scenarios. The EMD-EEG is initiated by decomposing EEG signals via EMD, and then the decomposed components are spliced. The spliced matrix is used as the input of the CNNs. Building upon EMD-EEG, the EMD-PSD further processes each EMD-derived component through DFT, followed by computation of the Power Spectral Density (PSD) for each component. The PSD sequences obtained are spliced and then fed into the CNNs for learning and detection. Compared to traditional deep learning methods that directly employ EEG signals, the EMD-EEG and EMD-PSD methods are capable of extracting more abundant feature information and significantly enhancing the accuracy of epilepsy detection.
2) We evaluate the performance of our proposed algorithms on a publicly available epilepsy detection dataset. Experimental results indicate that, in comparison to traditional deep learning-based detection methods, our approaches achieved higher detection accuracy in scenarios with limited sample sizes. Especially, when the number of training samples was reduced to 10%, our methods exhibited improvements of 23%, 19%, and 26% in accuracy, sensitivity, and specificity, respectively.

## II. RELATED WORK

Existing deep learning-based epilepsy detection algorithms usually use LSTMs and CNNs. Specifically, in terms of epilepsy detection based on CNNs, Acharya et al. [18] proposed an end-to-end automatic seizure detection algorithm based on deep CNN in 2018. They built a CNN with a one-dimensional convolution kernel and tested it on the single-channel Bonn EEG data set, realizing an accuracy of 88% for the three types of EEG data of epileptic period, interictal period, and normal. Since then, a variety of epilepsy detection methods based on different CNN architectures have been proposed, such as the deep network model using the fully convolution network without pooling layer as the automatic extraction module of epileptic EEG features [22], the pyramidal one-dimensional CNN model with fewer parameters [23], and the multi-channel epilepsy detection neural network using 3D convolution kernel [24]. In addition, relatively mature CNN architectures in the field of computer vision have also been used in the detection of epileptic EEG signals. Through time-frequency transformation, feature extraction, multi-channel integration and other methods, one-dimensional EEG signals are converted into two-dimensional images which are fed into the CNN architecture with two-dimensional convolution kernels for detection. For instance, Nogay and Adeli [19] employed short-time Fourier transform (STFT) to convert EEG signals into two-dimensional images and input them into the pre-trained AlexNet for epilepsy detection.

In the aspect of epilepsy detection based on LSTM, Hussein et al. [25] constructed an LSTM framework suitable for processing original EEG signals to classify multiple types of epileptic EEG data. Geng et al. [16] first obtained the time-frequency spectrum of the original EEG signal by time-frequency transform, and then established a bidirectional LSTM model for time-frequency feature detection. Abbasi et al. [26] used EEG signals to generate various non-stationary arbitrary signals, including Auto-Regressive Moving Average (ARMA) features and Hurst Exponent, and used them to design a double-layer effective LSTM classifier to detect epilepsy in the EEG signal.

In terms of the methods based on hybrid CNN and LSTM, in recent years, there have also been some researches [27], [28], [29] exploring that the CNN module is used as an automatic feature extraction module to extract EEG features, and then the LSTM is used to learn the long-term correlation of EEG features at different times, and good detection performance has been achieved. Anita and Kowshalya [17] used the Fourier-Bessel Series Expansion-Based Empirical Wavelet Transform (FBSE-EWT) method and the relief-F feature ranking method to extract important signal features from EEG signals and designed LSTM and multi-scale hole-based deep convolutional neural network (MSA-DCNN) to detect epileptic seizures. Qiu et al. [30] designed the differential attention ResNet-LSTM network (DARLNet) using ResNet and LSTM. It utilizes a channel attention module to capture temporal and spatial dependencies to focus on relevant epileptic seizure information, showing superior performance compared to other state-of-the-art methods. In general, the deep learning-based methods have achieved better epilepsy detection performance than traditional feature-based methods.

In a few-shot scenario, if the original data is directly used for training, the model is likely to fall into a local optimum, causing overfitting, and the accuracy in the test phase will be greatly reduced. Therefore, some studies use preprocessing of EEG signals to extract richer and more detailed information, thereby making subsequent neural networks more direct and easier to learn, thereby improving the performance of epilepsy detection. For example, Türk and Özerdem [20] used continuous wavelet transform to obtain the time-frequency image of EEG signals, and designed a CNN with appropriate structure to classify them. Ozdemir et al. [31] proposed a new epilepsy detection method based on high-resolution Fourier synchronous compression transform and CNN, and obtained advanced detection performance on multiple epilepsy EEG databases. Amiri et al. [32] introduced synchronized squeezing transform (adaptive FSST) and sparse common spatial pattern (sCSP) efficient models based on adaptive STFT to identify epileptic seizures in EEG signals. In our prior work [21], we used multiple time-frequency inputs to feed into the CNN to improve the detection performance of seizure. However, the above works are all based on DFT or wavelet transform for epilepsy detection. Decomposing EEG signals through EMD enables the extraction of more informative feature components. Murariu et al. [33] adopted the spectral power density of intrinsic mode function (IMF) obtained by EMD of EEG signals and then used K nearest neighbor (KNN) and naive Bayes (NB) classifiers for epilepsy detection. This method has significant performance improvements compared with previous research. Note that even though EMD has been applied in feature-based seizure detection, its application in deep learning-based seizure detection has not been thoroughly explored yet.

## III. METHOD

### A. PROBLEM FORMULATION

Seizure detection is to determine whether there is seizure based on the collected EEG signals. There are two possible results: normal (without seizure) or abnormal (with seizure). Therefore, the problem can also be expressed as a binary classification problem:

$$y = \underset{k=0,1}{\operatorname{argmax}} \Pr\{y = k \mid r(n)\}, \tag{1}$$

where $r(n)$ is the EEG signal, $n$ is the length of the sequence, $y$ is the result. $y = 1$ represents there is seizure and $y = 0$ represents there is no seizure. For the problem of seizure detection in the few-shot scenario, it is required to use a small number of EEG signals to establish a high-performance binary classification model. In this paper, we adopt deep learning with EMD to solve this problem.

### B. OVERALL FRAMEWORK

As discussed earlier, in this paper, we propose two methods of epilepsy detection based on EMD deep learning in few-shot scenarios: EMD-EEG and EMD-PSD. The EMD-EEG method first decomposes the EEG signals by EMD, and then splices the decomposed components into a matrix, which is used as the input of the CNN. The output of the CNN is the vector of two elements corresponding to the probabilities that the input signal is with seizure or not. We take the category with higher confidence as the

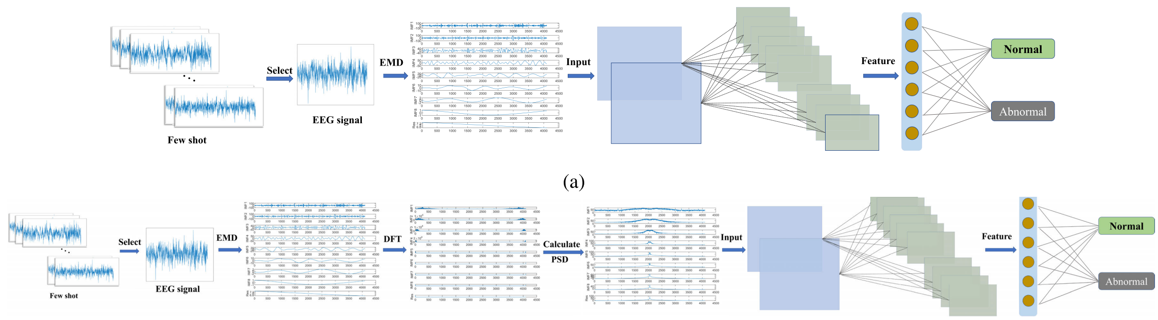



**FIGURE 1. Overall framework of the proposed methods. (a) EMD-EEG; (b) EMD-PSD.**

detection result. Compared with EMD-EEG method, EMD-PSD method adds DFT steps. After EMD decomposition, DFT is calculated for each component and the PSD of each component is obtained by calculating the amplitude. Then the PSD sequences are spliced into a matrix which is used as the input of CNN. Similarly, in the network output, we take the category with higher confidence as the detection result. The overall frameworks of the methods are shown in Fig. 1. Regardless of the method, the parameters of the CNN network used need to be optimized on the training set consisting of a small amount of EGG signals. It is worth emphasizing that compared with the original EEG signal, the components obtained after EMD decomposition contain richer and more detailed time-frequency information, which is crucial to prevent overfitting problems in few-shot learning, and providing the model with more information so that it can better adapt to different data distributions.

### *C. INPUT OF NETWORKS*

In the proposed EMD-EEG, the decomposed EMD components are used as the input of the subsequent neural networks for learning, while in the proposed EMD-PSD, PSDs of the decomposed EMD components are used as the input. We'll discuss the detail of this processing in the following.

#### 1) EMD OF EEG SIGNALS

EMD [34] is a method for adaptive decomposition of time series. This method is based on the time scale characteristics of the received signal itself to decompose the signal without presetting any basis function. EMD has the following three advantages. (1) Adaptive time-frequency analysis. EMD establishes the physical meaning of instantaneous frequency. Multiple components are obtained through the decomposition of the signal and the Hilbert spectrum of the original signal is obtained by Hilbert transformation of these components. This method defines a set of basis functions with adaptive decomposition characteristics according to the characteristics of the original signal so that the method has good adaptive analysis advantages in practical applications. (2) Local characterization of the original signal. The method of deriving the instantaneous frequency of multiple components reflects the ability of EMD method to describe the local characteristics of the original signal accurately. (3) Principal component analysis. EMD method can separate and extract the frequency components in the original signal from high to low to meet signal analysis needs.

EMD decomposes the fluctuations and trends of different scales in the signal step by step to generate a series of data sequences with different characteristic scales, and each sequence is called an IMF. The decomposition can be expressed as

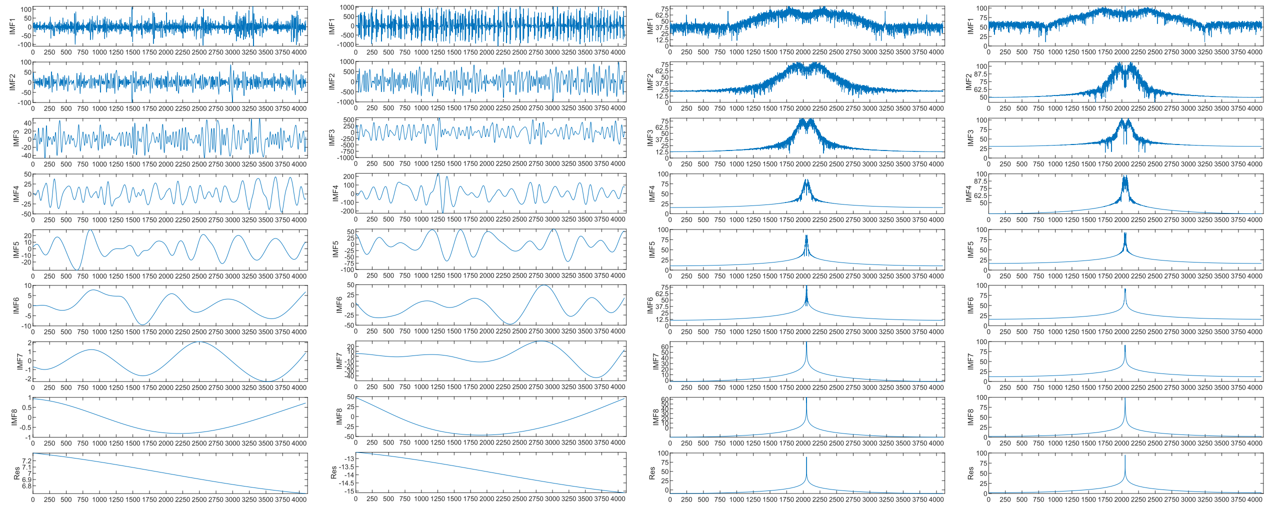
$$r(n) = \sum_{i=1}^{K} \mathrm{IMF}_i(n) + \mathrm{Res}(n), \tag{2}$$

where $r(n)$ is the sensed EEG signal, $\mathrm{IMF}_i$ (n) is the $i$-th IMF of decomposition, and $Res(n)$ is the residual component. By this, any EEG signal can be regarded as the sum of $K$ different IMFs and a residual component.

In the process of decomposition, IMF must meet the following two properties. (1) The number of extreme points of the received signal is equal to or greater or smaller than the number of zero crossings by one. (2) The average value of the upper envelope formed by the local maximum and the lower envelope formed by the local minimum is zero. The IMFs obtained after EMD decomposition are adaptive, reflecting the characteristics of multi-scale filtering. Different IMF components are arranged from high to low frequency after decomposition. Based on the iterative method, the EMD first finds out all the extreme points of the signal in the decomposition process, and uses cubic spline interpolation to obtain the upper and lower envelope curves, and the mean value of the local envelope of the signal is defined as the slow oscillation component. The fast-oscillating component is selected by subtracting the slow oscillating component. A set of IMFs with local symmetry in time domain and definite physical significance in instantaneous frequency are obtained adaptively. The specific decomposition method of EMD is as follows [34].

*Step1:* Calculate all local extremum points of the sensed EEG signal $r(n)$.

*Step2:* Find the upper envelope $r_U(n)$ formed by all maximum points and lower envelope $r_L(n)$ formed by all minimum values.



(a) (b) (c) (d)

**FIGURE 2.** **EMD of EEG signals. (a) EMD of EEG without seizure, (b) EMD of EEG with seizure, (c) PSD of EMD without seizure, and (d) PSD of EMD with seizure.**

*Step3:* Calculate the mean value of the envelope, $r_1(n) = \frac{1}{2}[r_U(n) + r_L(n)]$.

*Step4:* Let $I_1(n) = r(n) - r_1(n)$, if $I_1(n)$ satisfies the properties 1) and 2), the first IMF component is obtained, i.e., $\text{IMF}_1(n) = I_1(n)$. If $I_1(n)$ does not satisfy the properties, return to the first step for iteration until the first IMF component is obtained.

*Step5:* $r_2(n) = r_1(n) - IMF_1(n)$, let $r(n) = r_2(n)$, repeat step 1 until $r_k(n)$ is a monotone signal.

After decomposition, $K$ IMFs and a residual component can be obtained. Two stopping criteria have been proposed for EMD decomposition. The first is the relative tolerance which is defined as

$$\text{RelTol} \triangleq \frac{\left\|\text{IMF}(n)_{\text{previous}} - \text{IMF}(n)_{\text{current}}\right\|^2}{\|\text{IMF}(n)_{\text{current}}\|^2}. \quad (3)$$

When the current relative tolerance is less than sift relative tolerance, the iteration can be terminated. Because relative tolerance does not calculate the number of local extrema and zero crossings, it is possible that the decomposed IMFs do not satisfy two conditions for the strict decomposition of an intrinsic mode function. In those cases, reducing the value of the sift relative tolerance can solve these problems.

The second metric is energy ratio which is the ratio of the energy of the signal at the beginning of sifting and the average envelope energy. Energy ratio is defined as

$$\text{EneRat} \triangleq 10\log_{10}\left(\frac{\|r(n)\|^2}{\|\text{Res}(n)\|^2}\right). \quad (4)$$

When current energy ratio is greater than the predefined maximum energy ratio, decomposition can stop.

### 2) SPECIFIC INPUT FORMATS

As mentioned earlier, the decomposed EMD components and PSDs of the decomposed EMD components are used as the input in the proposed EMD-EEG method and the proposed EMD-PSD method, respectively. To illustrate this, we apply EMD to the single-channel EEG samples and the resulting components are shown in Fig 2. It can be observed from Fig. 2(a) and Fig. 2(b)) that there are 8 decomposed IMFs. Obvious difference in the first three IMFs can be observed for EEGs with and without seizure. We also plot example PSDs of the decomposed components in Fig. 2(c) and Fig. 2(d). The logarithm is taken for the sake of illustration. Similarly, difference in the first three PSDs of IMFs can be observed for samples with and without seizure.

#### *a: INPUT OF EMD-EEG*

In the proposed EMD-EEG, in order to deal with EMD of EEG with CNN, we splice the IMFs and the residual component after EMD compuatation into a matrix $M_{\text{EMD}-\text{EEG}}$ as

$$\begin{bmatrix} \text{IMF}_1(0) & \text{IMF}_1(1) & \cdots & \text{IMF}_1(N-1) \\ \text{IMF}_2(0) & \text{IMF}_2(1) & \cdots & \text{IMF}_2(N-1) \\ \vdots & \vdots & & \vdots \\ \text{IMF}_K(0) & \text{IMF}_K(1) & \cdots & \text{IMF}_K(N-1) \\ \text{Res}(0) & \text{Res}(1) & \cdots & \text{Res}(N-1) \end{bmatrix}. \quad (5)$$

This matrix $M_{\text{EMD-EEG}}$ is used as the input of the EMD-EEG method. Note that in EMD decomposition, the number of IMFs obtained may be different for different EEG signals. In order to keep the size of $M_{\text{EMD-EEG}}$ fixed for different signals, we set a maximum number of IMFs $K_{\max}$. If the number of IMFs is smaller than $K_{\max}$, the corresponding components are padded with zeros. Thus, the size of $M_{\text{EMD-EEG}}$ remains unchanged as $(K_{\max}+1) \times N$.

#### *b: INPUT OF EMD-PSD*

In the proposed EMD-PSD, the PSDs of the IMFs and the residual component are computed as

$$\text{PIMF}_i(k) = \frac{1}{N}\left|\sum_{n=0}^{N-1} \text{IMF}_i(n)e^{-j2\pi kn/N}\right|^2, \quad (6)$$

$$\mathrm{PRes}(k) = \frac{1}{N}\left|\sum_{n=0}^{N-1} \mathrm{Res}(n) e^{-j2\pi kn/N}\right|^2, \tag{7}$$

where $k = 0, 1, \ldots, N-1$.

All of the PSDs of the IMFs and the residual component are spliced into a matrix $M_{\mathrm{EMD-PSD}}$ as

$$\begin{bmatrix} \mathrm{PIMF}_1(0) & \mathrm{PIMF}_1(1) & \cdots & \mathrm{PIMF}_1(N-1) \\ \mathrm{PIMF}_2(0) & \mathrm{PIMF}_2(1) & \cdots & \mathrm{PIMF}_2(N-1) \\ \vdots & \vdots & & \vdots \\ \mathrm{PIMF}_K(0) & \mathrm{PIMF}_K(1) & \cdots & \mathrm{PIMF}_K(N-1) \\ \mathrm{PRes}(0) & \mathrm{PRes}(1) & \cdots & \mathrm{PRes}(N-1) \end{bmatrix}. \tag{8}$$

The matrix $M_{\text{EMD-PSD}}$ is used as the input of the EMD-PSD method. Similarly, if the number of IMFs is smaller than $K_{\max}$, the corresponding components are padded with zeros. Thus, the size of matrix $M_{\text{EMD-PSD}}$ is the same as that of matrix $M_{\text{EMD-EEG}}$. Therefore, we can adopt the same network structure to deal with these two kinds of input in the proposed two methods. Note that for convenience of computation, we place the first dimension of $M_{\text{EMD-EEG}}$ and $M_{\text{EMD-PSD}}$ in the channel dimension of the input of CNN.

### D. ADOPTED NETWORKS

In the classification tasks based on deep learning, CNN [35] has proven to be a mainstream and effective network. For epilepsy detection, various types of CNN networks [22], [23], [24] have been used and have achieved excellent performance. A CNN generally includes convolution layer, activation layer, pooling layer and fully connected layer. The purpose of convolution layer is to extract features from the input. The convolution layer is composed of several convolution kernels, and the weights and bias of each convolution kernel are optimized in the training process. The activation layer is used to make a nonlinear mapping of the output of the convolution layer. The pooling layer is used to reduce the dimension of the feature maps learned with the convolution layer by taking the maximum or average value, thus reducing over-fitting and improving the fault-tolerance of the model. As for the fully connected layer, each neuron in it is fully connected with all the neurons in the previous layer.

To verify the performance of the proposed method at different depth network models, in this paper, we construct 3 CNNs, which are denoted as EsNet, CNN1D-4Res and CNN1D-5Res. Their specific structures are shown in Fig. 3(a), Fig. 3(b) and Fig. 3(c). EsNet is a shallow network model we built, it is mainly composed of 2 two-dimensional convolution layers, 2 maximum pooling layers and 3 fully connected layers. In the field of classification based on deep learning model, to a certain extent, the more layers of neural network, the more information can be obtained, and the richer features are, the more conducive to classification. But in practice, with the deepening of the network, the optimization effect will decline. He et al. [36] solved this problem by using the method of skipping or bypassing the connection, so that the deep learning model can obtain better classification performance in deeper situations. Similarly, we design a residual stack structure to deepen the network in order to achieve better classification performance. The structure of residual stack is shown in Fig. 3(d). Based on the designed residual stack, we construct a neural network model CNN1D-4Res using 4 residual stacks and a network CNN1D-5Res using 5 residual stacks, as shown in Fig. 3(b) and Fig. 3(c) respectively.

### E. TRAINING ALGORITHM

The parameters of the CNNs need to be trained with a training dataset. Cross entropy is used as the loss function for optimization. It can be represented as

$$\ell = -\frac{1}{B}\sum_{i=1}^{B}\sum_{j=1}^{2}\left[y_{i,j}\log\widehat{y_{i,j}} + \left(1-y_{i,j}\right)\log\left(1-\widehat{y_{i,j}}\right)\right], \tag{9}$$

where $B$ is the mini batch size, $y_{(i,j)}$ is the correct probability that the $i$-th sample belonging to class of $j$, and $\widehat{y_{i,j}}$ is the predicted probability that the $i$-th sample belonging to the class of $j$. At the beginning of training, the hyperparameters of the neural network are randomly initialized. Then, in the training process, these parameters are iteratively updated through the optimization algorithm to make the loss function continuously reduce. We use time adaptive momentum optimization algorithm (Adam) [37] for the optimization.

The update process of Adam algorithm is as follows. Firstly, we define $\lambda_1$ and $\lambda_2$ as the parameter attenuation coefficient, $\lambda_1, \lambda_2 \in [0, 1)$. The update formulas for the biased moment estimate $m_t$ and $n_t$ are

$$m_t \leftarrow \lambda_1 \cdot m_{t-1} + (1-\lambda_1)\cdot g_t, \tag{10}$$

$$n_t \leftarrow \lambda_2 \cdot n_{t-1} + (1-\lambda_2)\cdot g_t^2, \tag{11}$$

where $g_t$ is the gradient of the time step of Loss. The bias-corrected moment estimates of $m_t$ and $n_t$ are

$$\widehat{m}_t \leftarrow \frac{m_t}{\left(1-\lambda_1^t\right)}, \tag{12}$$

$$\widehat{n}_t \leftarrow \frac{n_t}{\left(1-\lambda_2^t\right)}. \tag{13}$$

Therefore, the parameter $\mu_t$ update expression of neural network can be expressed as

$$\mu_t \leftarrow \mu_{t-1} - \sigma \cdot \frac{\hat{m}_t}{\left(\sqrt{\widehat{n}_t} + \varphi\right)}, \tag{14}$$

where $\sigma$ is learning rate, $\varphi$ is a very small value. For instance, $\varphi = 10^{-8}$.

## IV. RESULTS AND DISCUSSION

### A. DATASET

In the following experiments, we use the EEG dataset published by Andrzejak et al. [38]. This dataset comprises EEG recordings obtained from a cohort consisting of 5 epilepsy patients and 5 healthy individuals, delineated into five distinct subsets denoted as F, S, N, Z, and O. Each subset

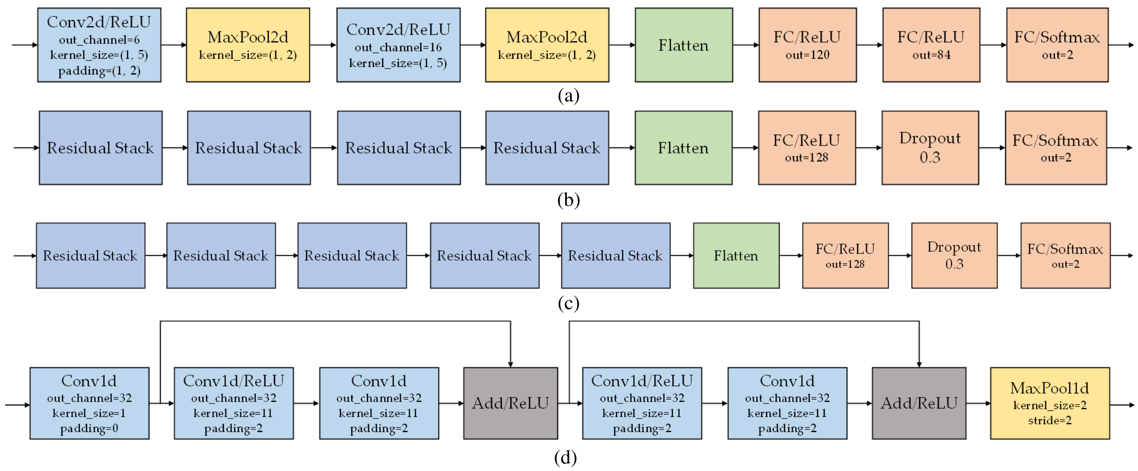



**FIGURE 3.** Specific structures of constructed networks. (a) EsNet, (b) CNN1D-4Res, (c) CNN1D-5R, (d) Residual Stack.

**TABLE 1.** Simulation parameters.

| Parameters | Value |
|---|---|
| Batch Size | 32 |
| Optimizer | Adam |
| Learning Rate | 0.001 |
| Dropout Rate | 0.1 |
| Epochs | 50 |

encompasses 100 EEG signals acquired utilizing a standard 10-20 electrode placement system. The length of each EEG signal is fixed at 4097. Notably, subsets Z and O constitute EEG data collected from healthy subjects, distinguishing between participants with their eyes either open (Z) or closed (O). Conversely, subsets N, F, and S pertain to patients diagnosed with epilepsy. Subsets N and F represent EEG recordings obtained from the hippocampus and the focal area during epileptic seizures, respectively, while subset S entails recordings specifically from the focal area during epileptic seizures. Due to our focus on epileptic seizure detection in a few-shot scenario, it is used to detect ictal cases to overcome the lack of detection accuracy caused by the lack of training samples. Therefore, samples of subset Z and subset S are selected for experiments, where subset Z represents the presence of epileptic seizures and subset S represents the absence of epileptic seizures. There are 100 EEG signal samples for each category. In the EMD decomposition, we set the maximum number of IMFs as 10, which means for each sample, the size of the $M_{\text{EMD-EEG}}$ and $M_{\text{EMD-PSD}}$ are $11\times4097$.

### B. EXPERIMENTAL SETTING

All of the experiments are conducted in a computer configured with NVIDIA GeForce RTX 2080 and Keras 2.3.1. The maximum number of epochs is set 50. As we focus on few-shot scenarios, the mini-batch size is set with a small number, say 2 in all of the experiments. The initial learning rate is set 0.001 for Adam optimization. Piecewise learning rate strategy is used. Specifically, after every 10 epochs, we change the learning rate to half of the previous value. The dropout rate is 0.1. The specific simulation parameter settings are shown in Table 1.

### C. PERFORMANCE METRICS

We use accuracy, sensitivity, and specificity for performance metrics of seizure detection.

#### 1) ACCURACY

Accuracy is the ratio of the number of samples that correctly detect epileptic seizures to the total number of samples, and is used to measure the overall performance of epileptic seizure detection. The expression for calculating accuracy is as follows:

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}}, \tag{15}$$

where TP is the true negative indicates correct identification of seizures, TN is true positive indicates correct identification of normal activity, FP is false positive indicates that missed epileptic seizure, i.e. seizure identified as episode of normal activity, and FN is false negative indicates incorrectly identification of seizures, i.e. episode of normal activity identified as seizure. A high accuracy indicates a strong overall predictive capability of the model.

#### 2) SENSITIVITY

Sensitivity represents the percentage of a specific detection out of the total number of accurate and incorrect detections of disease, that is, among all actual epilepsy patients:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{16}$$

Sensitivity focuses on the model's ability to capture real epilepsy patients. High sensitivity means the model can effectively detect patients with epilepsy, reducing the risk of missed diagnosis.

#### 3) SPECIFICITY
Specificity represents the ratio of accurate detections of negative values to the total number of true negatives and misclassified positive detections, i.e. the proportion of samples that the model successfully predicted as non-epileptic:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}. \tag{17}$$

Specificity focuses on the model's ability to avoid incorrectly predicting non-epileptic patients as epileptic patients. High specificity indicates that the model performs well at excluding non-epileptic patients, reducing the risk of false positives.

### D. EXPERIMENTAL RESULTS
In order to verify the superiority of our proposed epilepsy detection methods, we compare our proposed EMD-empowered methods with those methods without EMD. Specifically, we take EEG, EMD-EEG, PSD and EMD-PSD as the input of the network model to identify normal EEG signals and epileptic EEG signals. In order to ensure the universality of our epilepsy detection method based on EMD enhancement, we use three neural network models with different depths for simulation. In addition, in view of the small number of signal samples in the EEG dataset used, in order to reduce the impact of data segmentation on the evaluation results, we use different K-fold cross-validation method for simulation verification, including 5-fold cross-validation (the training set contains 20 normal samples and 20 epileptic samples, and the remaining 80 normal EEG signals and 80 epileptic EEG signals constitute the test set), 10-fold cross-validation (the training set contains 10 normal samples and 10 epileptic samples) and 20-fold cross-validation (the training set contains 5 normal samples and 5 epileptic samples). For a more comprehensive comparison, we use three indicators to measure the performance of epilepsy detection methods, namely accuracy, sensitivity and specificity. For K-fold cross-validation, we take the average and variance of the three metrics for each fold to measure the effectiveness and stability of the method.

#### 1) ILLUSTRATION OF THE TRAINING PROCESS
We check the losses and accuracy of the four algorithms on the training set and test set in the training stage to verify the convergence of the model. The dataset is constructed using 5-fold cross validation. Training loss and training accuracy are shown in Fig. 4(a) and 4(b) respectively. Both training loss and testing loss of EMD-EEG and EMD-PSD decreases with increasing epochs. When the number of epoch is greater than 11, the loss is stably close to 0. The training accuracy and testing accuracy of EMD-EEG and EMD-PSD both increases with the increase of the epochs. When the epoch is greater than 11, both training accuracy and testing accuracy tends to stabilize. Overall, the EMD-EEG model and EMD-PSD model are not overfitting and have good performance.

#### 2) CHOICE OF IMF NUMBER
For our proposed EMD enhancement method, the IMF number after EMD decomposition has a great impact on the performance of epilepsy detection. In this regard, we change the number of IMF components of EMD decomposition by EMD-PSD method, and test the performance of the model under different IMF components. We adopt 5-fold cross-validation, and the results are shown in Table 2. Under the three network models with different depths, the three indicators of the network increase first and then decrease with the increase of the number of IMF components. The performance of the network model is the best when the IMF number is 10. Therefore, for the following experiments, we adopt the IMF component number of 10 for the EMD enhancement method.

#### 3) PERFORMANCE ON DIFFERENT FOLD CROSS VALIDATION
We first consider 5-fold cross validation. Results are shown in Table 3 and Fig. 5. For the shallow network model EsNet, it can be seen that the three metrics when the input of the model is the original EEG signal is the lowest. Accuracy, sensitivity and specificity in this case are 0.9338, 0.9200 and 0.9475, respectively. The three metrics obtained by inputting the data obtained after EMD decomposition of the original EEG into the model are 0.9888, 0.9875 and 0.9900, which are significantly improved by about 5%, 6% and 5%. When the input data is PSD, the three metrics are 0.9863, 0.9925 and 0.9800, which are higher than the metrics when using the original EEG signal data as input. Similarly, the three metrics of EMD decomposition based on PSD are 0.2%, 0.5% and 0.0% higher than these metrics obtained by using PSD as input. In addition, it can be seen from Table 3 and Fig 5that the variance of the EMD-EEG method is less than that of the EEG input method, and the variance of the EMD-PSD method is less than that of the PSD input method. These show the effectiveness and stability of our epilepsy recognition method based on EMD enhancement.

For the two deeper network models, CNN1D-4Res and CNN1D-5Res, as shown in Table 3, Fig. 5. We can draw the same conclusion as in the case of the EsNet model. Compared with the original EEG input and PSD input, the three metrics of the EMD-enhancement methods are improved, while the variance are reduced thus the stability be improved.

Next, in order to verify the performance of our methods in the case of less training samples, we also carry out simulations in the case of 10-fold cross-validation and 20-fold cross-validation. Table 4 and Fig. 6 show the simulation results obtained by using the net-work models EasyNet, CNN1D-4Res and CNN1D-5Res with 10-fold cross-validation. Table 5 and Fig. 7 are the corresponding simulation results in the case of 20-fold cross-validation. These simulation results prove that even in the case of few training data, the three metrics can be improved by EMD decomposition, and it is basically more stable.

**TABLE 2.** The seizure detection performance of different IMF number with 5-fold cross-validation.

| Number of IMF | Network | Accuracy | | Sensitivity | | Specificity | |
|---|---|---|---|---|---|---|---|
| | | Mean | Variance | Mean | Variance | Mean | Variance |
| 8 | EsNet | 0.9650 | 0.0267 | 0.9625 | 0.0293 | 0.9675 | 0.0338 |
| | CNN1D-4Res | 0.9688 | 0.0319 | 0.9775 | 0.0271 | 0.9600 | 0.0479 |
| | CNN1D-5Res | 0.9825 | 0.0162 | 0.9925 | 0.0168 | 0.9725 | 0.0240 |
| 10 | EsNet | 0.9887 | 0.0149 | 0.9875 | 0.0217 | 0.9900 | 0.0105 |
| | CNN1D-4Res | 0.9900 | 0.0105 | 0.9925 | 0.0068 | 0.9875 | 0.0153 |
| | CNN1D-5Res | 0.9975 | 0.0056 | 1.0000 | 0.0000 | 0.9950 | 0.0112 |
| 12 | EsNet | 0.9837 | 0.0196 | 0.9900 | 0.0105 | 0.9775 | 0.0298 |
| | CNN1D-4Res | 0.9688 | 0.0147 | 0.9825 | 0.0274 | 0.9550 | 0.0274 |
| | CNN1D-5Res | 0.9863 | 0.0179 | 1.0000 | 0.0000 | 0.9725 | 0.0358 |

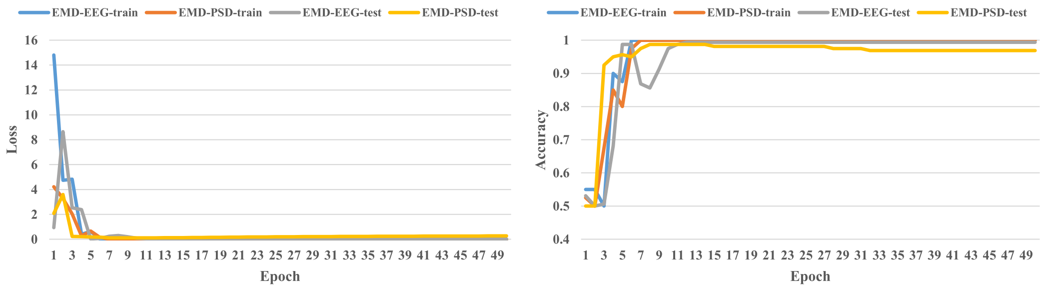
**TABLE 3.** The seizure detection performance with 5-fold cross-validation.

| Method | Network | Accuracy | | Sensitivity | | Specificity | |
|---|---|---|---|---|---|---|---|
| | | Mean | Variance | Mean | Variance | Mean | Variance |
| EEG | EsNet | 0.9338 | 0.0260 | 0.9200 | 0.0505 | 0.9475 | 0.0358 |
| | CNN1D-4Res | 0.9525 | 0.0295 | 0.9450 | 0.0401 | 0.9600 | 0.0224 |
| | CNN1D-5Res | 0.9863 | 0.0209 | 0.9925 | 0.0068 | 0.9800 | 0.0381 |
| EMD-EEG | EsNet | 0.9888 | 0.0149 | 0.9875 | 0.0217 | 0.9900 | 0.0105 |
| | CNN1D-4Res | 0.9900 | 0.0105 | 0.9925 | 0.0068 | 0.9875 | 0.0153 |
| | CNN1D-5Res | 0.9975 | 0.0056 | 1.0000 | 0.0000 | 0.9950 | 0.0112 |
| PSD | EsNet | 0.9863 | 0.0149 | 0.9925 | 0.0112 | 0.9800 | 0.0190 |
| | CNN1D-4Res | 0.9913 | 0.0130 | 0.9975 | 0.0056 | 0.9850 | 0.0205 |
| | CNN1D-5Res | 0.9975 | 0.0034 | 1.0000 | 0.0000 | 0.9950 | 0.0068 |
| EMD-PSD | EsNet | 0.9888 | 0.0052 | 0.9975 | 0.0056 | 0.9800 | 0.0143 |
| | CNN1D-4Res | 0.9925 | 0.0081 | 0.9975 | 0.0056 | 0.9875 | 0.0125 |
| | CNN1D-5Res | 0.9988 | 0.0028 | 1.0000 | 0.0000 | 0.9975 | 0.0056 |

**TABLE 4.** The seizure detection performance with 10-fold cross-validation.

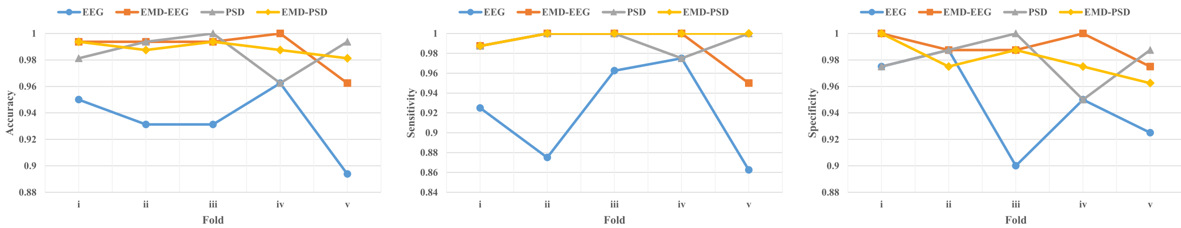
| Method | Network | Accuracy | | Sensitivity | | Specificity | |
|---|---|---|---|---|---|---|---|
| | | Mean | Variance | Mean | Variance | Mean | Variance |
| EEG | EsNet | 0.8594 | 0.0834 | 0.8867 | 0.0995 | 0.8322 | 0.0978 |
| | CNN1D-4Res | 0.8756 | 0.1190 | 0.8711 | 0.1593 | 0.8800 | 0.1192 |
| | CNN1D-5Res | 0.9461 | 0.0528 | 0.9511 | 0.0824 | 0.9411 | 0.0665 |
| EMD-EEG | EsNet | 0.9583 | 0.0295 | 0.9644 | 0.0412 | 0.9522 | 0.0571 |
| | CNN1D-4Res | 0.9783 | 0.0140 | 0.9811 | 0.0235 | 0.9756 | 0.0250 |
| | CNN1D-5Res | 0.9789 | 0.0154 | 0.9867 | 0.0202 | 0.9711 | 0.0263 |
| PSD | EsNet | 0.9544 | 0.0304 | 0.9778 | 0.0335 | 0.9311 | 0.0462 |
| | CNN1D-4Res | 0.9722 | 0.0363 | 0.9944 | 0.0079 | 0.9500 | 0.0679 |
| | CNN1D-5Res | 0.9789 | 0.0254 | 0.9933 | 0.0119 | 0.9644 | 0.0510 |
| EMD-PSD | EsNet | 0.9706 | 0.0291 | 0.9967 | 0.0075 | 0.9444 | 0.0590 |
| | CNN1D-4Res | 0.9889 | 0.0131 | 0.9978 | 0.0047 | 0.9800 | 0.0261 |
| | CNN1D-5Res | 0.9917 | 0.0137 | 0.9944 | 0.0141 | 0.9889 | 0.0181 |

Finally, we summarize the average and variance of three metrics for each fold in all cases, as shown in Fig. 8 and Fig. 9 respectively. Fig. 8 illustrates that epilepsy detection accuracy can be improved by EMD decomposition. Under the same conditions, increasing the number of layers of neural networks is beneficial to improve the detection accuracy to a certain extent. In addition, we can see that the method based on EMD decomposition can effectively reduce performance loss when the number of training samples is reduced. For example, when using the EsNet model, as the number of samples in the training dataset decreases from 40 to 10, the three metrics with EEG input decreases from 0.9338, 0.9200, 0.9475 to 0.7061, 0.7258, 0.6863, respectively, with a reduction of about 23%, 19%, 26%, while the performance loss of EMD-EEG input is only about 9%, 9%, 12% from 0.9888, 0.9875, 0.9900 to 0.8824, 0.8968, 0.8672. Similarly,




(a) Loss (b) Accuracy

**FIGURE 4.** The loss and accuracy during training process. (a) Loss, (b) Accuracy.

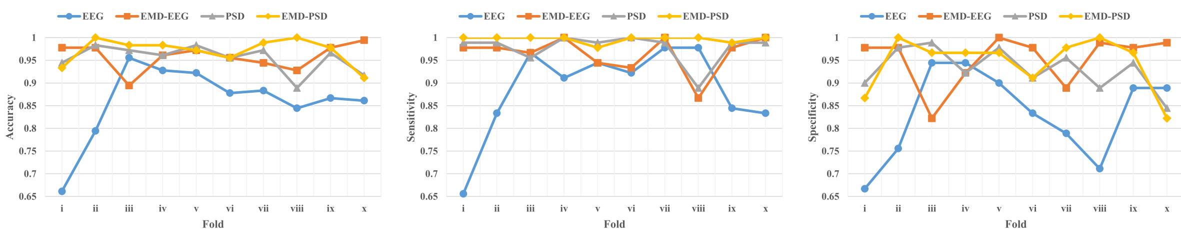



(a) Accuracy (b) Sensitivity (c) Specificity

**FIGURE 5.** The three metrics of model EsNet with 5-fold cross-validation. (a) Accuracy, (b) Sensitivity, (c) Specificity.

**TABLE 5.** The seizure detection performance with 20-fold cross-validation.

| Method | Network | Accuracy | | Sensitivity | | Specificity | |
|---|---|---|---|---|---|---|---|
| | | Mean | Variance | Mean | Variance | Mean | Variance |
| EEG | EsNet | 0.7061 | 0.0859 | 0.7258 | 0.1713 | 0.6863 | 0.2200 |
| | CNN1D-4Res | 0.7695 | 0.0934 | 0.7668 | 0.1725 | 0.7721 | 0.1426 |
| | CNN1D-5Res | 0.8645 | 0.1125 | 0.8589 | 0.1851 | 0.8700 | 0.0940 |
| EMD-EEG | EsNet | 0.8824 | 0.0843 | 0.8968 | 0.0974 | 0.8679 | 0.1543 |
| | CNN1D-4Res | 0.8966 | 0.0718 | 0.9079 | 0.0994 | 0.8853 | 0.0938 |
| | CNN1D-5Res | 0.9089 | 0.0482 | 0.9200 | 0.0803 | 0.8979 | 0.0849 |
| PSD | EsNet | 0.9468 | 0.0221 | 0.9858 | 0.0185 | 0.9079 | 0.0454 |
| | CNN1D-4Res | 0.9503 | 0.0316 | 0.9900 | 0.0143 | 0.9105 | 0.0602 |
| | CNN1D-5Res | 0.9532 | 0.0348 | 0.9895 | 0.0145 | 0.9168 | 0.0684 |
| EMD-PSD | EsNet | 0.9645 | 0.0241 | 0.9937 | 0.0158 | 0.9353 | 0.0450 |
| | CNN1D-4Res | 0.9666 | 0.0327 | 0.9932 | 0.0150 | 0.9400 | 0.0592 |
| | CNN1D-5Res | 0.9782 | 0.0249 | 0.9847 | 0.0396 | 0.9716 | 0.0368 |



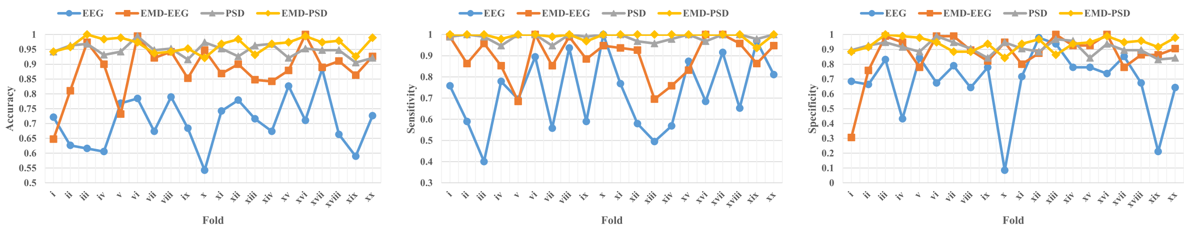

(a) Accuracy (b) Sensitivity (c) Specificity

**FIGURE 6.** The three metrics of model EsNet with 10-fold cross-validation. (a) Accuracy, (b) Sensitivity, (c) Specificity.

when using the CNN1D-5Res model, the performance loss of EMD-PSD input is 2%, 1.5%, 2.5% (from 0.9988, 1.0000, 0.9975 to 0.9782, 0.9847, 0.9716), which is less than the performance loss of PSD input by 4.4%, 1.1%, 7.9% (from 0.9975, 1.0000, 0.9975 to 0.9532, 0.9895, 0.9168). Fig. 9 shows the variance under different conditions. It can be seen that in most cases, our proposed epileptic classification method based on EMD decomposition can enhance the stability of detection.

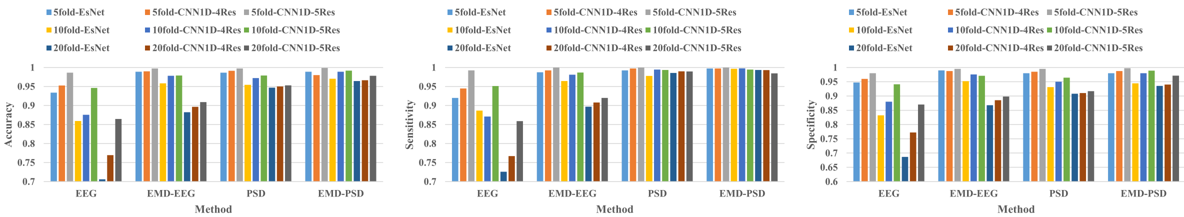
### 4) COMPARISON WITH THE STATE-OF-THE-ART METHODS

We now compare the proposed methods with the state-of-the-art epileptic seizure detection methods, including CWT-CNN [20], HE-ARMA-LSTM [26] and Hybrid [21]. CWT-CNN



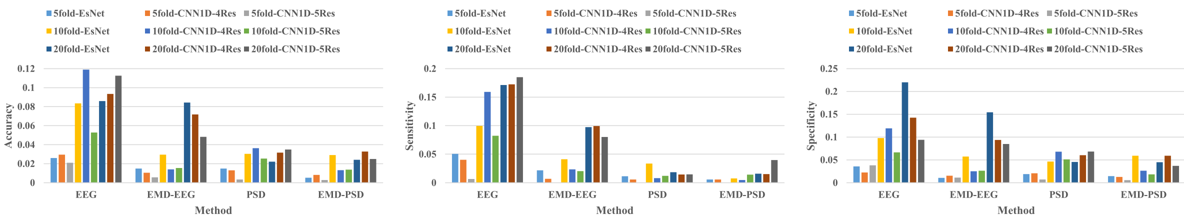

(a) Accuracy (b) Sensitivity (c) Specificity

**FIGURE 7.** The three metrics of model EsNet with 20-fold cross-validation. (a) Accuracy, (b) Sensitivity, (c) Specificity.




(a) Accuracy (b) Sensitivity (c) Specificity

**FIGURE 8.** The performance of the four methods under different fold cross-validations. (a) The mean of Accuracy, (b) the mean of Sensitivity, (c) the mean of Specificity.




(a) Accuracy (b) Sensitivity (c) Specificity

**FIGURE 9.** The performance of the four methods under different fold cross-validations. (a) The variance of Accuracy, (b) the variance of Sensitivity, (c) the variance of Specificity.

**TABLE 6.** Comparison with the state-of-the-art methods.

| Method | Few-shot | | | Adequate-sample | | |
|---|---|---|---|---|---|---|
| | Accuracy | Sensitivity | Specificity | Accuracy | Sensitivity | Specificity |
| CWT-CNN [20] | 0.8867 | 0.9500 | 0.9000 | 1.0000 | 1.0000 | 1.0000 |
| HE-ARMA-LSTM [26] | 0.8495 | 0.8811 | 0.8178 | 0.9778 | 0.9892 | 0.9570 |
| Hybrid [21] | 0.9622 | 0.9878 | 0.9367 | 0.9920 | 1.0000 | 0.9890 |
| EMD-EGG | 0.9789 | 0.9867 | 0.9711 | 0.9950 | 1.0000 | 0.9900 |
| EMD-PSD | 0.9917 | 0.9944 | 0.9889 | 1.0000 | 1.0000 | 1.0000 |

uses continuous wavelet transformation of EEG to obtain two-dimensional frequency-time scalograms, and adopts convolutional neural network to learn the properties of these scalograms to seizure detection. HE-ARMA-LSTM uses EEG to generate autoregressive moving average (ARMA) features and Hurst exponent, and designs a two-layer LSTM classifier to seizure detection in EEG signals. Hybrid uses the mixed input format of EEG, including original EEG, fourier transform of EEG, STFT of EEG and wavelet transform of EEG, to construct a feature fusion convolutional neural network for seizure detection. Both CWT-CNN and HE-ARMA-LSTM were subjected to 10-fold cross-validation experiments under a scenario of adequate-sample, which deviates from the few-shot setting established in this paper. In order to provide a comprehensive and fair comparison, we conduct additional experiments comparing the performance of all algorithms under scenarios of both adequate-sample and few-shot. In the adequate-sample scenario, the entire dataset was divided into 10 equal parts, with nine parts used as training data in each fold and the remaining part used as test data. The comparison results are shown in Table 6.

It can be seen that in adequate-sample scenario, all five methods demonstrate good performance, with CWT-CNN and EMD-PSD achieving 1.0000 for three metrics. In few-shot scenario, the EMD decomposition method has significant improvement in all three metrics compared with the existing methods, which are about 6.7%, 12.9%, and 1.8%

compared with CWT-CNN, HE-ARMA-LSTM, and Hybrid, respectively. Similarly, PSD-based EMD decomposition also shows significant improvement compared to EMD decomposition only, with the three metrics improving by 1.2%, 0.7%, and 1.7%, respectively. These results further demonstrate the effectiveness of the EMD enhancement based epilepsy detection method.

## V. CONCLUSION

In this paper, we focus on epileptic seizure detection based on deep learning in few-shot scenarios. We have proposed two methodologies, EMD-EEG and EMD-PSD, which leverage EMD alongside deep learning for seizure detection. We conduct extensive experiments and adopt multiple performance metrics to evaluate the performance of our proposed method. Experiments include performance on different cross-validation and comparison with the state-of-the-art methods. Performance metrics include accuracy, sensitivity, and specificity. Results have shown that the epilepsy detection performance of the EMD-EEG method is better than that of EEG-based deep learning methods. Similarly, the EMD-PSD method exhibits superior performance compared to direct PSD-based approaches. Moreover, the EMD-PSD method outperforms existing state-of-the-art epilepsy detection methods. These results have validated the advantages of our proposed methods in seizure detection in few-shot scenarios.

In the future, considering the high computational complexity and high demand of computational resources for deep learning methods, a lightweight network will be exploited to improve the efficiency of epilepsy detection in order to solve the practical deployment problem. Meanwhile, we will consider applying the proposed method to other medical fields, such as the diagnosis of schizophrenia (SZ) [39], autism spectrum disorder (ASD) [40] and attention deficit hyperactivity disorder (ADHD) [41].

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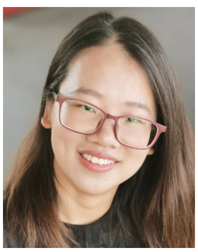

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