Journal of Ambient Intelligence and Humanized Computing
https://doi.org/10.1007/s12652-019-01220-6

ORIGINAL RESEARCH

Mean amplitude spectrum based epileptic state classification for seizure prediction using convolutional neural networks

Wenbin Hu[1] · Jiuwen Cao[1,2] · Xiaoping Lai[1] · Junbiao Liu[2]

Received: 19 August 2018 / Accepted: 18 January 2019

Abstract

An increasing number of algorithms have been proposed for epileptic seizure prediction in recent years. But most of them are based on a partition of the electroencephalograph (EEG) signal of an epileptic patient into preictal, ictal (seizure), and interictal states. In this paper, we propose to further divide the preictal interval into multiple subintervals. Besides discriminating the seizure state from the preictal and interictal states, we also distinguish the preictal subintervals from each other. An epileptic state classification algorithm for epileptic EEG signals is then developed. The amplitude spectrums of EEG signals from 18 channels are firstly calculated and divided into 19 frequency subbands. The mean amplitude spectrum (MAS) on each of the 19 frequency subbands is then computed for each channel to form a MAS map of size 18×19. Finally, the MAS map is fed to a convolutional neural network (CNN) for feature extraction and a support vector machine (SVM) is employed for the epileptic state classification. Experiments show that, for a three-subinterval partition of the preictal state, a classification accuracy of 86.25% has been achieved on the CHB-MIT database by the MAS-based epileptic state classification algorithm using CNN and SVM.

Keywords Seizure prediction · Preictal state · CNN · Mean amplitude spectrum · Support vector machine · EEG

1 Introduction

Epilepsy is a chronic neurological disorder of the brain and poses a serious threat to patients due to its high burstiness and recidivity (Skjei and Dlugos 2011). Hence, investigating preventive methods for epileptic seizure becomes important and significant (Elger 2001).

The electroencephalogram (EEG) signal has been demonstrated to be effective for epileptic seizure classification (Perucca et al. 2013; Mormann et al. 2005, 2006; Witte et al. 2003). Fruitful feature extraction methods for the epileptic EEG had been reported in the past, including the maximum Lyapunov index (Iasemidis and Sackellares 1996), Fourier spectrum entropy (Blanco et al. 2013), cumulative energy curve (Litt et al. 2001), autocorrelation and correlation density (Martinerie et al. 1998), similarity index (Le Van et al. 2001) and power spectral density (Park et al. 2011; Alarcon et al. 1995; Celka and Colditz 2002). For epileptic seizure classification, many machine learning algorithms had been adopted. To name a few, Netoff et al. (2009) extracted the power spectral density on frequency subbands of the EEG signals to characterize the epileptic seizure and utilized the cost-sensitive support vector machine (CSVM) for classification. An average classification accuracy of 80% was derived in Netoff et al. (2009). Williamson et al. (2011) developed the multivariate signal coherence features for epileptic seizure representation from multichannel EEGs. The principal components analysis (PCA) was then adopted for dimensionality reduction and the SVM was applied for epileptic seizure classification. A classification rate of 90.8% and a false positive rate of 9.4% can be achieved in Williamson et al. (2011). Park et al. (2011) used the power spectra of nine specific frequency bands as the features and applied the

✉ Jiuwen Cao
jwcao@hdu.edu.cn

Wenbin Hu
162060148@hdu.edu.cn

Xiaoping Lai
laixp@hdu.edu.cn

Junbiao Liu
liujunbiao@neurotech.cn

1 Institute of Information and Control, Hangzhou Dianzi University, Hangzhou, China

2 Hangzhou Neuro Science and Technology Co. Ltd, Hangzhou, China

Published online: 02 February 2019

CSVM as the classifier. The approach obtained a 97.5% classification rate and a false recognition rate (FPR) of 0.27/h in all 80 seizure events with bipolar preprocessing. Zhang and Parhi (2016) designed a patient-specific epileptic seizure prediction algorithm with a low hardware complexity, where the spectral power and the spectral power ratios were first computed and then selected in a patient-specific manner. The linear SVM was then adopted for seizure classification, and a recognition rate of 98.68% was obtained on the Freiburg database. Song and Zhang (2017) studied the seizure detection using the lagged Poincaŕe plots of EEG with the popular extreme learning machine algorithm (Cao et al. 2018).

With the rapid development of deep learning algorithms, convolutional neural networks (CNNs) have been explored for epileptic seizure prediction in recent years (Achilles et al. 2018; Acharya et al. 2017; Mirowski et al. 2008; Truong et al. 2017). Comparing with conventional epileptic seizure classification algorithms, deep learning algorithms are superior in feature extraction from complex EEG signals. Achilles et al. (2018) aimed to develop a non-invasive automatic home monitoring system for epileptic seizure detection with a video-EEG system. The CNN had been applied to learn the sleep motions of patients in the ictal phases and interictal phases through video frames recorded by a combined depth and infrared (IR) sensor. Acharya et al. (2017) utilized a 13-layered deep convolutional neural network for seizure prediction where the raw EEGs were directly fed to the CNN as inputs. An average classification rate of 88.67% on the benchmark Bonn dataset (Nigam and Graupe 2004; Srinivasan et al. 2005, 2007) was obtained. Mirowski et al. (2008) compared the seizure prediction performance on the Freiburg database by three algorithms, namely the ℓ_1-reguralized logistic regression, CNN and SVM, where the aggregated EEG features consisting of the cross-correlation, nonlinear interdependence, Lyapunov exponents, and wavelet based synchrony had been analyzed. The Freiburg EEG dataset, which contains data of 21 patients, was used in Mirowski et al. (2008). It was reported that among the three algorithms, at least one method could predict 100% of the seizure without false alarms for each patient. Truong et al. (2017) designed a robust and patient-specific seizure prediction algorithm based on CNN, where the amplitude spectrums on different frequency bands calculated from EEG signals were used as the inputs of CNN. Experiments on the CHB-MIT database shew a 81.2% sensitivity.

Although extensive studies on epileptic seizures had been presented, most of them focused on epileptic seizure classification or seizure/non-seizure detection and little attention had been paid to the preictal state classification. An accurate preictal state classification of epileptic seizure is significant for patients to take precaution to reduce the harm caused by epileptic seizure due to its burstiness and recidivity. Along with the recent rapid development of portable and wearable EEG recording and monitoring devices, designing effective epileptic state classification algorithms becomes urgent as well as valuable for practical applications. In this paper, we present a novel epileptic state classification algorithm for seizure prediction based on the mean amplitude spectrum (MAS) of the EEG signals and CNNs. The main contributions of the paper are threefold: (1) The 1 h preictal interval is divided into several consecutive non-overlapped subintervals and the preictal state prediction is transferred to a multi-class classification problem. By identifying which subinterval the EEG signal frames belong to, we may be able to predict how long later a seizure will happen. (2) The amplitude spectrums of the 18-channel EEG signals are divided into 19 frequency subbands and the MASs of the 18 channels on the 19 frequency subbands, and an 18×19 MAS map consisting of the subband spectra is adopted for the signal representation. (3) An epileptic state classification algorithm that consists of a CNN for feature extraction and an SVM for classification, and uses the MAS map as the input is constructed. The CNN has convolutional layers for feature learning, each followed by a max-pooling layer for downsampling, and a softmax layer to derive the class probability distribution of the input sample. The extracted class probability distributions are finally fed to the SVM for epileptic seizure state classification. To demonstrate the effectiveness of the proposed algorithm, experiments on the benchmark CHB-MIT database are conducted and comparisons with several state-of-the-art approaches are provided. Two different preictal state partitions are studied in the experiments, one dividing the 1 h preictal interval into three and the other into six consecutive non-overlapped equi-length subintervals, respectively

2 The proposed classification algorithm

2.1 Partition of the preictal interval

Epilepsy is one of the common diseases of the nervous system. Its outward effects are varied, including the uncontrolled jerking movement, the complex partial seizure, the momentary loss of awareness, etc. The recurrence rate of epilepsy is high. It is presented in Wilden and Cohen-Gadol (2012) that following the first seizure, the risk of more seizures in the next 2 years is as high as 40–50%. The preictal state classification is crucial to taking precaution to reduce the harm caused by epileptic seizures. A 10–20 min ahead prediction of the epileptic seizure can help prevent the potential collateral damages by the seizures. Electroencephalogram (EEG) signals, which record the scalp potential resulting from brain activities, are shown to be effective for the investigation of the electrical activity of human brain. EEG signals have been widely used in epilepsy analysis and

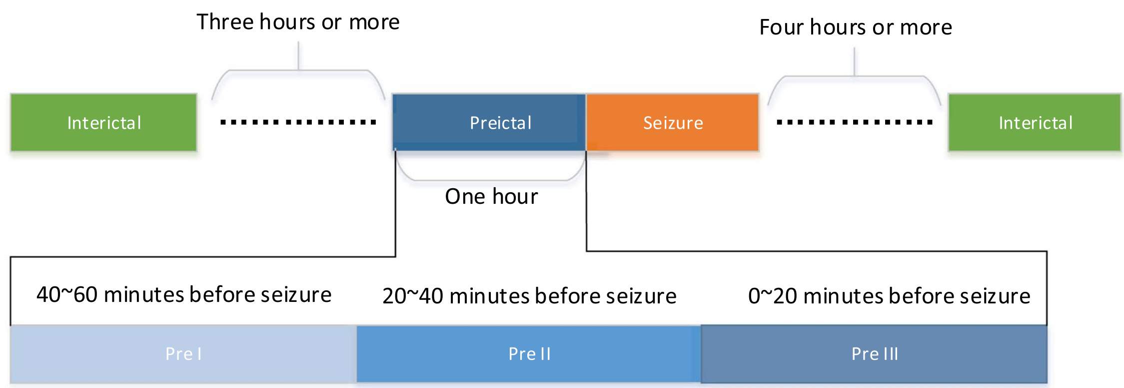

Fig. 1 Partition of an EEG signal with a division of the preictal interval into three subintervals

seizure detection. The rapid development of wearable EEG recording and processing devices makes the preictal state classification for epilepsy seizure prediction realizable. But there still lacks of effective preictal state classifications. To this end, we focus on analysing the preictal state of the epilepsy for prediction of its seizure in this paper. The 1 h preictal time interval of an EEG signal before the seizure is partitioned into several non-overlapped time segments. Then, the seizure can be predicted by identifying which segment a preictal EEG signal falls in.

Typically, we divide the preictal EEG signal into three consecutive non-overlapped segments in this paper, each with a 20-min duration of the EEG signal. A five-category classification problem is then formulated, where the five categories of the epilepsy states includes one interictal state, three preictal states named as PreI, PreII, and PreIII, and one seizure state, as shown in Fig. 1. The three preictal states represent the states 40–60 min, 20–40 min, and 0–20 min before the seizure, respectively. Though an accurate seizure time prediction is difficult for the epilepsy, a time-interval prediction of the epileptic seizure is very possible and also useful if the five epileptic states, especially, the three preictal states can be accurately classified. In addition, we will also experiment on partitioning the preictal interval into more and smaller segments and compare with the partition of the preictal interval into three segments.

2.2 MAS map of EEG signals

The EEG signal reflects the scalp potential difference between electrodes in different positions on the scalp surface. Describing the EEG in terms of rhythmic activities has become a standardization in epilepsy analysis and the effectiveness of the method had been justified in many researches. The frequency range of an EEG signal is mainly concentrated in 0.3–70 Hz. The δ rhythm of the EEG signal denotes the activity with frequency lower than 4 Hz. The frequency ranges of the θ, α, β, and low-γ rhythmic activities are 4–8 Hz, 8–13 Hz, 13–30 Hz, and 30–70 Hz, respectively. Adults generally have no δ waves in their sober state. The frequency, amplitude, and spatial distribution of the α wave are important indicators of the brain state. It is also shown that the β rhythm is the main brain waves when the cerebral cortex is in an excitement state. In general, EEG signal is very complicated and its relevance to epilepsy is still not fully exploited. The sharp waves, spike waves, sharp slow complex waves, spinous slow complex waves and other paroxysmal abnormalities in EEG are called the epileptiform discharges.

To derive an effective EEG feature representation for the epileptic state classification, we exploit the amplitude spectrums on various bands and employ the convolutional neural network for feature learning. The general flowchart of the proposed epileptic state classification algorithm is drawn in Fig. 2. In the flowchart, the EEG signal has been assumed to be of 18 channels. For each channel, the raw EEG signal is first transformed using FFT to frequency components, and those frequencies lower than 70 Hz are employed for feature extraction as they cover the typical rhythmic activities well. Then the frequency band 0–70 Hz is divided into 19 frequency subbands, where each of the frequency bands of the δ rhythm, θ rhythm, and α rhythm is divided into three subbands, each of the frequency bands of the β rhythm and low-γ rhythm is divided into five subbands. It is suggested that the frequency near 60 Hz should be filtered out for eliminating power frequency interference. Hence, for the low-γ rhythm, the frequency interval 57–63 Hz is discarded during feature extraction. The amplitude spectra are computed for the EEG signals of the 18 channels. The 19-band mean amplitude spectra (MAS) are then derived for all of the 18 channels. Finally, an 18×19 MAS map is constructed as the feature for each frame of the EEG signal. The detailed calculation of MAS is elaborated in the following.

For each channel, the discrete Fourier transform (DFT) on a frame of EEG signal is:

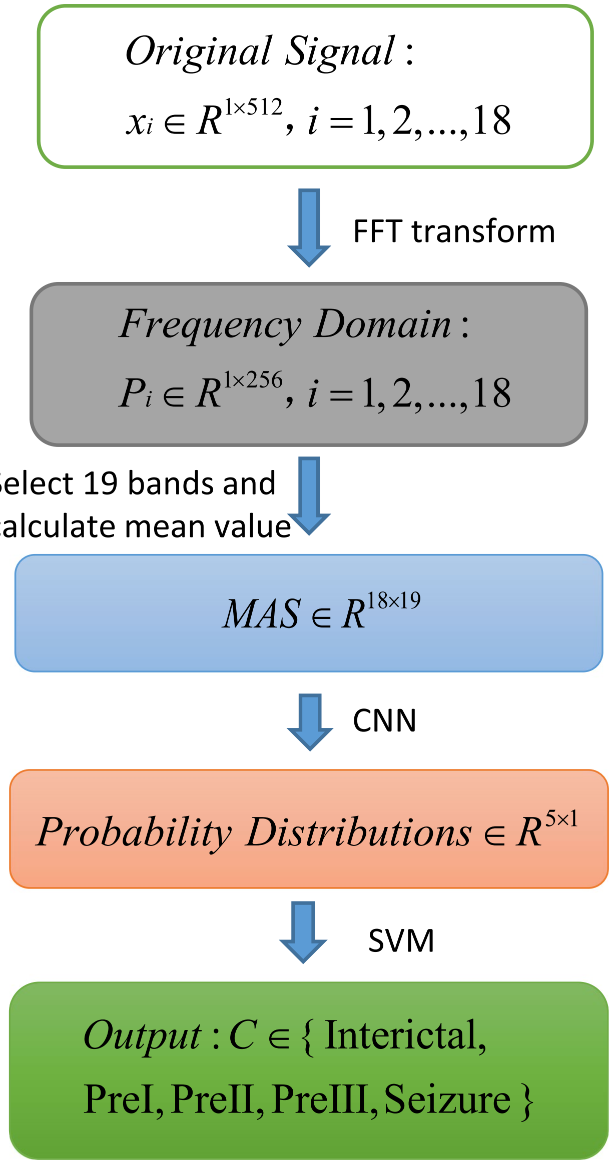

Fig. 2 The flowchart of the proposed preictal state classification algorithm

$$X_k = \sum_{n=0}^{N-1} x(n) e^{-\frac{2\pi j}{N}kn}, \tag{1}$$

where N denotes the frame length and $k = 0, \ldots, N-1$. The amplitude spectrum can be calculated as

$$P(k) = |X_k|. \tag{2}$$

For the δ, θ, α, β, and low-γ rhythms, the ranges of k are 1–8, 8–16, 16–24, 24–60, 60–140, respectively. Using the aforementioned method to decompose the frequency bands of the five rhythmic waves, three frequency subbands for the δ, θ, α rhythms and five subbands for the β and low-γ rhythms are obtained. For the δ rhythm, as an example, the frequency band $0 \sim 4$Hz is divided into the 0.5–1.5 Hz, 1.5–2.5 Hz, and 2.5–4 Hz subbands corresponding to $k \in \{1, 2, 3\}, \{3, 4, 5\}, \{5, 6, 7\}$, respectively. Totally, the whole frequency range 0–70 Hz is divided into 19 subbands.

To characterize the amplitude spectrum on different rhythmic activities, the 19-band MAS is computed by

$$\mathrm{MAS}_i = \mathrm{mean}(P(k), k \in K_i), \tag{3}$$

where $i = 1, 2, \ldots, 19$ represents the i-th frequency sub-band and K_i denotes the set of values of k of the i-th subband. For each channel, an MAS vector $\boldsymbol{v}_{\mathrm{MAS},\kappa}$ is then derived, where κ represents the channel index. Finally, for each frame of the EEG signal, an 18×19 MAS map is constructed from the 19-dimensional MAS vectors obtained for the 18 channels.

To illustrate the the difference between MAS's of the EEG in different epileptic states, we show the raw time-domain signals, the extracted MAS's, and the power spectra of one-channel signal in five different states of the epilepsy in Fig. 3a–c, respectively. The EEG data are from the CHB-MIT database which recorded 23 channels of EEG signals in a sampling rate of 256 Hz. We chose 18 channels, i.e., the FP1–F7, F7–T7, FP1–F3, to compute the MAS's in our experiments. From Fig. 3a we can see that the time-domain signal vibrates increasingly heavily with the seizure coming close. From Fig. 3b, the amplitude of the MAS at low frequency increases gradually with the coming seizure. Similarly, Fig. 3c also shows an obvious difference on the power spectra among the five states, especially at the frequencies below 30 Hz. It is noteworthy that, in Fig. 3b, only the most informative components with the frequency range 0–70 Hz are used, but in Fig. 3c, all components in the whole frequency range 0–128 Hz are shown. The components in 70–128 Hz will be further studied in one of our experiments in Secti 3 to compare the classification accuracies based on EEG signals in different frequency bands.

2.3 Convolutional neural network

Convolutional neural network (CNN) is effective in for large scale and high-dimensional data learning. In this paper, we adopt a CNN with dropout to perform local feature learning on the MAS map derived from the EEG signal. Two convolutional layers, the first layer with 128 kernels and the second layer with 256 kernels, are used in the CNN. The learnable kernel size in each layer is set to be 5×5. The popular ReLU activation function is employed in each convolutional layer. Followed each convolutional layer, a max-pooling layer is applied to perform downsampling such that the redundant information and noises can be reduced. The patch size used in max-pooling is 2×2. Hence, for each 18×19 input sample, a feature map with the size of 14×15 can be obtained in the first convolutional layer. The size of the feature map in each kernel is reduced to 7×7 after the

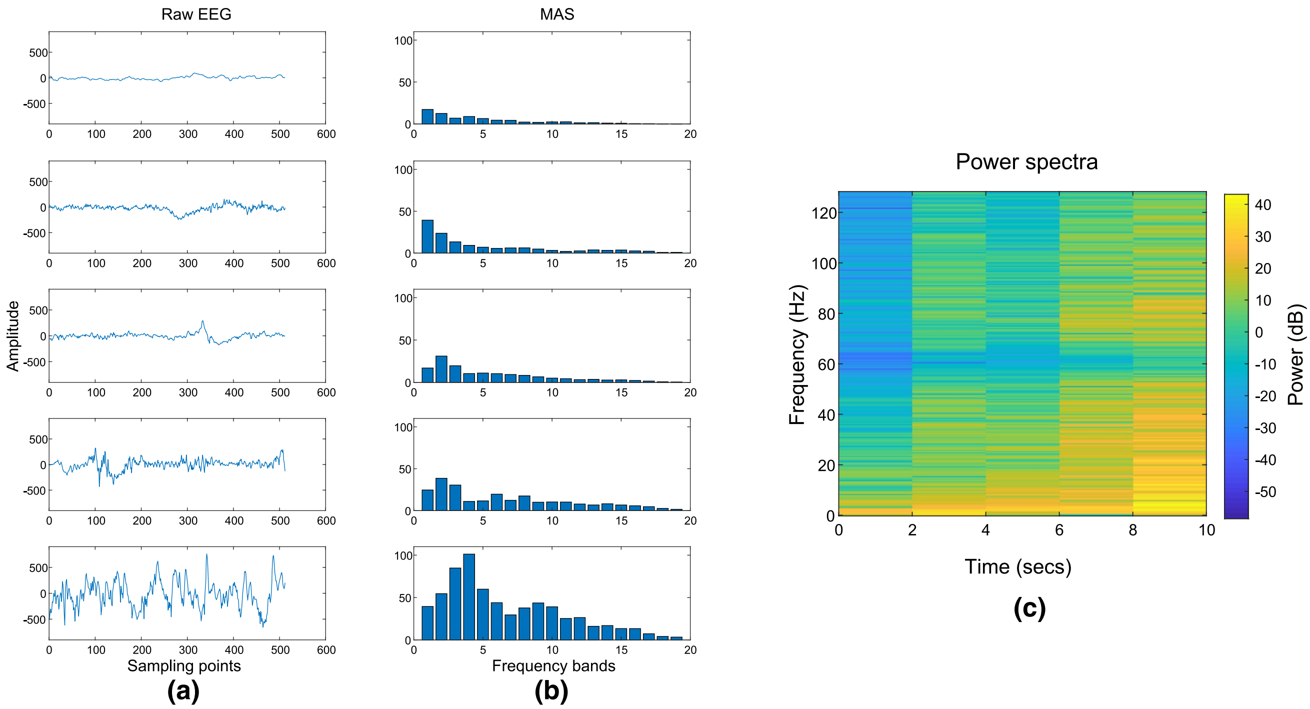

Fig. 3 EEG signals and their spectra in the five epileptic states. **a** The raw 2s-length signals in the time domain. Each picture from the top to bottom represents the Interictal, PreI, PreII, PreIII and Seiture stage of the epilepsy, respectively. **b** The 19-bands MAS's of the EEG signal (containing EEG data from 0 to 70 Hz) in the five epileptic states. **c** The power spectra of the EEG signal (including EEG data from 0 to 128 Hz) in the five epileptic states. Every 2-s interval from the left to the right represents the power spectrum in the Interictal, PreI, PreII, PreIII and Seizure states, respectively

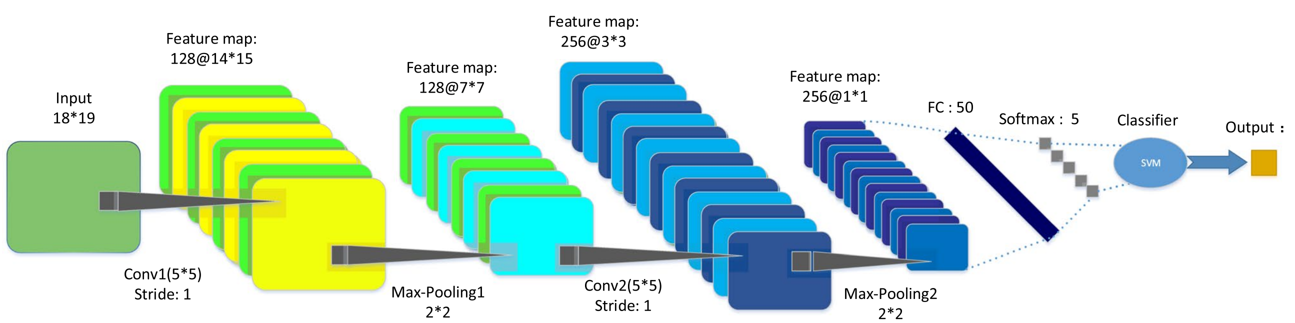

Fig. 4 The CNN structure used in the paper

max-pooling layer. Similarly, in the second convolutional and max-pooling layers, the sizes of the extracted feature maps for each kernel are 3×3 and 1×1, respectively. After the convolution and max-pooling layers, a fully connected (FC) layer with 50 neurons is applied to learn the global features, and a max-pooling is performed in the FC layer to prevent overfitting. Before feeding to the classification layer, a softmax layer is adopted to derive the probability distribution across the different classes corresponding to different epileptic states. The network structure used in this paper is shown in Fig. 4. More details of the CNN are given below:

2.3.1 Convolutional layer

Denote the k-th input map and i-th output map of a convolution layer as $\mathbf{H}_k^{in}$ and $\mathbf{H}_i^{out}$. Then,

$$\mathbf{H}_i^{out} = f\left\{ \sum\nolimits_k \mathbf{H}_k^{in} \otimes \mathbf{W}_{ki} + \mathbf{b}_i \right\}, \tag{4}$$

where the symbol $\otimes$ represents the convolution operation, $\mathbf{W}_{ki}$ and $\mathbf{b}_i$ are the convolution filter between the k-th input map and the i-th output map and the i-th offset matrix of the neurons corresponding to the i-th output map. The function $f(\cdot)$ is an element-wise nonlinear activation function.

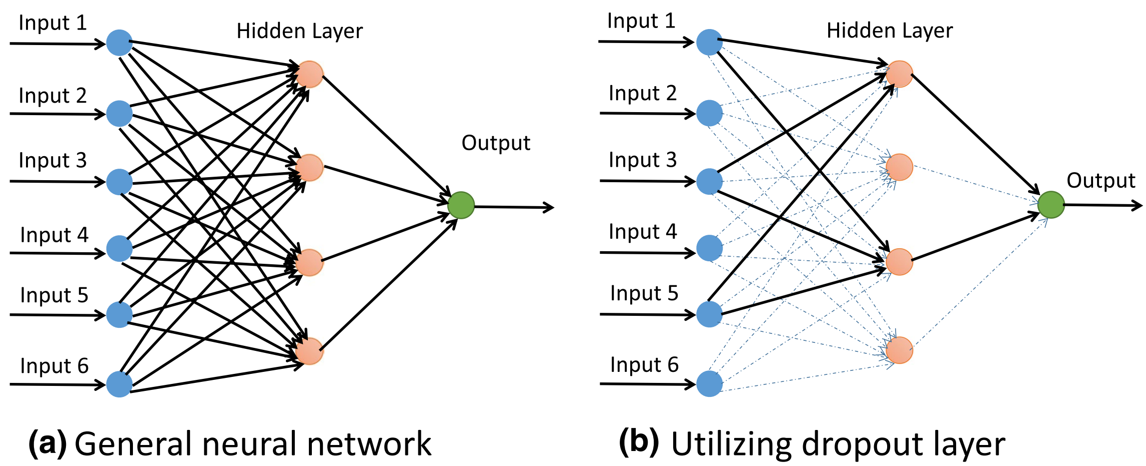

Fig. 5 The FC layer **a** before **b** after the dropout

In this paper, the ReLU function is used as the activation function, i.e.,

$$f(x) = \max(0, x). \tag{5}$$

2.3.2 Max-pooling layer

The max-pooling layer is added after each convolutional layer to reduce the dimension of the feature map and to maintain the translation invariant of the feature to some extent. The rule of the max-pooling layer is shown in (6) and the maximum value of each region will be retained and used as the input of the next layer. The size of the max-pooling filter is set to be 2×2 in this paper.

$$\mathbf{H}^{out} = \mathrm{subsampling}(\mathbf{H}^{in}). \tag{6}$$

2.3.3 Dropout

Overfitting is a common issue in the gradient descent algorithm. To prevent the overfitting, a dropout is performed in the FC layer. The basic idea of the dropout operation is throwing away the activation of some neurons randomly during the training of the CNN. For illustration, Fig. 5a shows the FC layer of the CNN before the dropout and Fig. 5b depicts the FC layer after the dropout. Some of the neurons and weights are randomly discarded with a certain probability during the training. In our proposed epilepstic state classification algorithm, the probability of dropout is set to be 0.5.

2.3.4 Softmax layer

The last layer of the CNN in the proposed epileptic state classification algorithm is a softmax layer. It has 5 neurons, each with the softmax activation function. The output of the softmax layer is a vector, the dimension and entries of which are equivalent to the number of categories associated with the epileptic states and the probabilities of the sample belonging to the categories. The output of softmax layer is calculated by:

$$S_j = \frac{e^{a_j}}{\sum_{k=1}^{T} e^{a_k}} \tag{7}$$

where T, a_j and S_j represent the total number of categories, the net input of the j-th neuron of the softmax layer, and the output of the j-th neuron. That is, S_j represents the probability of the sample belonging to the j-th epileptic state respectively.

2.4 Support vector machine

For a two-class classification problem, given a dataset $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_n, y_n)$, $\mathbf{x} \in R^m$, $y \in \{+1, -1\}$, the SVM aims to find a hyperplane $(\mathbf{w} \cdot \mathbf{x}) + b = 0$ to

$$\min_{\mathbf{w},\mathbf{b}} \ \phi(\mathbf{w}) = \frac{1}{2}(\mathbf{w}^T\mathbf{w}) + C\sum_{i=1}^{n} \xi_i \tag{8a}$$

$$\text{subject to} \ \ y_i[(\mathbf{w} \cdot \mathbf{x}) + b] \geq 1 - \xi_i \quad i = 1, 2, 3 \ldots n. \tag{8b}$$

Here, ξ_i denotes the slack variables and C is a penalty parameter.

In a multi-classification task with M categories, a total of $M * (M - 1)/2$ binary SVMs are trained using the "one-against-one" rule, where $M \geq 2$ represents the number of categories. Then for each sample, the class with the most votes by the binary SVMs is the winner.

In general, the CNN uses the output of the softmax layer to perform the classification. To have a robust and convincing epileptic state classification performance for seizure prediction, we add a multi-classification SVM to build a classifier based on features extracted by the CNN. The extracted probability feature vector by the softmax layer of the CNN is taken as the input of the multi-classification SVM.

Algorithm 1 gives a brief summary of the proposed epileptic state classification algorithm.

Algorithm 1: The epileptic state classification algorithm

Input : Raw EEG data, learning rate and momentum value of the gradient descent method, maximum iterations n, stride and size of max-pooling layer, the number and size of convolution kernels in convolutional layers, the number of neurons in two fully connected layers.
Output : The category of the testing EEG.

Training process:
Divide the original data into interictal, PreI, PreII, PreIII, seizure five categories as trainning set;
Frame the samples of each class into a 2s-length segments;
Calculate the DFT of the fragmented EEG signals and compute their amplitude spectra;
Compute the MAS's of the EEG signals in all channels;
Construct the MAS maps of all training sample EEG signals;
Train the CNN with the proposed structure and parameters;
Obtain the probability vectors from the softmax layer for all input MAS maps;
Train the SVM classifier using the probability vectors obtained in the softmax layer.
Testing processs:
Load model and test data;
Frame the test data into 2s-length segments;
Construct the feature map for each test segment;
Obtain the output for each segment using the model trained before.

3 Experiments and discussions

Experiments are conducted in this section to validate the performance of the proposed epileptic state classification algorithm for seizure prediction. The results on three testing scenarios are reported. The first experiment tests the parameter sensitiveness of the proposed CNN based epileptic state classification algorithm. The second experiment shows the performance comparisons on different preictal interval segmentation strategies. In this experiment, two partitions are studied and discussed, one divides the 1-h preictal interval into three and the other into six non-overlapped sub-intervals, respectively. The last experiment shows the performance comparisons with algorithms based on the state-of-the-art EEG feature extraction and machine learning methods.

The EEG data in our experiments are from the CHB-MIT database[1] collected at the Children's Hospital Boston (CHB) and contributed to PhysioNet by investigators from CHB and the Massachusetts Institute of Technology (MIT). The database is composed of EEG recordings from pediatric patients with intractable epilepsy. The EEG signals are collected from 23 patients and are grouped into 24 cases, each recorded in 23 channels with a sampling rate of 256 Hz. The data of case 1 and case 21 are collected from the same patient at different time with 1.5 years interval. All these EEG signals are divided into three categories, namely, the interictal, preictal and ictal states, respectively, where the duration of the preictal state is 1 h. In this experiment, we manually slice the preictal state into three non-overlapped signal segments in the three states PreI, PreII, and PreIII we previously defined in Sect. 2.2, respectively. In the experiments, the EEG signals recorded in 18 selected channels are used for the epileptic state classification. The database includes 178 min of EEG signals in the ictal state, and 180 min of EEG signals in the preictal and interictal states. The frame length of the EEG signal used in DFT is set to be 2 s and the frame overlap is one second. For the seizure state, there are 10719 MAS map samples, and for each of the rest four states, there are 10799 MAS map samples.

3.1 Performance on network parameters

In this section, we test the parameter sensitiveness of the proposed MAS-based epileptic state classification algorithm using the CNN+SVM, including the learning rate, the momentum, and the number of convolutional layers, etc. The robust stochastic gradient descent algorithm (SGD) with a learning momentum (SGDM) is adopted for the network training. In this experiment, the CHB-MIT database with five categories and three preictal states is adopted. The training and testing data are randomly selected from the whole dataset with a ratio $4:1$. The momentum in the SGDM algorithm determines the contribution of the gradient during the error propagation. The value of momentum is set within the region [0, 1]. The learning rate controls the convergence speed of the training algorithm. In general, a large learning rate can speed up the training, but the training is more likely to get stuck in a suboptimal result. We test the performance on different combinations of the learning rate and the momentum. For each parameter combination, the average classification accuracy on multiple trials is reported. The maximum iterations of the SGDM algorithm in the proposed CNN method are set to be 80 for all trials. The learning rate and the momentum value are taken from the regions $\in [0.006, 0.012]$ and $\in [0.5, 0.8]$, respectively. Fig. 6 depicts the classification accuracy on the CHB-MIT database with respect to different combinations of the learning rate and momentum value. It is readily seen that besides

[1] The CHB-MIT EEG database, Available: https://epilepsy.uni-freiburg-seizure-prediction-project/eeg-database/

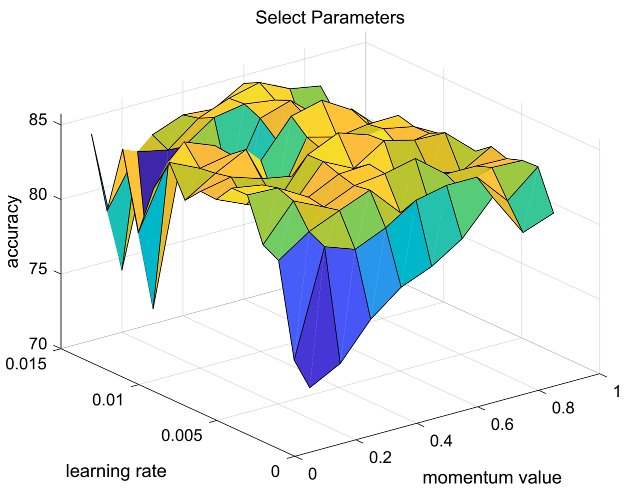

Fig. 6 Classification accuracy on different momentum values and learning rates

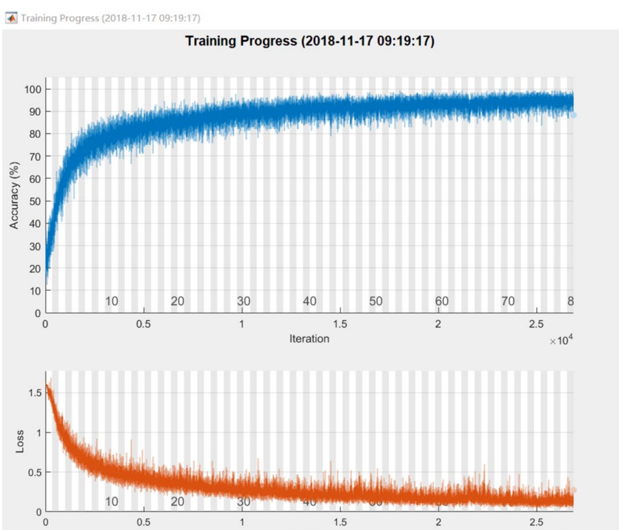

Fig. 7 The confusion matrix of classification rate with the proposed CNN+SVM and MAS-based classification algorithm

the parameter combination with the very small learning rate (less than 0.004) and momentum value (less than 0.4), the proposed CNN based epileptic state classification algorithm for seizure prediction shows a stable classification performance on various parameter combinations. In addition, the performance improvement of the model with increasing of training iterations is shown in Fig. 7, which indicates that setting the parameter for training epoch to 80 is sufficient for the algorithm to converge.

Particularly, to show the detailed accuracy, we give the confusion matrix of the classification accuracy on each category with the proposed MAS-based prediction algorithm using the CNN+SVM in Fig. 8. In this experiment,

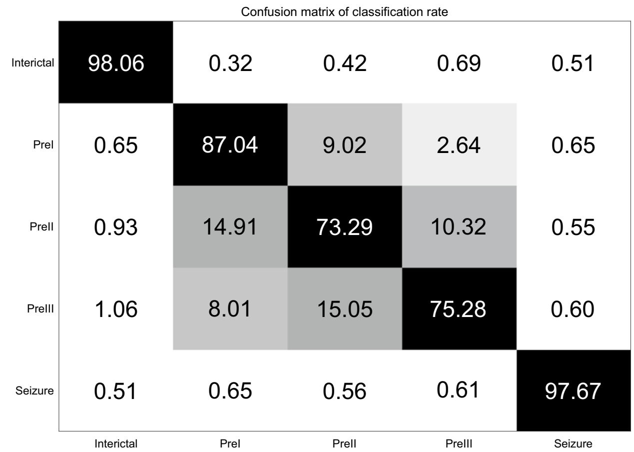

Fig. 8 The confusion matrix of classification rate with the proposed CNN+SVM and MAS-based classification algorithm

the learning rate and momentum are set to be 0.005 and 0.8, respectively. The classification rates presented in the diagonal represents the correct accuracy of each category. The other values in each row indicate the percentage of samples which are misclassificated to other classes. It can be seen that the correct classification rates of the interictal and seizure categories are as high as 98.06% and 97.67%, respectively. Most of the misclassifications happen within the three preictal categories. It is obvious that the EEG signals of the three preictal categories have similar features, leading to high misclassification rates. For example, for the PreII category, more than 14% and 10% samples have been wrongly assigned to the PreI and PreIII categories, respectively. Similar observations of rates can be found for the PreI and PreII categories misclassification. The classification performance with respect to different numbers of convolutional layers in CNN is further studied in this section. In general, the deeper the network structure is, the longer the training phase tend to be. Besides using the aforementioned CNN structure, one more convolutional layer containing 64 kernels with the size of 3×3 is added before the first convolutional layer of the aforementioned CNN. It is found that the classification accuracy slightly increased from 86.25 to 86.31% but the increased computation burden in terms of the CPU time is more than 20 min. Hence, increasing the depth of the network improved very little on the classification performance, but led to a lot of computation increment on the network training.

3.2 Performance on different preictal state partition strategies

An accurate detection on the preictal state is crucial to patients with a history of epilepsy seizure. As shown in the

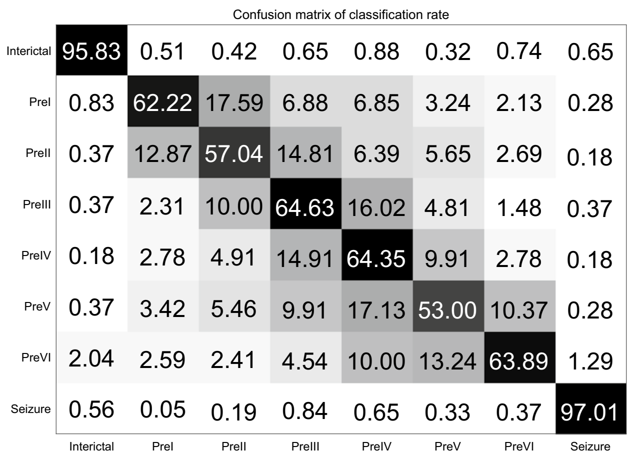

Fig. 9 The confusion matrix of classification rate obtained by CNN+SVM based on MAS algorithm on eight category EEG signal

Table 1 Performance on different partition strategies to preictal

Accuracy(%)	Category	
	5 categories	8 categories
Algorithm		
CNN+MAS	86.25	72.87

previous experiment, most of the misclassifications happen within the three preictal states when a 20-min interval segmentation is imposed. It is normally due to that the features of the EEG signal within segmentations of the preictal state are similar. In general, a finer segmentation on the preictal state has the possibility of a more accurate prediction of the seizure time, but may lead to a higher misclassification rate between the preictal states.

To further illustrate the preictal state classification performance, we test the proposed CNN+SVM based on MAS algorithm on another preictal state partition strategy, where the 1 h signal in preictal state is partitioned into six non-overlapped segments, each with a 10-min duration. An eight-category classification problem is then formulated. Table 1 shows the comparisons on the overall classification rates obtained by the proposed CNN+SVM based on MAS algorithm with the two preictal state partition strategies. As previously commented, the classification rate reduces to 72.87% when a finer segmentation with the 10-min duration is used in the preictal state.

The confusion matrix obtained on the partition EEG dataset is shown in Fig. 9. Similar observations to those in the previous subsection can be found. Although the overall classification rate is not high, the classification rates of the interictal and the seizure states are as high as 95.83% and 97.01%, respectively. Misclassifications are generally within the six preictal categories, as none of the preictal categories can have a classification rate higher than 65%. It is also noteworthy that for each preictal state category, the highest misclassifications happens between the nearest categories of the preictal state. For instance, the two highest misclassifications of the PreI category are 17.59% and 6.88%, one with respect to the PreII category and PreIII category. Same observations can be found in Fig. 9 for the rest five preictal categories PreII~PreVI. It is true that in general, the closer the segments (categories) are, the more similar the features of EEG signals of these categories tend to be.

3.3 Performance comparisons with state-of-the-art algorithms

In this experiment, we compare the epileptic state classification performance of the proposed algorithm with several algorithms based on state-of-the-art EEG feature extraction methods and machine learning models. The traditional popular wavelet packet decomposition features, the histogram of gradient (HOG) of the amplitude spectrum image, and the Principal Component Analysis (PCA) combining SVM and CNN are tested. Besides SVM, two other representative algorithms, i.e., the k-NearestNeighbor (kNN) and the Random forest (RF), are also used as the classifier after the softmax layer of the CNN.

For the wavelet packet decomposition feature, the frame length of EEG signal is set to be 4 s and only the frequency lower than 30 Hz is considered. Six features on the wavelet packet decomposition coefficients, including the power, mean, median, variance, skewness and kurtosis are extracted for EEG signal representation. Then, the SVM is adopted for the classifier (Wavelet+SVM). For the MAS map of the EEG signal, the histogram of gradients (HOG) is further extracted and the SVM is adopted for the classification of the epilepsy preictal state. To reduce the feature dimension, the PCA algorithm is adopted for both the MAS map and the features extracted by CNN. Employing PCA, the feature dimensions are reduced from the 342 to 289 and more than 99% of the information are retained after the dimension reduction. Then, two classification algorithms based on the PCA, which use the SVM (PCA+SVM) and CNN (PCA+CNN) as the classifiers are adopted for epileptic state classification, respectively. In addition, the performance of the combinations CNN+kNN and CNN+RF are also presented in Table 2 for comparisons. The number of nearest trees in RF is 50 and the number of variables that used for decision making is set to be the square root of the total number of variables. It is also noted that besides the wavelet packet decomposition based method, we test the performance of all other algorithms with the EEG signals on two different frequency bands, i.e., 0–70 Hz and 70–128 Hz, respectively, as their inputs.

Table 2 Performance comparisons with state-of-the-art algorithms

Accuracy(%)	Algorithms						
	HOG+SVM	PCA+SVM	PCA+CNN	**CNN+SVM**	CNN+KNN	CNN+RF	Wavelet+SVM
Frequency band							
0–70HZ	46.32	39.26	78.24	**86.25**	85.14	85.50	60 (0–30Hz)
70–128HZ	42.64	37.52	77.57	77.75	75.83	76.45	

The algorithm with the best recognition performance is highlighted using boldface

Table 2 shows the average classification results on all these state-of-the-art algorithms. These results are derived by carrying out the experiment with 40 trials. As listed in the table, the proposed MAS-based CNN+SVM algorithm achieves the highest accuracy on the epileptic state classification. In general, using the low frequency band has resulted in a better performance than using the frequency band 70–128 Hz. Comparing with the conventional wavelet/PCA/HOG features, employing the CNN for feature learning on the MAS map provides a better classification performance. What is more, SVM generally provides a higher classification rate than kNN and RF.

4 Conclusions

The preictal state detection of epilepsy is more important than seizure detection in reducing the damages by the seizure recurrence. In this paper, we have developed a novel epileptic state classification algorithm based on the mean of amplitude spectrum (MAS) of multichannel EEG signals and the convolutional neural network (CNN). To improve the performance of the epilepsy state classification, the 1 h preictal state EEG signals have been divided into multiple non-overlapped segments. Two partition strategies on the 1 h preictal interval, one with 20-min and the other with 10-min sub-intervals, respectively, have been studied in the paper. Experiments on the benchmark CHI-MIT EEG dataset have been conducted for performance validation and comparisons with several state-of-the-art algorithms have been provided. Experimental results reveal that: (1) the proposed MAS-based CNN+SVM algorithm has successfully classified the preictal states and an overall accuracy of 86.25% for the epileptic state classification has been achieved with the 20-min segmentation strategy on the CHI-MIT dataset, (2) the classification performance is generally degraded when a finer segmentation on the preictal signal is applied, (3) the proposed MAS-based CNN+SVM outperforms several competitive algorithms based on the state-of-the-art EEG signal feature extraction methods and classifier learning algorithms.

Acknowledgements This work was supported by the National Nature Science Foundation of China under Grant 61503104, and supported in part by the K. C. Wong Education Foundation and DAAD, the Zhejiang basic public welfare research program LGF18F010007, and the special fund project of information development in Shanghai: XX-XXFZ-02-18-2862.

Compliance with ethical standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

Acharya UR, Oh SL, Hagiwara Y (2017) Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. Comput Biol Med 100:270–280

Achilles F, Tombari F, Belagiannis V (2018) Convolutional neural networks for real-time epileptic seizure detection. Compu MethodsBiomech Biomed Eng Imaging Vis 6:264–269

Alarcon G, Binnie CD, Elwes RDC (1995) Power spectrum and intracranial EEG patterns at seizure onset in partial epilepsy. Electroencephalogr Clin Neurophysiol 94:326–337

Blanco S, Garay A, Coulombie D (2013) Comparison of frequency bands using spectral entropy for epileptic seizure prediction. ISRN Neurol 2013:287327. https://doi.org/10.1155/2013/287327

Cao J, Zhang K, Yong H, Lai X, Chen B, Lin Z (2018) Extreme learning machine with affine transformation inputs in an activation function. IEEE Trans Neural Netw Lear Syst 99:1–15. https://doi.org/10.1109/TNNLS.2018.2877468

Celka P, Colditz P (2002) A computer-aided detection of EEG seizures in infants: a singular-spectrum approach and performance comparison. IEEE Trans Biomed Eng 49:455–462

Elger CE (2001) Future trends in epileptology. Curr Opin Neurol 14:185–186

Iasemidis LD, Sackellares JC (1996) Chaos theory and epilepsy. The Neuroscientist 2:118–126

Le Van Quyen M, Martinerie J, Navarro V (2001) Anticipation of epileptic seizures from standard EEG recordings. The Lancet 357:183–188
Litt B, Esteller R, Echauz J (2001) Seizure precursors may begin hours in advance of temporal lobe seizures: a report of five patients. Neuron 29:51–64
Martinerie J, Adam C, Le Van Quyen M (1998) Epileptic seizures can be anticipated by non-linear analysis. Nat Med 4(10):1173
Mirowski PW, LeCun Y, Madhavan D (2008) Comparing SVM and convolutional networks for epileptic seizure prediction from intracranial EEG. In: Machine learning for signal processing, pp 244-249
Mormann F, Kreuz T, Rieke C (2005) On the predictability of epileptic seizures. Clin Neurophysiol 116:569–587
Mormann F, Andrzejak RG, Elger CE (2006) Seizure prediction: the long and winding road. Brain 130:314–333
Netoff T, Park Y, Parhi K (2009) Seizure prediction using cost-sensitive support vector machine. In: Engineering in medicine and biology society, pp 3322-3325
Nigam VP, Graupe D (2004) A neural-network-based detection of epilepsy. Neurol Res 26:55–60
Park Y, Luo L, Parhi KK (2011) Seizure prediction with spectral power of EEG using cost-sensitive support vector machines. Epilepsia 52:1761–1770
Perucca P, Dubeau F, Gotman J (2013) Intracranial electroencephalographic seizure-onset patterns: effect of underlying pathology. Brain 137:183–196
Skjei KL, Dlugos DJ (2011) The evaluation of treatment-resistant epilepsy. Semin Pediatr Neurol 18:150–170
Song J, Zhang R (2017) Application of extreme learning machine to epileptic seizure detection based on lagged Poincaŕe plots. Multidimens Syst Signal Process 28(3):945–959
Srinivasan V, Eswaran C, Sriraam N (2005) Artificial neural network based epileptic detection using time-domain and frequency-domain features. J Med Syst 29:647–660
Srinivasan V, Eswaran C, Sriraam N (2007) Approximate entropy-based epileptic EEG detection using artificial neural networks. IEEE Trans inf Technol Biomed 11:288–295
Truong ND, Nguyen AD, Kuhlmann L (2017) A generalised seizure prediction with convolutional neural networks for intracranial and scalp electroencephalogram data analysis. arXiv preprint arXiv:1707.01976v2
Wilden JA, Cohen-Gadol AA (2012) Evaluation of first nonfebrile seizures. Am Family Phys 86(4)
Williamson JR, Bliss DW, Browne DW (2011) Epileptic seizure prediction using the spatiotemporal correlation structure of intracranial EEG. In: Acoustics, speech and signal processing (ICASSP), pp 665-668
Witte H, Iasemidis LD, Litt B (2003) Special issue on epileptic seizure prediction. IEEE Trans Biomed Eng 50:537–539
Zhang Z, Parhi KK (2016) Low-complexity seizure prediction from iEEG/sEEG using spectral power and ratios of spectral power. IEEE Trans Biomed Circ Syst 10:693–706