Epileptic Seizure Prediction Using Deep Network with Transfer Learning

Jia Zhang
School of Electrical Engineering Shenyang University of Technology, Shenyang Liaoning China
zhangjia2023sy@163.com

Ling Han*
School of Electrical Engineering Shenyang University of Technology, Shenyang Liaoning China
hanling_bme@163.com

ABSTRACT

Epilepsy is a common brain disease, which can be predicted in advance by some methods. In this study, the epileptic EEG signal is processed by two-dimensional discrete wavelet transform. A algorithm of epileptic seizure prediction based on deep network transfer learning methods is proposed. The segments of EEG data containing epileptic seizure signals are grouped according to the ten-fold-cross validation methods. On the basis of classification by deep network transfer methods, combined with SPH/SOP rules and Kalman filtering algorithm, seizure prediction is carried out. The experimental results show that the longest prediction time is 24.25 minutes, the average prediction time is 18.50 minutes, the average SSP is 88.21%, and the average FPR_{max} is 0.31/h. The results of proposed approach show that the algorithm can accuracy predict epileptic seizures.

CCS CONCEPTS

• **Applied computer**; • **Life and medical sciences**; • **Health care information systems**;

KEYWORDS

EEG, Transfer learning, Deep network, Seizure prediction

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1 INTRODUCTION

Epilepsy is a neurological disease that affects people's health. The pathology of epilepsy is mainly due to the irregular sudden discharge of brain neurons, which leads to the functional obstruction of the brain, thus affecting the normal function of the brain [1]. Its main characteristics are repeatability and abruptness. Range of the disease is wide and it is difficult to predict accurately. The epileptic symptoms of Electroencephalogram (EEG) have the characteristics of sharp wave and spike wave, which is regarded as an important basis for diagnosing epilepsy in current medicine [2]. EEG can effectively detect and record abnormal discharges of brain neurons, so it is often used as a clinical basis to judge whether epilepsy occurs or not.

As early as the 1970s, Viglione and Walsh put forward that epilepsy did not change suddenly from the interictal period to the seizure period, and there was a certain prediction before the seizure period [3]. By the beginning of the 21st century, Sriram Ramgopaland and other researchers had given that if EEG data showed a downward trend in synchronization, it would indicate that epilepsy would occur [4]. Thomas Maiwald et al. raised the differential algorithm in the process of epileptic EEG processing, and obtained the characteristic data of epilepsy through time domain analysis [5]. Based on Ramy Hussein time domain analysis method, Khan et al. proposed a frequency domain discrete algorithm based on wavelet transform to obtain and analyze epilepsy feature data [6]. In 2012, Krizhevsky et al. applied the coherent connection matrix with time window function to the EEG study of epileptics, and proposed the method of multifactor analysis to predict early epilepsy [7]. With the further development of research, Khakon Das et al. applied nonlinear dynamics to establishment of epilepsy model and prediction of epilepsy, and proposed the application of signal complexity and approximate entropy in epileptic EEG [8]. With the deepening research, deep learning, short-term memory network, convolutional neural network and support vector machine are also gradually applied to the processing of epileptic signals. It has achieved remarkable outcome and the prediction accuracy has gradually improved.

On the basis of realizing the function of epileptic EEG classification, the above research results also have some problems to be solved. Due to shallow network level, simple network structure, so it is cannot achieve a certain accuracy of feature extraction and incomplete validation of data sets. Multiparameter also affect the classification performance. In this work, a deep convolutional network transfer learning methods is introduced to classify epileptic EEG signals. More features are extracted by using network structures such as InceptionV3. By fine-tuning the parameters and adjusting the network structure of the pre-training network, the network complexity and the amount of experimental data can be reduced. Combined with the role of SPH/SOP judgment rules in predicting EEG epilepsy signals, through the experiment and comparison of the whole dataset, the rationality of the method verification was increased.

*Corresponding author

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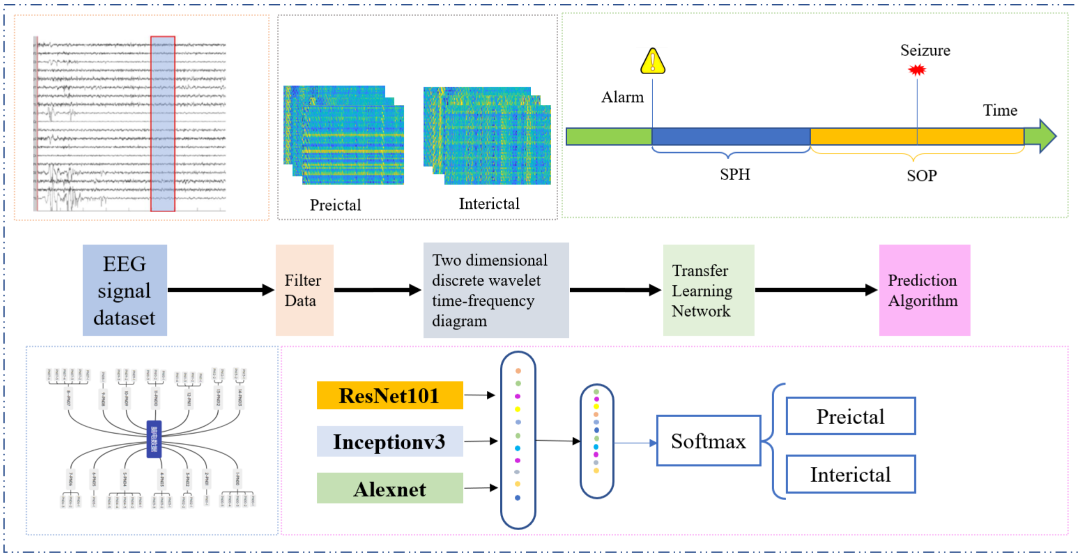

Figure 1: Flow chart of epileptic seizure prediction method

2 DATABASE

The selected database is the scalp EEG data set collected by Siena University in 2020 [9–11] (https://doi.org/10.13026/5d4a-j060).The dataset included EEG of 14 epileptic patients with total 128 hours. The data sampling rate is 512 Hz and the electrode arrangement follows the international 10-20 standard lead placement method. The dataset meanwhile includes one to two Electrooculogram (ECG) information. According to the seizure classification standard of the International League Against Epilepsy (ILAE), 60 seconds before the seizure was selected as the preictal signal, 60 seconds corresponding to 50 minutes before the seizure was marked as the epilepsy interictal, and seizure data was intercepted as the basic composition of each group of data for subsequent data processing. The EEG signals of all 47 epileptic seizures in the data set were selected as experimental samples.

3 METHODOLOGY

In this paper, the original EEG data was first pre-processing by filtering, notch wave and independent components analysis (ICA). Epileptic EEG signals were processed by segmented and two-dimensional discrete wavelet transform after screening channels. Through this method, the conversion from one-dimensional EEG signal to two-dimensional image signal was realized. Through the transfer learning training of three kinds of deep networks, the EEG data can be classified into two types: interictal and preictal. Then the trained model was applied to the epileptic seizure prediction model to verify the prediction performance. The method flow is shown in Figure 1.

3.1 Data preprocessing

When the original EEG signal was collected on the cerebral cortex, it will introduce noise interference in the human body, such as ocular artifact, electromyography interference. In order to better extract EEG features, it was necessary to carry out noise elimination processing [12]. In this paper, 50Hz and redundant frequency band EEG were removed by notching filter and filtering. The ECG was removed by ICA on the remaining EEG data. At EEG segmentation processing, the EEG data of patients were cut by sliding window of 5s and step size of 2.5s, and then the two-dimensional time-frequency wavelet transform was performed on each segment of data.

3.2 Wavelet transform

Discrete wavelet transform (DWT) uses the double scale equation. Each layer has a high-pass filter and a low-pass filter to decompose the signal. The filtering process uses recursive algorithm to obtain the smooth approximation signal and detail signal of the input signal at each decomposition level. Assuming that the original signal is $x(n)$, when passing through a series of half bandwidth low-pass filters $h(n)$ and high-pass filters $g(n)$. The different cut-off frequencies set in the filter are decomposed from the original signal into signals with different resolutions. This process can be expressed as:

$$x^j(k) = \sum_n x^{j-1}(n)h(n-2k) \tag{1}$$

$$d^j(k) = \sum_n x^{j-1}(n)g(n-2k) \tag{2}$$

Wherein, Equation 1) is the half bandwidth signal processed by the low-pass filter, and Equation 2) is the half bandwidth signal processed by the high-pass filter. In the two equations, n is an integer, and j is the current number of wavelet transform layers, j=1. . .,.. L. Then L is the total number of wavelet decomposition layers, $k$represents the k-th wavelet coefficient of the j-th layer, $x^j(k)$represents the discrete smooth approximation signal with a resolution of a = 2j, $d^j(k)$represents the discrete detail signal with a resolution of a = 2j. The wavelet coefficient was attained by the wavelet transformation at this resolution. This processed data is transformed from SSED(Siena Scalp EEG Database, SSED)

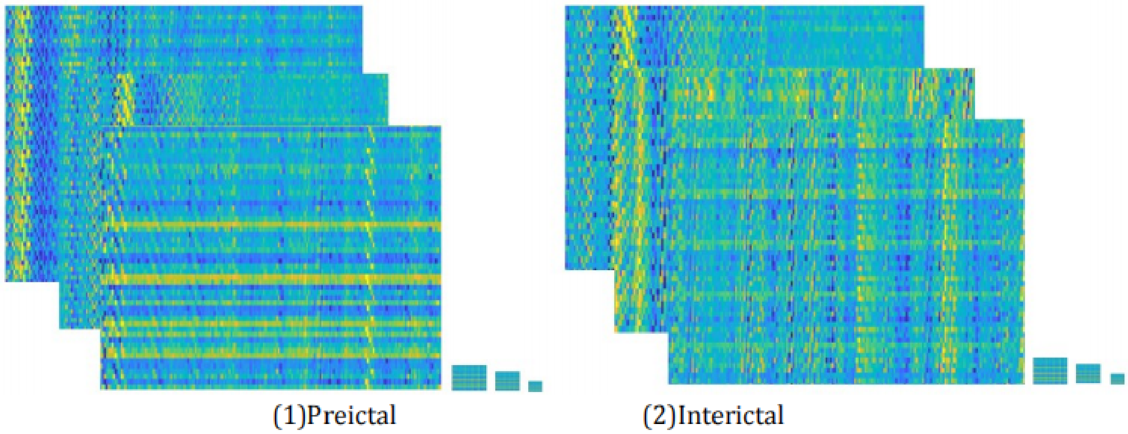

Figure 2: Color map of CA mapping generated by DWT2

to SSEDD (Siena Scalp EEG Database DWT2, SSEDD), as shown the color map of approximate coefficient for completing wavelet transform in Figure 2.

3.3 Depth convolution neural network

Depth convolution neural network is a kind of feedforward neural network. Its feature shows that each layer of neurons only transmits information with the previous layer of neurons [13]. DCNN has many network models, not only including the LeNet and AlexNet with fewer network layers, but also the GoogleNet and ConvoNet with complex networks and multiple layers. Among them, InceptionV3 is created by Google Group, it includes 159 layers of depth and more than 20 million parameters [14]. The model occupies 92 M memory. InceptionV3 is a network based on InceptionV1 and InceptionV2. After reducing the thickness of the feature map and increasing the Gaussian normalization, the depth and nonlinearity of the network are improved [15].

InceptionV3 is used for fine-tuning to achieve transfer learning. First, the InceptionV3 model is obtained based on the pre-training of ImageNet. Then replace the full connection layer and output layer of the InceptionV3 model with the newly built full connection layer (including the output layer) to get a new network model. Finally, parameters of the new network model are fixed. These parameters do not participate in training. The remaining unfixed parameters are trained based on the data set. The InceptionV3 network input image size is 299*299*3 and 2048 dimensional features vector as output.

When the CNN network layers reached a certain number, the classification effect cannot be improved by increasing the depth of network. It will cause degradation problems and lead to worse classification performance. Residual Network (ResNet) can effectively solve the degradation problem caused by too deep network. The ResNet101 is a ResNet network with deep network and excellent classification performance [16].

In this work, InceptionV3, ResNet101 and AlexNet are selected. The training complexity is reduced effectively while maintaining the network depth. The degradation problem caused by the network too deep is solved.

In the framework of transfer learning, at first load the corresponding ImageNet pre-training weights, and fine tune on the SSEDD dataset. Second, regard the three models as three feature extractors, and epileptic features are extracted from the SSEDD dataset. It is also a feature before the full connection layer is imported. The features extracted from the three DCNN models are spliced, then input the subsequent full connection layer for training and dimension reduction. Finally, the softmax classifier is used for binary classification.

3.4 Transfer learning

Transfer learning is a machine learning method. It transfers the experience value obtained in one field to another field which is not completely relevant [17]. This transfer method can reduce the sample size of the experiment and the difficulty of processing data. This paper adopts a model based transfer method, which divides the data into trained data and test data. In the process of optimizing the trained data, the network structure is adjusted and the network parameters are modified. By judging the matching degree between the data type and the network structure to realize the overall classification rate of training data and test data.

As shown in Figure 3, the InceptionV3 network is taken as example in this study. At the deep network transfer learning stage, first, the deep network InceptionV3 model is pre-trained, then combined with transfer learning to form a new network structure. The 'avg_pool' is the upper layer of 'full connection layer' in the transfer learning InceptionV3 network, and its output is used as a feature representation. At last, comparing the results of various classification methods to get the best classification results.

3.5 Seizure prediction model

3.5.1 Evaluation System. In this paper, two indicators including seizure prediction horizon (SPH) and seizure occurrence period (SOP) are used [18]. The SPH refers to the prediction period before seizure, and SOP refers to the period during which epilepsy is bound to occur.

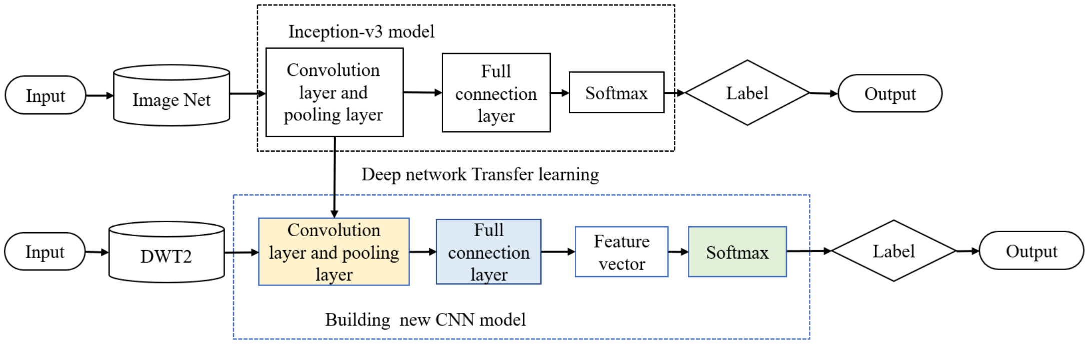

Figure 3: EEG Deep Network Transfer Learning Model Based on InceptionV3

In order to make a correct prediction, seizures must be after the SPH and within the scope of SOP. When the prediction system detects an epileptic seizure, false alarm will occur when there is no epilepsy during SOP. When the alarm sounds, it will continue until the end of SOP. In clinical medical applications, the SPH must be long enough to allow adequate intervention or prevention. SPH is also called intervention time. On the contrary, the SOP should not be too long to alleviate the anxiety of patients.

At the same time, in order to avoid false alarm of the methods, when the prediction results conform to the SPH/SOP rules, the judgment of Kalman filtering is also required. The Kalman filter alarm will sound if the following formula is met.

$$K_{out}\,[n] = \sum\nolimits_{k=n-T}^{n} O\,[k]\,/T \tag{3}$$

The $K_{out}\,[n]$ is the filter output and $O[k]$is the classifier output. The $O[k] = 0$ represents the interval between seizures and $O[k] =$ 1represents the preictal signal. The T represents the time required for continuous monitoring, which is set as 20min in this study. It is specified that when$K_{out}\,[n] > 1.5$, an alarm is given, which means that epilepsy will occur. Otherwise, $K_{out}\,[n]$ <= 1.5 no alarm will be issued.

In this paper, the evaluation indicators including sensitivity of prediction (SSP*)* and false prediction rate (FPR*)* are used. The maximum false prediction rate (FPR_{max}) is the number of false predictions per hour, and the unit is h^{-1} or (1/h). The formula is as follows:

$$SSP = \frac{Correctlypredictthenumberofseizures}{Totalnumberofseizures} \times 100\% \tag{4}$$

$$FPR_{\max} = \frac{Numberoffalsealarms}{Forecasttime} \tag{5}$$

3.5.2 Prediction Process. First, we need to ensure that the accuracy of classification performance reaches a certain degree of stability. Then it is applied to the field of prediction, in order to improve the ability of seizure prediction. At this time, the selected experimental data is a section of completed EEG data, the epileptic interictal data and preictal data and seizure period data are contained in it. In order to complete the classification and prediction function. The samples with different length of time are be chosen, then be sent to the deep network transfer learning after preprocessing. The whole experiment parameter values of seizure prediction time are set as the following: (1) SPH =10min, SOP=6min, K_t=10min; (2)SPH=10min, SOP=10min, K_t=10min; (3)SPH=20min, SOP=10min, K_t=20min; As shown in Figure 4 it is an example of the value of parameter method (3):

4 RESULTS AND ANALYSIS

4.1 Feature extraction results

The feature extraction process was completed through the training of deep network, in which the classification label of epileptic EEG signal is classified as 1 according to the preictal period and 0 according to the interictal period for training. The network training result are compared with the actual classification attribute to obtain the evaluation results of the network. Table 1 shows the best classification results by comparing various classification algorithms.

In Table 1, ACC = Accuracy, SEN = Sensitivity, SPE= Specificity.

4.2 Prediction results

Set SPH = 20min and SOP =10min, SSEDD method combined with deep network transfer learning can successfully predict 45 of 47 seizures. The prediction SSP reaches 95.72%. The evaluation results of 14 experimental patients are shown in the Table 2.

From the Table 2, we can see the longest prediction time of all patients is 24.25 minutes (patient No.2). The shortest prediction time is 8.86 minutes (patient No.6). The mean predictive time of all patients is 18.50 minutes. The highest SSP of all patients is 99%, the lowest SSP is 73%, and the average SSP of all patients is 88.21%. The highest FPRmax of all patients is 0.46/h (patient No.11), the lowest FPRmax is 0.15/h (patient No.14), and the average FPRmax is 0.31/h.

5 CONCLUSION

In this paper, two-dimensional DWT is used to convert one-dimensional EEG data into two-dimensional image signals, and the deep network transfer learning method is applied to epileptic seizure prediction. The goal of epileptic seizure prediction is achieved through SPH/SOP and Kalman filtering algorithm. The classification accuracy of InceptionV3, Resnet101, and AlexNet reached 90.3%, 89.42%, 84.56% respectively. When the setting of SPH=20min and SOP=10min, the system prediction SEN reached 95.72%, the average prediction SSP was 88.21%, and the average FPRmax was 0.31/h. The above research shows that the method

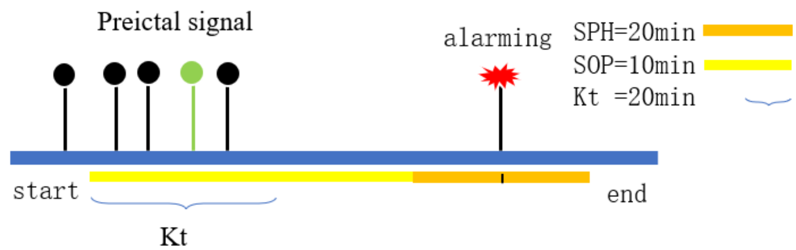

Figure 4: Schematic Diagram of Epilepsy Prediction Process Training

Table 1: Classification results of epileptic states in different transfer networks(%)

Transfer Net	ACC	SEN	SPE
InceptionV3	90.3	89.24	84.12
Resnet101	89.42	89.27	88.54
AlexNet	84.56	83.95	84.26

Table 2: Evaluation results of 14 patients

Patient ID	Average Forecast Time /min	SSP (%)	FPR_{max} (h^{-1})
1	16.66	90	0.25
2	24.25	88	0.36
3	22.56	85	0.23
4	19.85	99	0.35
5	12.92	92	0.42
6	8.86	96	0.36
7	21.66	73	0.29
8	19.47	81	0.37
9	13.75	83	0.26
10	18.56	84	0.34
11	22.6	95	0.46
12	22.89	83	0.25
13	15.55	92	0.28
14	19.46	94	0.15
Average	18.50	88.21	0.31

in this paper brings a new optimization way for the detection and prediction of epilepsy, which is beneficial to the prevention and treatment of patients.

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