

Epilepsy seizure detection using Transformer

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Abstract. Electroencephalogram (EEG) is a general examination method for doctors to diagnose epilepsy, and it is also an important tool for studying brain activity. Due to the time-consuming and uncertainty of manually extracting features from EEG signals, this paper will be based on an end-to-end deep learning method different from the classic CNN and RNN network structure. This paper uses a relatively novel Transformer network structure to identify EEG whether the signal is epileptic. The experiment in this paper was carried out on the public CHBMIT data set, and finally, the average result of the five-fold cross-validation was 94.46%, the specificity was 93.97%, and the sensitivity was 94.96%. The experimental results show that the Transformer model has a higher performance improvement than the classic Resnet and Bi-LSTM networks, and it has greater potential in future epilepsy detection applications.

Keywords: Electroencephalogram (EEG), Transformer, epilepsy detection.

1. Introduction

Epilepsy is a common chronic neurological disease caused by the abnormal discharge of human brain neurons. In clinical manifestations, there will be sudden body cramps, unconscious movements, absences, and other symptoms. At present, the diagnosis of epilepsy is mainly based on electroencephalogram (EEG) to carry out research. The abnormal EEG signals in epilepsy patients will have different rhythm waves and abnormal amplitudes compared with the waveforms in the normal period.

Based on the abnormality of EEG signals during epileptic seizures, many features obtained from EEG signal analysis can be used as indicators of epileptic seizures. EEG signal analysis methods can generally be divided into the time domain, frequency domain, and time-frequency domain. First, the time domain analysis of EEG signals is based on the analysis and calculation of traditional statistical parameters based on the voltage amplitude of the EEG, and then studies the time-domain waveform difference of EEG in the seizure and non-seizure period. E. Tessy et al. [1] extracted the two features of line length and energy in the time domain, and used some traditional algorithms k-nearest neighbor (KNN) classifier, linear discriminator analysis (LDA), quadratic discriminant analysis (QDA) is performed to determine whether the EEG signal is a seizure signal. Second, the frequency domain analysis of EEG signals is based on the Fourier transform of the signal and extracts the frequency domain components and frequency domain energy distribution of the signal as frequency domain features for epilepsy seizure detection. Third, the time-frequency domain analysis of EEG signals combines time-domain and frequency-domain information for analysis, including common analysis methods such as The Short-time Fourier Transform (STFT), The Discrete Wavelet Transform (DWT), and Continuous Wavelet Transform (CWT). Duo Chen et al. [2] used DWT to detect epileptic seizures and found that the reasonable setting of DWT has a greater impact on the performance of epileptic seizure detection.

With the popularity of deep learning in recent years, the method of using neural networks to automatically extract features and detect epilepsy seizure signals has been applied by many scholars. Amir H et al. [3] used a random forest to automatically select the features which are manually extracted, and then used a convolutional neural network (CNN) to replace the traditional machine learning classifier. Mengni Zhou et al. [4] used Convolutional Neural Network (CNN) in the original

EEG signal instead of manually extracted features, indicating that it is feasible to apply end-to-end deep learning to epilepsy seizure detection. The convolutional neural network extracts only local features and does not have temporal continuity. The Long Short Term Memory (LSTM) network structure may be better interpretive for sequential EEG signals. Shekokar KS et al. [5] used a three-layer LSTM for epilepsy seizure detection. Minxing Geng et al. [6] deploy the Stockwell transformation on the original EEG signal and then feed the Bidirectional Long Short Term Memory network (Bi-LSTM) for epilepsy seizure detection. But the LSTM network model always has limited memory content, and the attention mechanism is a module different from CNN and LSTM. It filters global information to filter out a large amount of irrelevant content, and only obtains the content that you care about. It is more in line with the mechanism of the human brain processing information. Google [7] proposed a new model Transformer based on Self-Attention and position embedding.

Based on the above, this paper will use the Transformer model for epilepsy seizure detection based on the public CHBMIT data set to prove the effectiveness of this model.

2. Methods

2.1 EEG data preprocessing

The public EEG dataset used in this paper was jointly contributed by Boston Children's Hospital and the Massachusetts Institute of Technology [8]. The data set contains 23 patient cases, and each case contains 9-42 edf files which most of the files contain 23 channel signals, and these channels are named using the electrode positions of the international 10-20 lead system name. This paper takes into account the artifacts of eye movement and ECG and excludes the electrodes Fp1 and Fp2 near the eyes and the electrodes FT9 and FT10 near the ears, as well as duplicate channels. According to the start and end time of the epileptic seizures marked by experts, each seizure period is divided into a 4s-length window, and the sliding step length of each segmentation is half of the window size to ensure the continuity of the sample slices before and after. Because the time of seizures is small relative to the time of non-seizures, to ensure the balance of positive and negative samples in the data set, this paper uses the negative sampling method to randomly sample the number of non-epilepsy samples (negative) equivalent to the number of epileptic seizure samples (positive). This paper finally got 10918 data samples, including 5428 positive samples and 5490 negative samples.

This paper does not use the traditional manual feature extraction method but uses the raw EEG signal to synthesize the three-channel signal directly as the input of the neural network for end-to-end epilepsy detection. Compared with the manual feature extraction method, it can save a lot of time. Based on the effectiveness of frequency domain information, this paper combines the original signal, frequency domain information, and filtered signal to form the three-channel EEG signal as the input of the neural network. The specific EEG signal preprocessing process is shown in Figure 1.

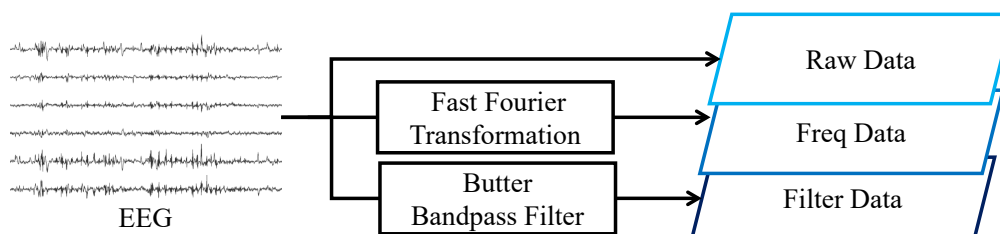


Figure 1. EEG signal preprocessing.

2.2 Transformer

Transformer[7] is a popular model in recent years and has achieved good results in various tasks of NLP. In essence, Transformer is an encoder-decoder network structure that is often used to implement sequence-to-sequence tasks. Since epileptic seizure detection is a two-class task, we only

need to connect the encoder structure in the Transformer to a fully connected layer to complete our classification task. The specific network structure is shown in Figure 2.

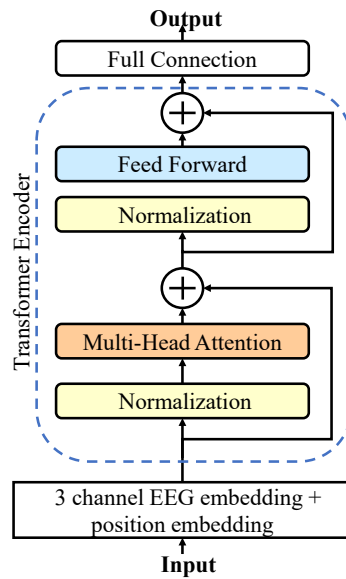


Figure 2. Model structure.

The key module part in the Transformer encoder is multi-head attention. Its main function is to calculate its attention score for the EEG vector after the input EEG signal is converted into a vector. First, calculate the query vector, key vector, and value vector by multiplying W_Q , W_K and W_V matrices obtained by training, and then calculate the attention score of the EEG vector according to the formula of the scaled dot product attention model. The formula is as follows:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where the d_k in the formula represents the dimension of the key vector.

3. Experimental results and analysis

To be able to show the superiority of the Transformer network structure, this paper compares Transformer with other classic CNN-based networks Resnet18, Resnet50, and Bi-LSTM. In this paper, five-fold cross-validation is performed on the preprocessed data set, using the SGD optimizer with momentum, the loss function is cross-entropy, and the standard two-category index is used to evaluate the quality of the model, and calculate accuracy, sensitivity, and specificity according to the confusion matrix in Figure 3(a). Among them, the accuracy rate refers to the proportion of the number of positive and negative samples that can be correctly identified, the sensitivity refers to the proportion of the number of samples that correctly identify epileptic seizures signals, and the specificity refers to the proportion of the number of samples that correctly identify non-seizure signals. The specific formula is shown in Figure 3(b).

Predicted \ Actual	Positive	Negative		
	Positive	Negative	Accuracy(AC)	$\frac{TP + TN}{TP + FN + TN + FP} \times 100\%$
Positive	TP	FN	Sensitivity(SE)	$\frac{TP}{TP + FN} \times 100\%$
Negative	FP	TN	Specificity(SP)	$\frac{TN}{TN + FP} \times 100\%$

(a)

(b)

Figure 3. Model evaluation methods.

From the experimental results in Table 1, it can be found that in CNN-based Resnet18 and Resnet50, the deep network performs better than the shallow network in all indicators, perhaps because the deep network extracts high-level features from three channels EEG signals. Compared with the Resnet50, the Bi-LSTM model has a slightly lower accuracy rate, and the recognition rate of non-seizure samples is higher than that of epileptic seizure samples. On the Transformer, although it is lower in sensitivity than the Bi-LSTM, its accuracy and specificity are higher than other models, indicating that the Transformer-based epilepsy seizure detection method has greater potential.

Table 1. Performance comparison of different models.

Model	AC	SP	SE
Resnet18	91.19	91.52	90.86
Resnet50	92.78	93.32	92.26
Bi-LSTM	92.52	88.22	97.73
Transformer	94.46	93.97	94.96

4. Conclusion

There are many epilepsy seizure detection methods based on EEG signals, but most of them are manual extraction of EEG signal characteristics to detect whether the EEG signal is abnormal, because the manual extraction process is time-consuming. Therefore this paper uses an end-to-end deep learning detection method. At the same time, few papers use the Transformer structure for EEG signals, so we tried Transformer-based epilepsy seizure detection, and in the experiments of this paper, the performance of the model was better than that of the network model based on CNN and LSTM. Finally, an average accuracy of 94.46%, 93.97% specificity, and 94.96% sensitivity was obtained in the five-fold cross-validation.

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