Epilepsy Detection Based on Graph Convolutional Neural Network and Transformer

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Abstracts: Epilepsy detection is a critical medical task, but traditional methods face challenges in accuracy and reliability due to the difficulty of EEG data acquisition and the limitation of the number of sample seizures. To overcome these challenges, this paper proposes a new model for epilepsy detection that combines Graph Convolutional Neural Network (Graph Convolutional Network, GCN) and Transformer, aiming to significantly improve the accuracy and sensitivity of detection. The core of the model adopts GCN, which utilizes its powerful inter-node relationship capturing capability and graph feature learning mechanism. However, due to the limitation of traditional GCN in integrating global features, this model incorporates the Transformer structure to enhance global feature aggregation and reduce irrelevant feature interactions. After multiple rounds of testing of the GHB-MIT dataset, the model demonstrated excellent performance, with an average sensitivity of 92.97%, specificity of 94.60%, and accuracy of 94.59%, which was significantly better than the traditional method. Further comparison with the latest literature also confirms the advantages of the present method. In summary, the epilepsy detection model we developed based on graph convolutional neural network and Transformer not only shows significant improvement in accuracy and sensitivity, but also provides more accurate and reliable technical support for epilepsy diagnosis, which provides a valuable reference for research in related fields.

1. Introduction

Epilepsy is a widely seen chronic brain disorder within the field of neuroscience, with approximately 30% of people with epilepsy being treated with antiepileptic drugs worldwide [1]. Epilepsy disorders span all age groups and are particularly common in children around the age of one year, when brain structures are in the early stages of development. Currently, EEG has become the method of choice for detecting brain activity in epilepsy patients and plays a crucial role in the diagnosis of epilepsy. Therefore, it is particularly important to develop an efficient and reliable intelligent diagnostic algorithm to assist physicians in diagnosing epilepsy and to alleviate patients' suffering caused by this disease.

Traditional Convolutional Neural Networks (CNNs) are mainly designed for Euclidean spatial data and are limited in their ability to process non-Euclidean data structures. The development of graph convolutional networks (GCNs) overcomes this challenge and provides new opportunities for processing complex data structures. Xu[2] and other researchers constructed an end-to-end spatio-temporal architecture by integrating graph convolutional networks and bi-directionally gated recurrent units (Bi-GRUs), effectively modeling spatial dependence and temporal dynamics of electroencephalography (EEG) data. Zhang[3] and other researchers introduced the a multi-view attention mechanism and a multi-branch graph convolutional network to distinguish abnormal brain discharges, which significantly improved the accuracy of epilepsy detection to 81.93%.Xu[4] and other researchers used an adaptive multi-channel graph convolutional network to mine the features of multimodal brain networks and extracted the spatio-temporal topological features, which enhanced the performance of epilepsy detection. Liu[5] and others enhanced the epilepsy detection performance by combining a graph convolutional network and bi-directional long- and short-term memory network (Bi-LSTM) to extract contextual and temporal features of EEG, and used an extensive learning system for automatic epilepsy detection. Li[6] and others proposed a novel spatio-temporal spectral hierarchical graph convolution network to achieve epilepsy prediction by fusing time and frequency domain features through an active pre-seizure learning scheme. Chen[7] and others designed a five-layer graph convolutional network structure, which effectively realizes epilepsy classification and detection by deeply mining the correlation between channels. Wang[8] and other researchers reduced edge redundancy by weighted neighbor graph method and extracted time-frequency domain features to improve detection efficiency and effectiveness. These research advances significantly demonstrate the potential and value of deep learning in the field of epilepsy detection.

Synthesizing the existing studies, it is found that most of the work focuses on the analysis and detection of single

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or fixed-channel data, while in-depth exploration of multi-channel data and their interactions is still insufficient. In view of this, this study proposes a novel epilepsy detection model incorporating graph convolutional neural network (GCN) and Transformer architecture, and evaluates the model performance based on the CHB-MIT dataset. The main innovations of this study include:

a) The graph structure constructed by Pearson's correlation coefficient improves the modeling capability of the model by reducing the interaction of irrelevant features through the introduction of an adjacency matrix to the Transformer framework.

b) Fuse the features that have passed through the Transformer with the features that have passed through the GCN layer to aggregate multi-scale features, enhance the generalization ability of the model and improve the detection accuracy.

2. Research methodology

In order to improve the accuracy of epilepsy detection, this study designed a model combining Graph Convolutional Neural Network (GCN) and Transformer framework, named Graph Convolutional Neural Network and Transformer Framework (GCTF) based. First, the study preprocessed the EEG data by segmenting the data into 4-second-long segments and labeling each segment to indicate the presence of seizures. Subsequently, the segmented data were subjected to feature extraction using a one-dimensional convolutional neural network (1D-CNN). The extracted features were analyzed by Pearson's correlation coefficient and used to construct a graph structure, which reflects the interrelationships between different data segments. The constructed graph structure is then fed into a deep learning module combining GCN and Transformer for further feature extraction and data analysis for accurate seizure detection. Thus, the model architecture of the GCTF framework is shown in Fig 1.

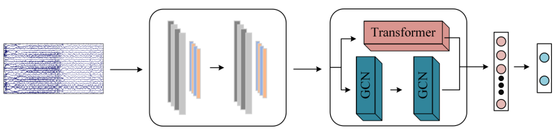

Fig. 1. Model diagram of the GCTF framework

2.1. Data preprocessing and graph construction

Since, EEG EEG data can be considered as a typical structured data that can be defined on a graph. In this paper, the construction of EEG data on a graph model is defined as follows:

$$\begin{aligned} &G=(v,E,\boldsymbol{A}) \\ &\mathrm{v}=(\mathrm{v}_i \mid \mathrm{i}=1,\ldots,\mathrm{N}) \\ &E=\{\mathrm{e}_{ij} \mid \mathrm{v}_i,\mathrm{v}_j \in \mathrm{v}\} \\ &\mathrm{A}=\{\mathrm{a}_{ij}\} \end{aligned} \tag{1}$$

In the graph, v represents the nodes in Graph G, i denotes the number of nodes, and E represents the edges connecting different nodes. e_{ij} indicates an edge exists between node i and node j, with each node representing an electrode channel. $\boldsymbol{A}$ is the adjacency matrix, where the element a_{ij} represents the connection weight between nodes v_i and v_j. Thus, the graph structure is constructed through the adjacency matrix.

In this paper, the input EEG data is denoised and feature extracted by 1D-CNN to obtain the feature map, and then the Pearson correlation coefficient is used to construct the graph structure of the feature data, which is shown in Fig 2.

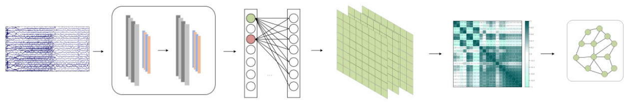

Fig. 2. Data preprocessing and graph construction

2.2. Global-Local Feature Collection Module

2.2.1 GCN Network

For graph convolutional neural networks, the node information and adjacency matrix in the generated graph are generally used as input data, and the graph data are trained and aggregated with the neighbor information between the nodes for the extraction of data features, which ensures the accurate realization of the subsequent detection tasks.

In general, it is known from the definition of graphical convolutional neural networks:

$$g * x = \mathrm{F}^{-1}(F(g) \odot F(x)) \tag{2}$$

Where, $\odot$ denotes the Hadamard product (elemental product), x is the graph signal representing the node feature information of the input, g is the filter, and $F(x)$ denotes the Fourier transform of x while $\mathrm{F}(x)=\mathbf{U}^T x$, so the inverse Fourier variation is $\mathrm{F}^{-1}(x)=\mathbf{U}x$, and $\mathbf{U}$ denotes the graph's corresponding eigenvector matrix.

According to the graph $G=(V,E)$, the normalized Laplace matrix $\mathbf{L}=\mathbf{I}-\mathbf{D}^{-1/2}\mathbf{A}\mathbf{D}^{-1/2}$, where $\mathbf{I}\in\mathbf{R}^{N\times N}$ is the unitary matrix. $\mathbf{D}$ is the diagonal matrix with respect to the degree of the nodes, and $\mathbf{A}$ is the adjacency matrix. Also according to $\mathbf{L}$ is a real symmetric semi-positive definite matrix, so $\mathbf{L}$ can be eigen-decomposed according to this property, so $\mathbf{L}=\mathbf{U}\mathbf{\Lambda}\mathbf{U}^T$, with $\mathbf{U}$ being the eigen-matrix consisting of the eigen-vectors, and $\mathbf{\Lambda}$ being the matrix consisting of the eigen-values. Thus, the graph signal x is a vector consisting of all nodes and their features.

So the form of graph convolutional neural networks can be rewritten as:

$$g * x = \mathbf{U}(\mathbf{U}^T g \odot \mathbf{U}^T x) \tag{3}$$

Also because graph convolution requires aggregating information from neighboring nodes, we set $\mathbf{U}^T g$ as a function of Laplace eigenvalues $g_\theta(\Lambda) = diag(\theta)$, with θ as the parameter thereof.

Therefore, the final form of the graph convolutional neural network is written as:

$$g_\theta * x = \mathbf{U} g_\theta \mathbf{U}^T x \tag{4}$$

Then where g_θ represents the graph convolution operator, so the formulation of the graph convolution neural network is simplified to this point, and the aggregation of neighboring nodes can be performed by the graph convolution operator as a way to perform the detection of epilepsy data.

2.2.2 Transformer Network

In the Transformer structure, the Self-Attention mechanism is the core component that enables the model to weight different parts of the input sequence in order to better understand the relationships and dynamics in the sequence. The Self-Attention process is as follows:

1） Input Vector Embedding: For any input vector X, it is first transformed into an intermediate vector Z by an embedding layer, which can be regarded as a patch-embedding mapping that transforms the original input into a form more suitable for model processing.

2） Generation of Query, Key, Value: The intermediate vector Z is later used to generate three different vectors: the query vector Q, the key vector K, and the value vector V. This process involves multiplying Z by three different matrices, W_q, W_k, and W_V, generating Q, K, and V, respectively. These matrices are the parameters of the model learning and are used to map the inputs to the appropriate space to perform the self-attention computation.

3） Self-attention arithmetic: the calculation of self-attention can be summarized by the following formula:

$$Attention\left(\mathrm{Q},\mathrm{K},\mathrm{V}\right) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{5}$$

In this formulation, Q, K and V represent query, key and value vectors respectively , Z denotes the input vector X through a linear mapping, W_q denotes the weight matrix corresponding to Q, W_k denotes the weight matrix corresponding to K, W_V denotes the weight matrix corresponding to V. The dot product of the query and key is first computed to obtain similarity scores between different locations in the input sequence. Then, these scores are scaled by dividing them by $\sqrt{d_k}$ (d_k is the dimension of the key vector), followed by normalization by the softmax function to obtain the attention weights. Finally, these weights are multiplied with the value vector V to generate a weighted representation, which reflects how much each part of the input sequence contributes to the current output.

2.2.3 GCNTrans Module

The GCN layer lies in the fact that it can directly perform feature extraction on the graph structure and obtain the neighbor information while keeping the graph structure unchanged, but it has to go through multiple layers before obtaining the global information, which increases the computation of the computation. The core of the self-attention layer in Transformer lies in the generated self-attention matrix. However, a multi-head attention layer will cover all the influences between the positional nodes, which leads to the introduction of irrelevant markers, thus affecting the data analysis results. In order to overcome the above limitations, this paper introduces the feature extraction via one-dimensional convolution to construct the graph structure, which improves the modeling quality by aggregating the neighbor information via two layers of GCN and inputting the adjacency matrix into the Transformer used to reduce the interactions of irrelevant features, and aggregating the features of GCN and Transformer. Therefore, the structure diagram of GCNTrans module is shown in Fig 3.

Where, in this paper, the graph structure obtained after feature extraction is used as an input, and subsequently this paper adds a position encoding P to the feature matrix to maintain the position information, namely:

$$G^{'} = G + P \tag{6}$$

It should be noted that $G \in R^{M \times N}$ denotes the input feature matrix, and P denotes the positional coding information, and P is defined by random initialization, which is adaptively updated during network training.

The query Q, key K and value A matrices are obtained by linear projection of the data features. With the application of the proximity matrix A to the self-attention layer in the Transformer layer, it is multiplied with the attention matrix in an element-by-element manner to mitigate misleading connections between the target matrix node and its unrelated nodes outside its neighborhood. Because, the weight matrix of the initial self-attention layer is not limited by connections and presents a dense character, i.e., all nodes are connected to each other. Therefore, the problem of irrelevant information interference can be mitigated by introducing the adjacency matrix A and after applying it to the self-attention layer, then its expression is shown as follows:

$$Attention\left(\mathrm{Q},\mathrm{K},\mathrm{V}\right) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}A\right)V \tag{7}$$

where $soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)$ denotes the self-attention layer of the GETM module and $Attention(.)$ denotes the self-attention layer. The design of Eq.6 makes it possible for the self-attention layer to extract both the local information in the graph structure and the neighboring information between the nodes of the graph structure, which greatly enhances the feature representation capability.

In addition, the multi-head attention mechanism employed allows each head to independently acquire different feature representations to enhance the diversity of feature representations, as denoted by the multi-head attention mechanism:

$$MHA(LN(G^{'})) = Concat\left[g_1, g_2, ..., g_s\right]W \tag{8}$$

$$g_i = Attention\left(Q_i, K_i, V_i\right) \tag{9}$$

where the subscript s denotes the number of multi-head attention mechanisms; Q_i denotes the query matrix of the i attention head; K_i denotes the key matrix of the i attention head; V_i denotes the value matrix of the i attention head; $Concat[.]$ denotes the splicing operation; LN denotes layer normalization, $MHA(.)$ denotes the multi-head attention mechanism; W denotes the weight matrix.

Therefore, multi-scale fusion of features is performed by Transformer aggregation of global features as well as GCN layer to get local features for multi-scale fusion of features on the input feature maps to achieve autonomous detection of epilepsy and to improve the performance of epilepsy detection.

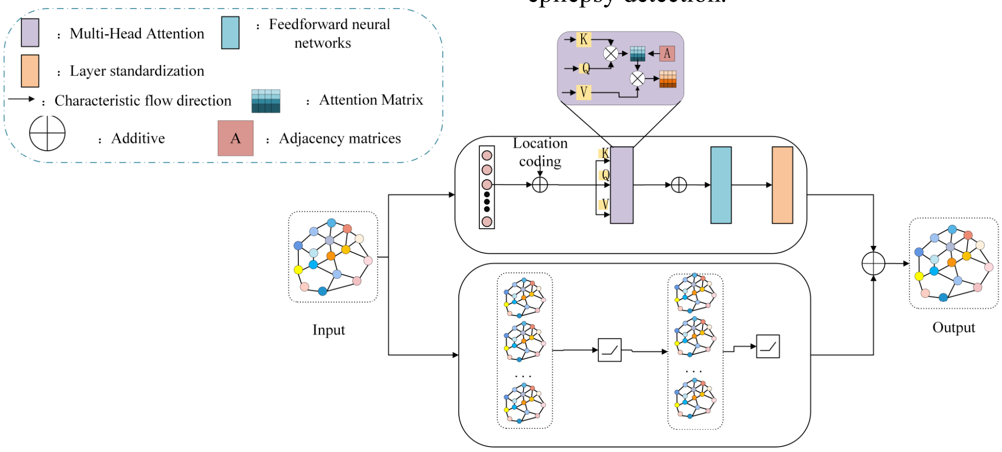

Fig. 3. Structure of GCNTrans module

3. Experimental results and analysis

3.1. Introduction to the dataset

Experiments were performed on the open-source CHB-MIT datasets at Boston Children's Hospital, Twenty-three case records were collected from 22 subjects. One of the info files contained the gender and age of each participant. Each patient's edf file contained 1-hour, 2-hour, or 4-hour EEG signals, which were sampled 256 times per second at 16-bit resolution and contained a total of 198 seizures. The prevented position of the electrodes on the patient's scalp during data acquisition followed the international standard 10-20 system. In the dataset, 23 channels were used for most of the data, and records with fewer or more than 23 channels were rounded off in this paper for data integrity as well as accuracy of the study.

3.2. Evaluation indicators

The performance of the algorithm is quantitatively analyzed using Sensitivity (Sen), Specificity (Spe) and Accuracy (Acc).

Sensitivity is defined as the proportion of correctly classified positive samples to all positive samples, i.e., the proportion correctly judged to be ill, and is calculated as:

$$Sen = \frac{TP}{TP + FN} \tag{10}$$

Specificity is defined as the proportion of correctly classified negative samples to all negative samples, i.e., the proportion correctly judged to be non-diseased, and is calculated as:

$$Spe = \frac{TN}{TN + FP} \tag{11}$$

Accuracy is defined as the proportion of correctly categorized samples to all samples and is calculated as:

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

3.3. Presentation and analysis of results

In this section, a series of experiments will be conducted to evaluate the proposed model. In addition, the corresponding experimental results will be given and experimental comparisons with other methods will be made. In order to demonstrate the performance of epilepsy detection, the selected one-to-one dataset will be used as the training data, while the remaining data will be used as the test data.

For the 24 patients in the selected CHB-MIT database, the patient-oriented epilepsy detection system was firstly established by training the dataset and completing the model training based on the GCTF framework. Then epilepsy detection was performed on the remaining data of each patient, and the results were shown in Table 1.

In Table 1, it can be seen that the average sensitivity of the 24 patients was 92.97%, specificity was 94.60% and accuracy was 94.59%. All patients had high sensitivity except for individual patients who had low sensitivity. Seven of the patients had a sensitivity of 100% and four patients had a lower sensitivity, of which Chb14 was due to the short duration of the seizure, Chb18 could be due to the lower amplitude, while Chb12 and Chb15 could be due to the lack of epileptic activity, which led to the lack of successful recognition.

In addition, the results obtained in this paper were compared with the results based on the same dataset in an epilepsy detection experiment conducted based on Boston Children's Hospital, as shown in Table 2.

Table 1. Detection results in the CHB-MIT dataset

Serial number	Length of training data (min)	Length of testing data (h)	Sensitivity /%	Specificity /%	Accuracy /%
Chb01	8.93	36.90	96.92	98.52	98.56
Chb02	5.33	34.98	100.00	93.80	93.81
Chb03	8.27	35.09	92.70	97.92	97.96
Chb04	10.93	148.05	94.63	90.74	90.73
Chb05	11.07	37.00	94.26	97.54	97.52
Chb06	4.53	56.47	100.00	96.46	96.44
Chb07	9.2	62.86	94.15	94.73	94.75
Chb08	17.33	14.78	93.13	96.38	96.36
Chb09	7.2	63.50	97.35	99.32	99.36
Chb10	11.73	46.01	93.78	96.94	96.93
Chb11	25.07	33.77	100.00	92.17	92.20
Chb12	10.27	19.25	69.91	66.79	66.72
Chb13	5.13	32.76	93.52	97.24	97.21
Chb14	4.53	23.67	70.10	99.74	99.73
Chb15	12	37.39	88.36	88.75	88.73
Chb16	0.2	18.85	100.00	88.31	88.33
Chb17	6.8	18.54	91.52	93.95	93.93
Chb18	8	32.95	81.26	98.25	98.19
Chb19	7.73	27.92	92.50	98.03	98.02
Chb20	8.8	26.59	100.00	96.46	96.45
Chb21	6.53	30.93	100.00	96.63	96.62
Chb22	6.67	29.72	91.66	99.45	99.42
Chb23	13.2	18.49	100.00	94.07	94.06
Chb24	10.4	13.53	95.64	98.17	98.16
average value	-	-	92.97	94.60	94.59

Table 2. Comparison with other methods on the CHB-MIT dataset

Documentation	Modeling Approach	Sensitivity /%	Specificity /%	Accuracy /%
1	CNN[9]	85.20	96.94	91.07
2	CNN+RNN[10]	86..06	94.08	94.17
3	CNN+WGAN[11]	72.11	95.89	84.00
4	The methodology proposed in this paper	92.97	94.60	94.59

In the comparison experiments, the method proposed in this paper is compared and analyzed with the results in the comparative literature, and the results can be seen: the results put in this paper are optimal in terms of sensitivity and accuracy, in which the results of specificity are not as good as those in the literature9, so it can be seen that the method proposed in this paper has certain superiority in epilepsy detection.

4. Conclusion

The experimental results show that the proposed GCTF framework based on graph convolutional neural network and Transformer model composition performs well in epilepsy detection classification accuracy, and its results are better than or close to many cutting-edge algorithms, showing good robustness. In particular, the model works by aggregating the multi-scale features of Transformer and GCN and fusing local and global features. This innovative point has important validity in epilepsy detection, far beyond traditional algorithms. When compared with other related literatures, the model achieved competitive test results, further confirming its significant value in clinical medical research. This innovative model not only provides an effective epilepsy detection method, but also provides a potential technical reference for other EEG-based applications.

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