An EEG Signal Recognition Algorithm During Epileptic Seizure Based on Distributed Edge Computing

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Received 2 July 2021 | Accepted 20 April 2022 | Published 12 July 2022

Abstract

Epilepsy is one kind of brain diseases, and its sudden unpredictability is the main cause of disability and even death. Thus, it is of great significance to identify electroencephalogram (EEG) during the seizure quickly and accurately. With the rise of cloud computing and edge computing, the interface between local detection and cloud recognition is established, which promotes the development of portable EEG detection and diagnosis. Thus, we construct a framework for identifying EEG signals in epileptic seizure based on cloud-edge computing. The EEG signals are obtained in real time locally, and the horizontal viewable model is established at the edge to enhance the internal correlation of the signals. The Takagi-Sugeno-Kang (TSK) fuzzy system is established to analyze the epileptic signals. In the cloud, the fusion of clinical features and signal features is established to establish a deep learning framework. Through local signal acquisition, edge signal processing and cloud signal recognition, the diagnosis of epilepsy is realized, which can provide a new idea for the real-time diagnosis and feedback of EEG during epileptic seizure.

Keywords

Clinical Feature, Cloud Computing, Deep Learning, Edge Computing, EEG Signal, Epilepsy, Seizure, Takagi-Sugeno-Kang (TSK).

DOI: 10.9781/ijimai.2022.07.001

I. Introduction

The epilepsy is a brain disease. Although most people with epilepsy are the same as normal people during the period of non-seizure, the unpredictability of epileptic sudden occurrence is the main cause of disability and even death of epileptic patients. The uncertainty of seizure seriously affects the life of patients [1]. Epilepsy is a chronic brain disease with recurrent seizures. Epilepsy is mainly caused by excessive discharge of brain neurons. It has the characteristics of paroxysmal, transient, repetitive and stereotyped. It can be manifested in sensory, motor, consciousness, spirit, behavior and autonomic nerve dysfunction. Human epilepsy has two characteristics: epileptiform discharges on electroencephalogram (EEG) and clinical seizures. The medical history is the main basis for the diagnosis of epilepsy. Doctors need to know through medical history: the characteristics of generalized tonic clonic seizures are loss of consciousness and generalized convulsions. If there is only general convulsion without sudden loss of consciousness, this does not support the diagnosis of epilepsy. Absence of consciousness, pseudoseizures or hypocalcemic convulsions should occur to tumble down. If the loss of consciousness is accompanied by a fall, the possibility of syncope is greater than that of absence attack. Automatism is characterized by abnormal behavior with disturbance of consciousness, seemingly purposeful but actually aimless. If the details of the seizure can be repeated after the seizure, it does not support the diagnosis of epilepsy. Epileptiform discharge on EEG is an important diagnostic evidence of epilepsy. It uses electrophysiological indexes to record the changes of electrical waves in the cerebral cortex when the brain is active. It is the overall reflection of the activity of neurons in the cerebral cortex [2]. In the field of electrical signal research in biomedical research, the EEG intelligence has been promoted, and a series of achievements have shown that signal in abnormal state is different from that in normal state due to the abnormal discharge of brain neurons during epileptic seizure. Therefore, recognizing the EEG signal is an effective epileptic detection method [3].

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In recent years, with the development of artificial intelligence, edge computing and cloud computing, the development of the medical field been promoted [4]. Gu et al. [5] construct a fog computing framework to manage medical big data. Abirami et al [6] compare the brain tumor data collected locally with the cloud to realize the focus detection. Shi et al. [7] analyze the opportunities and challenges of edge computing, and they indicate that edge computing is the development trend of smart medicine. Aggarwal et al. [8] establish a model from data security to realize data protection. Hosseini et al. [9] construct an edge computing framework to model multimodal data to detect epilepsy. Singh et al. [10] use edge computing to describe medical semantics. Li et al. [11] implement heart rate detection in the cloud. Oueida et al.

[12] implement medical data management based on edge computing. Abdellatif et al. [13] analyze the problems and challenges of edge computing in the medical field. Lin et al. [14] applie edge calculations to data allocation. Pustokhina et al. [15] move a deep learning network to an edge computing framework. Dou et al. [16] analyze short-time signals based on cloud computing. Rahman et al. [17] establish an edge computing framework to track the disease through the analysis of network data. Although cloud computing and edge computing have made a lot of achievements in medical treatment, there are few researches on epilepsy recognition, which are mostly based on clinical data analysis stage. A lot of researches have been carried out in epilepsy recognition: Xu et al. [18] analyze the methods of epilepsy treatment. Jefferys et al. [19] analyze the mechanism of epilepsy. Berg et al. [20] study the epilepsy characterization from clinical perspective. Koçer et al. [21] use the convolutional neural network to classify epilepsy. Pack et al. [22] analyze the cause of epilepsy from the perspective of Neurology. Margrove et al. [23] specify treatment plans based on different types of epilepsy. Rafiuddin et al. [24] establish the wavelet transform mechanism to analyze epilepsy. Pediaditis et al. [25] review the history of epilepsy. Musselman et al. [26] extract the epilepsy information from EEG signals. Chang et al. [27] use the machine learning to construct epileptic signal selection mechanism. Rosas et al. [28] analyze epileptic signals from the perspective of energy. Hosseini et al. [29] construct the quantitative and qualitative evaluation mechanism of EEG signals. Kiranyaz et al. [30] fuse time-domain and frequency-domain information to realize epileptic signal recognition. Gomez et al. [31] identify seizures by facial and eye movements. Villar et al. [32] use the signal acceleration to analyze EEG. Tao et al. [33] establish the Adaboost to realize EEG signal classification. Samiee et al. [34] use texture features to classify EEG. Yan et al. [35] establish the maximum entropy to measure epileptic patients. Qazi et al. [36] use the artificial intelligence technology to realize epileptic signal recognition. Li et al. [37] use a DWT algorithm to analyze EEG signals. Sepeta et al. [38] analyze the local EEG signal of epilepsy. Falco et al. [39] propose a new definition and classification of epilepsy. Qiu et al. [40] use the deep learning framework to detect signals. Jiang et al. [41] integrate the prior information to recognize epileptic signals. Parthiban et al. [42] establish a hybrid dragonfly optimization-based artificial neural network to realize epilepsy recognition. Si et al. [1] review the development of artificial intelligence in EEG signal detection. Thanaraj et al. [43] establish a convolutional neural network based on the entropy to detect epileptic signals.

The main problems of epilepsy recognition by EEG signals are as follows: 1) EEG signal processing has a large amount of computation and high local computational complexity. 2) It is difficult to distinguish between healthy period and epilepsy seizure. 3) It is limited to build the model only from the signal point of view.

To deal with these problems, our contributions are as follows: 1) We build a cloud-edge computing framework, manage data hierarchically, build a horizontal viewable model at the edge end and fully mining the signal correlation. 2) From the perspective of the fuzzy set, The Takagi-Sugeno-Kang (TSK) fuzzy system is established to analyze epileptic signals. 3) In the cloud, the deep learning framework is established by combining clinical features and signal features.

II. Algorithm

The signal is relatively stable during health and fluctuates greatly during seizures, as shown in . The algorithm pipeline is designed to build edge and cloud processing modules, as shown in Fig. 2. In order to enhance the difference between healthy signals and epileptic seizure, the EEG signals are sampled at the edge, the horizontal viewable algorithm is established, the strong correlation of the signals is established, and the weighted TSK fuzzy system is established. The EEG signal is predicted by an SVM classifier and the direct feedback display terminal with high prediction accuracy probability. For uncertain prediction, the advantages of cloud processor computing power are brought into full play to transmit data to the cloud in real time. Through the establishment of clinical big data, feature extraction and training model are built to achieve epileptic seizure recognition, and the database is updated by asynchronous transmission.

A. The Algorithm Based on Horizontal Viewable Image

The epileptic EEG signal belongs to time series. Each sampling point of time series is regarded as a viewable node, and the adjacent edges between nodes are regarded as viewable edges. The connectivity between different nodes depends on local convex constraints. When the connection between the sampling values at two times is not cut off by the sampling points at any other time within the interval there is an edge connection between two points; on the contrary, there is no edge connection, Fig. 3 shows the flow chart.

Based on the above analysis, we propose a horizontal viewable algorithm, which is defined as:

$$a_{ij} = \begin{cases} 1 & (n_k \le min(n_i, n_j)) \\ 0 & others \end{cases} \tag{1}$$

where n_i and n_j are nodes and a_{ij} are connected boundary values. When the value of any sampling time n_k between two nodes is less than the minimum value of the two nodes, there is an edge connection between two nodes, and a_{ij}=1, otherwise, there is no connection a_{ij}=0.

Each node in a complex network represents a point in the time series. When the values of other points between two points in the time series are less than these two points, the two points have edge connection.

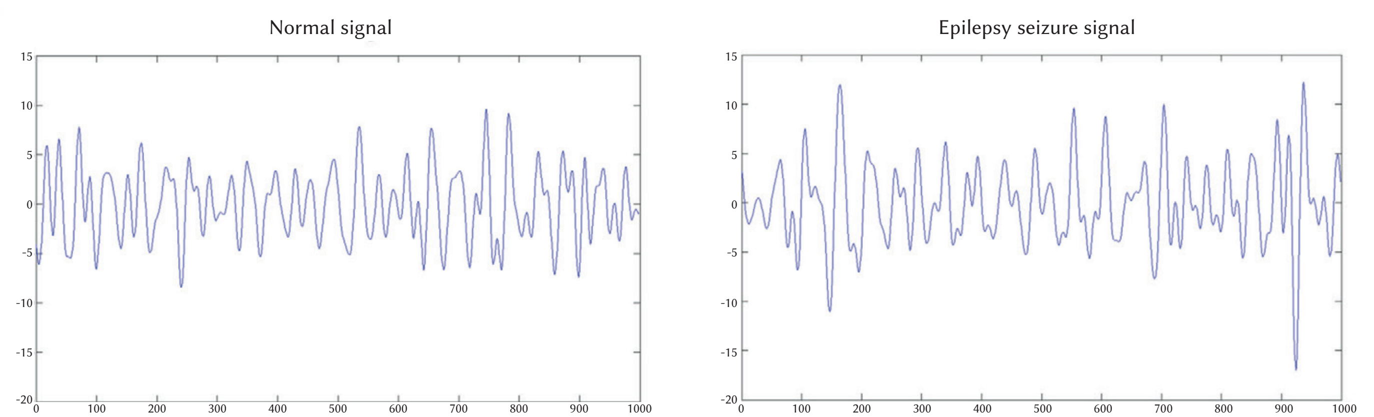


Fig. 1. EEG signal.

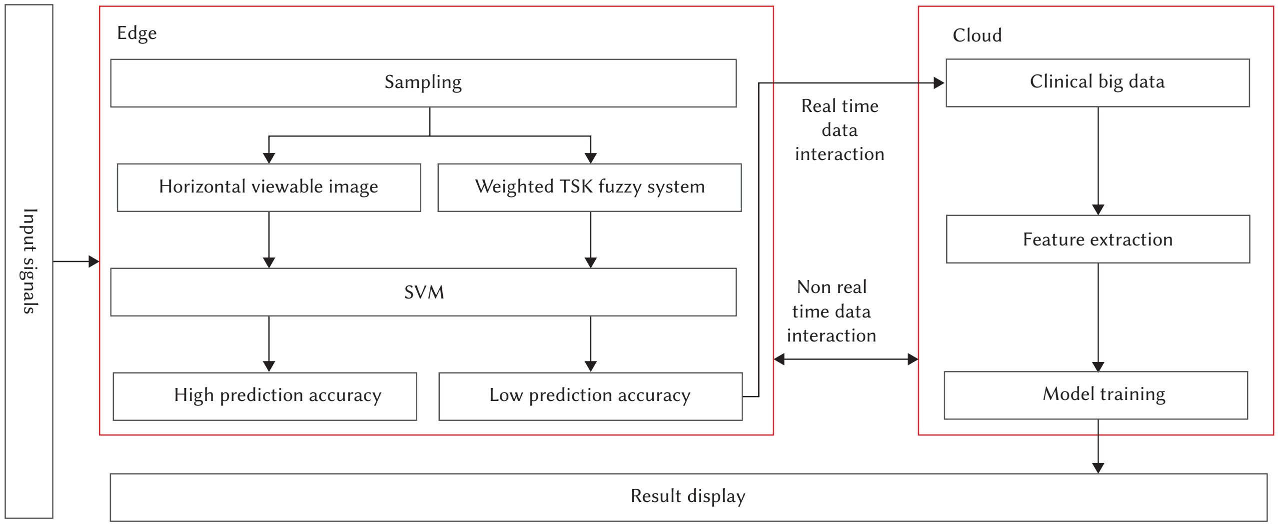


Fig. 2. Algorithm pipeline.

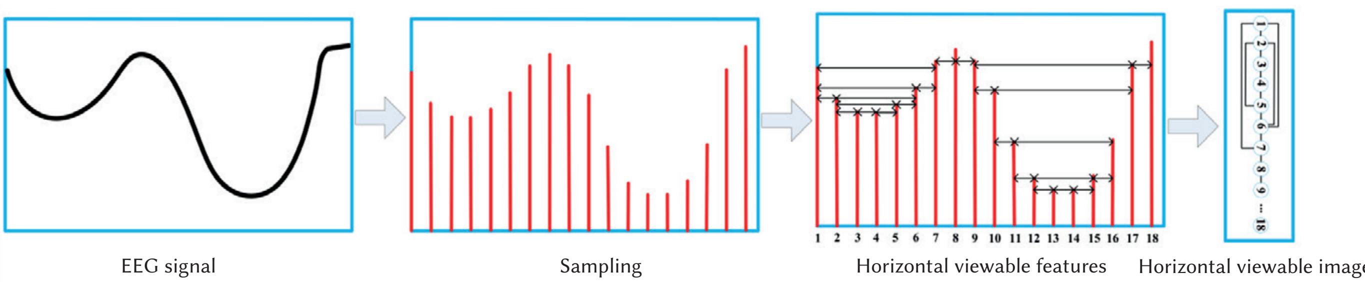


Fig. 3. Flow chart.

An important feature of complex network is the degree of complex network. Degree is defined as the number of adjacent edges of a node in the network, that is, several edges of the node are connected with other nodes. Suppose there are N nodes in the network, the expression of degree k_i of node i is:

$$k_i = \sum_{j=1}^{N} a_{ij} \tag{2}$$

Degree reflects the basic topological characteristics of complex networks, and describes the dynamic characteristics of the original time series. The average of different EEG signals is very different. In order to make the difference of degree more obvious, the power of degree is calculated as a new feature. The square of degree is extracted as the topological statistical feature from horizontal viewable image. The expression of the mean square is:

$$K_{DD} = \frac{1}{N}\sum_{j=1}^{N} k_i^2 \tag{3}$$

The complex network constructed by horizontal viewable image is a kind of binary complex network, with only 1 and 0 connected edges. On this basis, considering that there are different weights in the real complex network, this study improves the weighted level viewable algorithm. Under the criterion of horizontally viewable image, w_{ij} of edge connected a_{ij} is:

$$w_{ij} = \begin{cases} \left|\arctan\left(\dfrac{n_j - n_i}{j - i}\right)\right| & i < j, a_{ij} = 1 \\ 0 & others \end{cases} \tag{4}$$

where w_{ij} is the weight, which is expressed by the angle between two connected nodes, arctan is an arctangent transformation, and |.| is the absolute value. It is found that there are obvious differences between the angles of different complex network nodes, which reflect the fluctuation of the original time series. For time series with different dynamic structures, the complex network structures are different. Considering the concept of information entropy, this study proposes a new measurement feature for complex network structure, i.e., weight heavy distribution entropy, which reflects the topological structure information and connection complexity of complex networks. The entropy of complex networks with different features is very different. For the weighted level visualization graph, the entropy $E(i)$ of weight distribution of node n_i is:

$$E(i) = -\sum_{j=1}^{m} p_{ij}\log(p_{ij}) \tag{5}$$

$$p_{ij} = \frac{w_{ij}}{\sum_{k=1}^{m} w_{ik}} \tag{6}$$

where m is the number of nodes connected to n_i. The entropy of the average weight distribution of the weighted complex network is:

$$\bar{E} = \frac{1}{N}\sum_{i=1}^{N} E(i) \tag{7}$$

B. Weighted TSK Fuzzy System

The multi perspective features constructed from shallow and deep features have good expression ability and less information loss, but how to effectively use these features for epilepsy detection is very important. But at present, most of the researches lack the interpretability, which is very important in the practical application such as disease diagnosis. Therefore, in the development of the epileptic EEG detection technology based on multi perspective learning, a higher interpretable model is needed.

A TSK fuzzy system is an excellent model based on a rule system, which has better interpretability. Based on a TSK fuzzy system, we build an interpretable multi-view classifier for EEG detection. The TSK fuzzy system's output $f(x)$ is defined as:

$$f(x) = \sum_{k=1}^{K} \tilde{u}^k(x) f^k(x) \tag{8}$$

$$\begin{cases} \tilde{u}^k(x) = \frac{u^k(x)}{\sum_{k=1}^{K} u^k(x)} \\ f^k(x) = \sum_{i=1}^{d} p_i^k x_i \end{cases} \tag{9}$$

where p_i^k is the coefficient of x_i on the k-th rule of a linear function. $\mu^k(x)$ is the fuzzy membership degree of the k-th rule, $\tilde{u}^k(x)$ is the normalization of $\mu^k(x)$. The objective function of TSK fuzzy system is defined as:

$$\min_{\mathbf{P}_g} J(\mathbf{P}_{g,j}) = \frac{1}{2}\sum_{j=1}^{C}\sum_{i=1}^{N} \left\| (\mathbf{P}_{g,j})^T \mathbf{x}_{gi} - y_{ij} \right\|^2 + \frac{\lambda}{2}\sum_{j=1}^{C} (\mathbf{P}_{g,j})^T \mathbf{P}_{g,j} \tag{10}$$

where $\mathbf{P}_g$ is the parameter of the TSK fuzzy system. The first item expects to learn the best $\mathbf{P}_{g,j}$ to classify the training samples; The second term is the regularization penalty term, which improves the generalization ability of the TSK fuzzy system.

The calculation formula of $\mathbf{P}_g$ optimal value is:

$$\mathbf{P}_{g,j} = \left(\lambda_1 \mathbf{I}_{d\times d} + \sum_{i=1}^{N} \mathbf{x}_{gi}(\mathbf{x}_{gi})^T\right)^{-1} \left(\sum_{i=1}^{N} \mathbf{x}_{gi} y_{i,j}\right) \tag{11}$$

Given a multi-view epilepsy data set, the weighting mechanism of multi-view TSK fuzzy system is as follows:

$$Y = \frac{\lambda}{2}\sum_{k=1}^{K}\sum_{j=1}^{C}\sum_{i=1}^{N} \left\| (\mathbf{p}_{g,j}^k)\mathbf{x}_{gi}^k - \frac{1}{k-1}\sum_{l=1,l\neq k}^{K} (\tilde{\mathbf{p}}_{g,j}^k)^T \mathbf{x}_{gi}^k \right\|^2 \tag{12}$$

where $\mathbf{x}_{gi}^k$ is the k-th perspective of the i-th sample; $\mathbf{p}_{g,j}^k$ is a posteriori parameter of the k-th view of the multi-view TSK fuzzy system; $\tilde{\mathbf{p}}_{g,j}^k$ is the prior information, C is the total number of categories, K is the total number of perspectives, N is the number of samples in the data set, and λ is the regularization parameter.

It can realize multi-view cooperative learning mechanism, which ensures that all perspectives reach the same decision. λ controls the consistency between different views. If λ is too large, the prediction value of the k-th view will be too close to the prior decision value of all other views. The value of λ can be determined by the cross validation.

Based on the weighting mechanism and cooperative learning mechanism of multi-view fuzzy system, the objective function of multi-view TSK fuzzy system is constructed as follows:

$$\begin{aligned} &\min_{\mathbf{p}_g^k, w} J(\mathbf{P}_g^k, \mathbf{w}) = Q(\mathbf{P}_g^k, \mathbf{w}) + V(\mathbf{P}_g^k) + B(\mathbf{P}_g^k) \\ &V(\mathbf{P}_g^k) = \lambda_1 \sum_{k=1}^{K}\sum_{j=1}^{C} (\mathbf{P}_{g,j}^k)^T \mathbf{P}_{g,j}^k \\ &B(\mathbf{P}_g^k) = \frac{\lambda_2}{2}\sum_{k=1}^{K}\sum_{j=1}^{C}\sum_{i=1}^{N} \left\| (\mathbf{P}_{g,j}^k)^T \mathbf{x}_{gi}^k - \frac{1}{k-1}\sum_{l=1,l\neq k}^{K} (\tilde{\mathbf{P}}_{g,j}^l)^T \mathbf{x}_{gi}^l \right\|^2 \end{aligned} \tag{13}$$

where $Q(\mathbf{P}_g^k, \mathbf{w})$ is the improved multi-view weighting mechanism, w_k is the weight of the k-th view, m is the fuzzy index of w_k. By introducing the perspective weight index, we can study the updating rules of the weight in the optimal multi perspective model. $V(\mathbf{P}_g^k)$ is the regularization term, which can prevent the over-fitting phenomenon of the multi-view model. λ_1 is the coefficient of the regularization term, which is used to change the penalty of the regularization term. $B(\mathbf{P}_g^k)$ is a multi-perspective collaborative learning item, which expects each perspective to acquire the same decision value.

When updating $\mathbf{P}_g^k$, w_k is treated as a constant. Calculate $\mathbf{P}_g^k$ to acquire the gradient solution:

$$\begin{aligned} &\mathbf{P}_g^k = \mathbf{D}^{-1}\mathbf{H} \\ &\mathbf{D} = (w_k)^m \sum_{i=1}^{N} (\mathbf{x}_{gi}^k)^T \mathbf{x}_{gi}^k + \lambda_1 \mathbf{I} + \lambda_2 \sum_{i=1}^{N} (\mathbf{x}_{gi}^k)^T \mathbf{x}_{gi}^k \\ &\mathbf{H} = (w_k)^m \sum_{i=1}^{N} \mathbf{x}_{gi}^k y_{ij} + \frac{\lambda_2}{K-1}\sum_{l=1,l\neq k}^{K}\sum_{i=1}^{N} (\mathbf{x}_{gi}^l)^T \mathbf{x}_{gi}^l \tilde{\mathbf{p}}_{g,j}^l \end{aligned} \tag{14}$$

when updating w_k, $\mathbf{P}_g^k$ is treated as a constant. Calculate w_k to acquire the gradient solution:

$$w_k = \frac{\left(\sum_{j=1}^{C}\sum_{i=1}^{N} \left\| (\mathbf{p}_{g,j}^k)^T \mathbf{x}_{gi}^k - y_{i,j} \right\|^2\right)^{\frac{1}{1-m}}}{\left(\sum_{h=1}^{K}\sum_{j=1}^{C}\sum_{i=1}^{N} \left\| (\mathbf{p}_{g,j}^k)^T \mathbf{x}_{gi}^h - y_{i,j} \right\|^2\right)^{\frac{1}{1-m}}} \tag{15}$$

After multiple iterations, the optimal parameters $\mathbf{P}_g^k$ and w_k of the model are obtained. The final decision value of the model can be obtained by linear combination of decision values from different perspectives:

$$f(\mathbf{x}_{gi}^k) = sign\left(\sum_{i=1}^{N} w_k (\mathbf{p}_{g,j}^k)^T \mathbf{x}_{gi}^k\right) \tag{16}$$

C. Deep Learning Framework of Clinical and Signal Features

Epilepsy disease can be analyzed from the images and clinical information, so we fuse clinical information and signal information and propose an algorithm. Diagnosis can generally be made according to the medical history, clinical manifestations, such as recurrent muscle twitch, disturbance of consciousness and the results of relevant auxiliary examinations, such as EEG, positron tomography, etc. In the process of diagnosis, doctors need to exclude pseudoepileptic seizures, convulsive syncope, hypertensive encephalopathy, febrile convulsion and other diseases. The specific clinical features mainly include: age, gender, blood pressure, weight, disease, etc.

Due to the certain difference between healthy EEG signals and epileptic EEG signals, not all SVM classifiers can achieve good results, and there is also a correlation between the parameter setting of SVM and the quality of data. Therefore, we abandon the SVM classifiers with low accuracy, but these classifiers should also contain some information. In the future, we will carry out further research based on this.

The convolution neural network is used to automatically extract the viewable information and fuzzy information of the EEG signal, and obtain the corresponding deep features. The CNN network uses the back propagation mechanism in training. Since the eigenvector calculated by the penultimate layer only passes through one full connection layer to the output layer, it can be considered that the expression of the output eigenvector of the penultimate layer is optimized while the network structure is optimized according to the output layer training. Its network structure as shown in Fig. 4. Two types of structures are adopted. Class A and B structures that we design are mainly based on the following three reasons: 1) Class A structure learns bottom layer information. 2) Class B structure learns top layer information. 3) Class A and B structures can be effectively connected. Through the expansion of data set, the stability of a deep learning network is improved.

III. Experiment and Result Analysis

A. Experiment Data

We used Linux operating system and wrote programs with Python software. In this paper, the CHB_MIT dataset [44] is used for experimental studies. The data set collected EEG signals from 23 patients at Boston Children's hospital. These records from 23 patients were divided into 24 groups (Group 21 is the data of the first patient after resampling a few years later). Each group contains the EEG signals of one patient for more than ten consecutive hours. These consecutive signals are sampled at 256Hz, which means that there are 256 sampling points for one second signal. Each patient's EEG signal is collected from 18 points to form a single channel data set, and the subsequent processing becomes multi-channel data of 23 channels. Because the data is highly unbalanced, that is, the ratio of epileptic samples to non-epileptic samples is 1:100, if all the data are used directly, the effect of the proposed algorithm will face serious

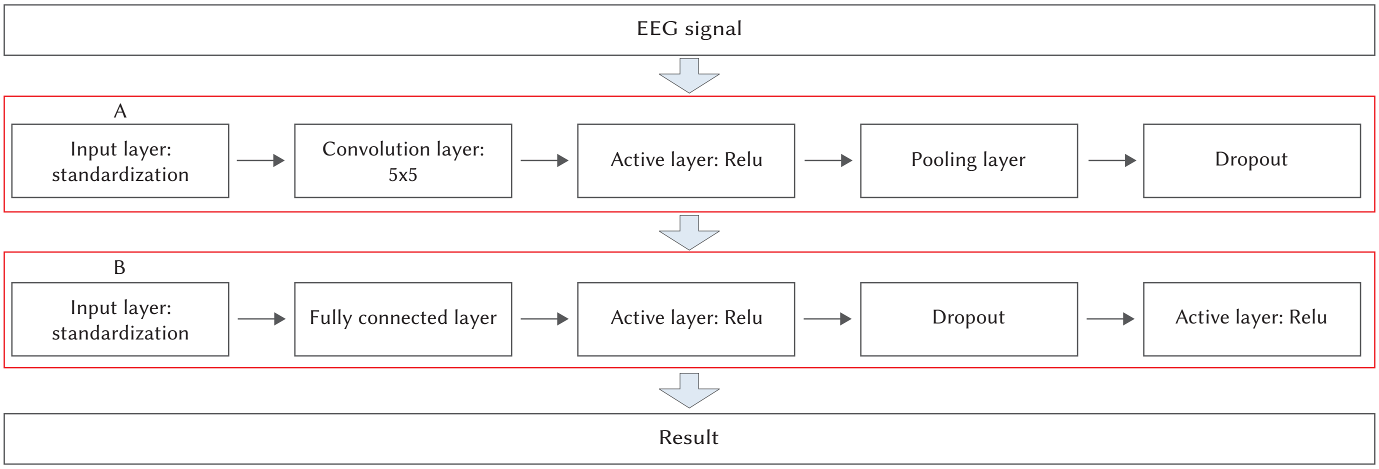


Fig. 4. The network structure.

over-fitting problem. In order to solve this problem, we discard some EEG signal data of non-epileptic, and apply over sampling technology to EEG signal data of epilepsy. A sliding window is used to divide the continuous EEG signal into several signal segments with a length of one second. The EEG signal of epilepsy is oversampled by allowing the overlap between the two windows.

B. Algorithm Performance

We verify the performance of the algorithm from the iterative curve of the algorithm, the target recognition curve with different signal-to-noise ratios, and the processing time of the algorithm.

Fig. 5 is the iteration curve of the algorithm. It can be seen that the algorithm shows an upward trend before the number of iterations reaches 50, reaches the maximum when the number of iterations is 53, and then shows a downward trend, so we will conduct research under the condition of 53 iterations.

Fig. 6 shows the detection performance of the algorithm under different signal-to-noise ratio conditions. It can be seen that as the signal-to-noise ratio increases, the effect is on the rise. In the case of a low signal-to-noise ratio, if it is less than -8DB, it still has a better recognition effect. This is because the horizontally visible image algorithm proposed in this article comprehensively considers the surrounding information and has strong noise suppression ability.

Table I shows the Time consumption. Because the transmission process is related to bandwidth, we do not count the transmission time. Normal signal is better than paroxysmal signal, and normal signal can be distinguished by primary operation. The signal processed at the edge is lower than that in the cloud. It is because the algorithm of edge processing is relatively simple, and complex signals need to be transmitted to the cloud for further processing. However, cloud is a deep learning algorithm composed of clinical big data, which is time-consuming. From the stability analysis, the variance of normal signal is better than that of paroxysmal signal because the normal signal has strong regularity. To sum up, the processing time of the algorithm can be controlled within 4s.

TABLE I. Computing Time

	Edge		Cloud	
	Normal	Seizure	Normal	Seizure
Mean	0.41 s	0.68 s	1.50 s	2.31 s
Variance	0.06 s	0.09 s	0.07 s	0.12 s
Maximum	0.72 s	0.95 s	2.10 s	2.68 s
Minimum	0.34 s	0.51 s	1.23 s	2.01 s

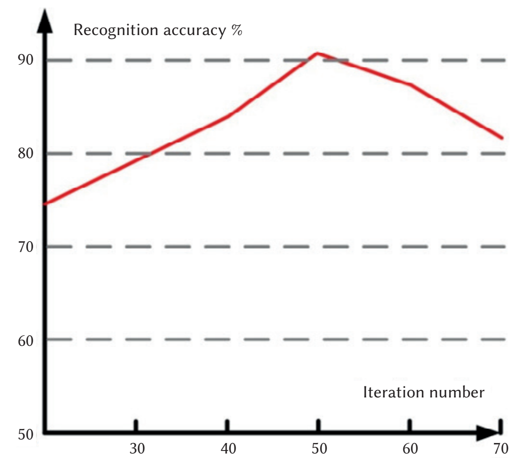


Fig. 5. The iteration curve of the proposed algorithm.

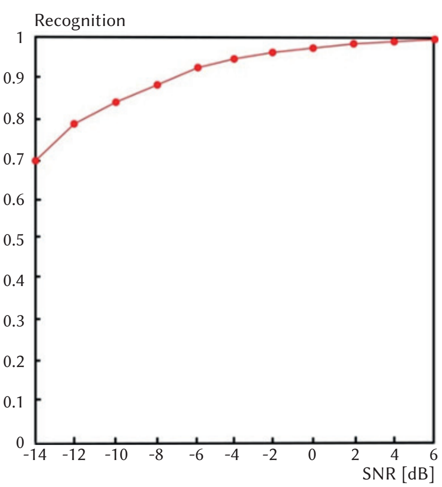


Fig. 6. Detection performance of the algorithm under different SNR.

C. Feature Extraction

To verify the detection performance of different algorithms, we introduce Sensitivity, Specificity and Accuracy as evaluation metrics.

$$Sensitivity = \frac{TP}{TP+FN} \tag{17}$$

$$Specificity = \frac{TN}{TN+FP} \tag{18}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{19}$$

where *TP* is the number of correctly predicted epileptic fragments, *FN* is the number of epileptic fragments that are predicted as non-epileptic fragments, *FP* is the number of non-epileptic fragments that are predicted as epilepsy, *TN* is the number of non-epileptic fragments that are predicted as non-epileptic fragments.

Accuracy represents the proportion of the correct classification of the classifier, and the higher the ratio represents, the better the classification performance of the classifier; Sensitivity represents the proportion of the correct classification of all epileptic fragments, and the higher the ratio represents, the higher the prediction accuracy of the classifier for epileptic fragments; Specificity indicates the proportion of all non-epileptic fragments correctly classified, and the higher the ratio, the higher the prediction accuracy of non-epileptic fragments.

Kiranyaz et al. [30] do not use cross validation to fuse time-domain and frequency-domain information, which could not effectively prove the performance of epilepsy detection. Tao et al. [35] use the AdaBoost multi-scale decomposition for signals in order to avoid too few epileptic samples in the verification set. Only 25% samples were used for training. Samiee et al. [34] use the amplitude features of the EEG signal to recognize epileptic signals. Jiang et al. [41] integrated prior information into the model to recognize epileptic signals. Parthiban et al. [42] analyze epileptic signals from the perspective of energy entropy. Different oversampling methods are used to increase the number of epileptic samples. Due to the data imbalance, the accuracy and sensitivity of most algorithms are relatively low, but the proposed algorithm in this paper shows better accuracy and sensitivity under the condition of maintaining the same specificity, as shown in Table II.

D. Comparison of Classification Algorithms

We constructed time-domain similarity data set and frequency-domain similarity data set, to analyze the classification of EEG signals. ROC curves can show the performance of different algorithms. Musselman et al. [26] establish time domain model to realize EEG signal. Rafiuddin et al. [24] establish energy domain model to classify EEG signal. Kiranyaz et al. [30] establish time-energy model to realize EEG signal.

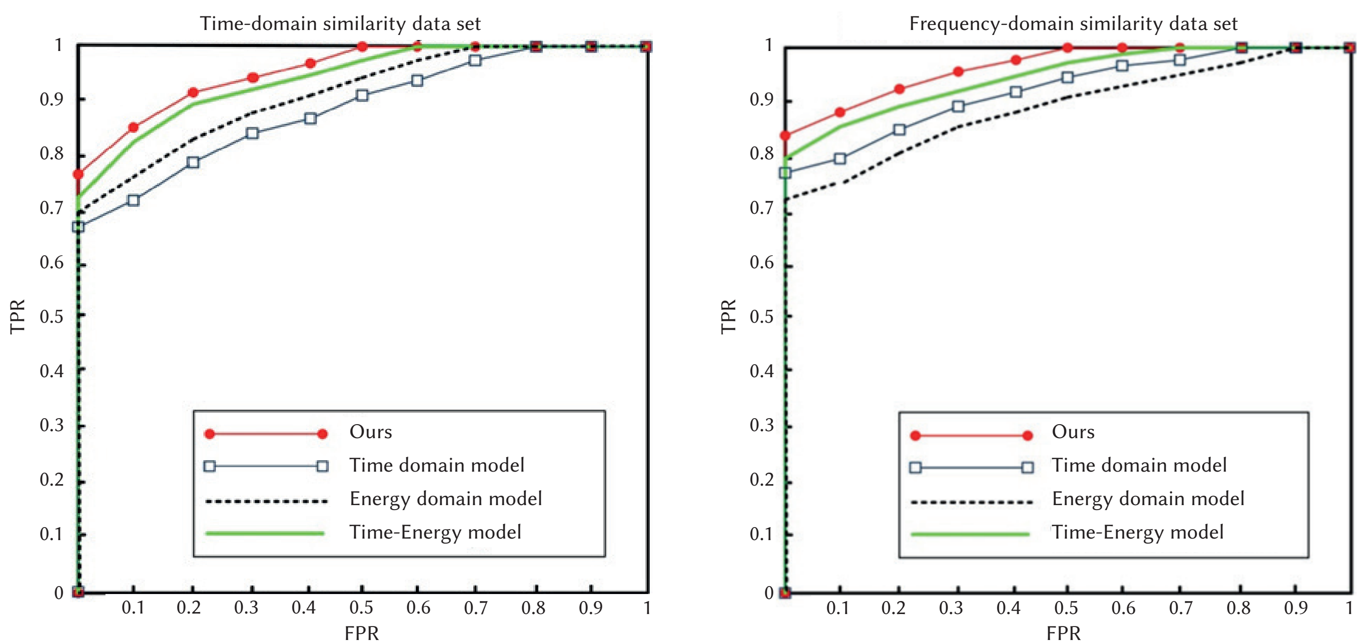
As shown in Fig. 7-a, the time domain model cannot effectively distinguish the time-domain similarity data. The energy domain model transforms time domain signals into frequency domains for research. Based on the difference of frequency domains, it can achieve better data classification. As shown in Fig. 7-b, the energy domain model cannot effectively distinguish the frequency-domain similarity data. The time domain model realizes signal classification based on the significant difference of Time domain. The time-energy model comprehensively considers the difference between time domain and frequency domain, so they have a good effect in the face of similar classification effects in Time domain or frequency domain. The proposed algorithm establishes the Horizontal Viewable model from the time domain, enhances the anti-noise ability of the algorithm, establishes the TSK model from the frequency domain to realize the energy, and achieves accurate classification based on clinical diagnosis and clinical representation data.

IV. Conclusion

Epilepsy is acute, which is of great significance for its early recognition. Through the study of EEG signals, aiming at the problem of difficult recognition of epileptic signals, an epileptic brain signal

TABLE II. Detection Effect

	Fusion [30]	AdaBoost [35]	Texture [34]	Prior [41]	Entropy [42]	Ours
Specificity	0.802	0.814	0.812	0.841	0.865	**0.915**
Sensitivity	0.821	0.836	0.835	0.865	0.879	**0.925**
Accuracy	0.814	0.845	0.812	0.865	0.912	**0.934**



(a) The model ROC curve of time-domain similarity data

(b) The model ROC curve of frequency-domain similarity data

Fig. 7. ROC curve.

recognition algorithm based on cloud edge computing is proposed. A horizontal visualization model is constructed at the edge to enhance the internal correlation of signals, and a TSK fuzzy analysis system of epileptic signals is established. For more complex data, the deep learning network of clinical representation is constructed through cloud to identify the EEG signals during seizures, which provides the accuracy of epilepsy diagnosis. Our research can be extended to other intelligent medical fields.

Acknowledgment

This work is supported by Science and Technology Rising Star of Shaanxi Youth (2021KJXX-61), The Shanxi National Science Foundation (2020JQ-518), Natural Science Foundation of China (62062003), North Minzu University Research Project of Talent Introduction (2020KYQD08), Key Research and Development Project of Ningxia (2020BEB04022), The Open Project Program of the State Key Lab of CAD&CG (A2206).

Conflicts of Interest

The authors declare no conflict of interest.

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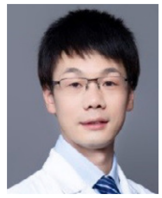

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