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EEG-based Methods of Epilepsy Seizure Detection: A Review

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Abstract. The electroencephalogram plays an important diagnostic role in epilepsy and provides supporting evidence of a seizure disorder, as well as assisting with the classification of seizures and epilepsy syndromes. This paper reviews epileptic seizure detection and classification methods based on recorded EEG signals. We compared the traditional automatic recognition method with recently innovated detection and classification methods. These innovative methods, based on the same process of data segmentation, feature extraction, and feature classification, introduced new algorithms: convolutional neural network (CNN), K nearest neighbor (kNN), support vector machine (SVM), random forest (RF), graph-generative neural network (GGN), common spatial pattern (CSP), deep learning algorithm and model training algorithm. We found that all these innovative methods have better classification performance (detection accuracy, sensitivity, false prediction rate) than automatic recognition. From a future perspective, this emerging technique gives a quick and more efficient way of dealing with EEG signals, improving the original shortcomings in detection and classification, especially in neural disorders.

Keywords: electroencephalography, epileptic detection, automatic recognition, deep learning, machine training.

1. Introduction

Epilepsy is a major contributor to the global disease burden, affecting approximately 50 million people worldwide. An epilepsy seizure is a transient, abrupt disruption of brain function caused by abnormal electrical discharges from neurons in the brain. These discharges lead to temporary functional impairments in certain areas of the brain, manifesting as a range of clinical symptoms, such as loss of consciousness, muscle spasms, sensory disturbances, unconscious behaviors, and, in some cases, incontinence or tongue biting. Electroencephalography (EEG) is the most useful diagnostic procedure for epilepsy. Interictal epileptic form discharges (IEDs) in EEG help to differentiate between epileptic and other non-epileptic paroxysmal attacks. Before the invention of EEG, the treatment of epilepsy mainly relied on herbal medicines and chemical substances, as well as some surgical methods. As shown in Fig. 1, Electroencephalography (EEG) is the most useful diagnostic procedure for epilepsy. Its sensitivity and specificity depend on several factors, such as

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age and recording procedures [1]. In this paper, we will discuss how to detect epilepsy from EEG signals. Comparing different methods and analyzing their benefits and drawbacks, classification of these methods.

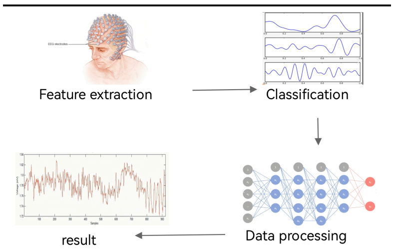

Figure 1. Basic processes of EEG epilepsy seizure detection

2. EEG-based seizure detection system

2.1. Pre-processing

When EEG signals are extracted, the noise will be accompanied. It will corrupt the signals and impact signal analysis. In that case, signal preprocessing is essential to improve the signal-to-noise ratio (SNR). There are many preprocessing methods (see Table 1). In Aslam's article, a method called PREP pipeline was used. They used a band-stop filter to remove the artifacts and powerline noise [1]. Celka's group used adaptive algorithms and time-frequency analysis to preprocess signals under nonstationary and non-Gaussian environments, respectively. Linear / Nonlinear filter structure and normalized stochastic least mean square (NLMA) adaptive algorithm were used based on the environment. ECGs and EOGs were removed in Celka's experiment [2]. In Bogaarts's experiment, a Band pass filter was used to remove artifacts that were not seizure discharges or NS EEGs [3]. Zaid used the following operation: standardization, differentiating the signal, and the magnitude of fast Fourier transform (FFT) [4].

Table 1. Different preprocessing methods

	Preprocessing Method	Artifacts Removal	Use of Filters
Aslam (2022) [1]	PREP pipeline	Powerline noise	Band-stop Filter
Celka (2001) [2]	Adaptive Algorithms Time-frequency Analysis	ECGs EOGs	Linear/Nonlinear filter structure
Bogaarts (2014) [3]		Not seizures NS EEGs	NLMS adaptive algorithm Band pass filter
Zaid (2023) [4]	Standardization Signal differentiation FFT		

Note: NLMA: normalized stochastic least mean square; “-”: not clearly mentioned in the article

2.2. Feature extraction

Fast Fourier Transform (FFT) is a method that transforms the temporal domain into the frequency domain, making data analysis easier. The data collected needs to be divided into different segments for analysis. FFT makes it easy to construct an ensemble model to classify data.

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Wavelet transform (WT) can analyze temporal domain signals. This means it can deal with data in two dimensions, including time and frequency, which is better than FFT. It also has more advantages when handling unstable signals, so it is skilled at brain signals when detecting epilepsy. But it also has some drawbacks compared to FFT. For example, it does not have adaptivity, which means it cannot deal with complex signals.

Common spatial pattern (CSP) divides the EEG signal into different graphs with variables of time and frequency. It considers time-varying spatial distributions and assigns the weight of time-frequency graphs to analyze data. It uses a spatial filter to get valuable data on brain activity.

2.3. Classification techniques

2.3.1. Support Vector Machine (SVM)

Support vector machine (SVM) is a kind of machine learning algorithm. Machine learning algorithms can adjust themselves to achieve higher accuracy and lower false rates by self-training with a set of training data automatically [5]. In SVM's application in classification, a feature vector extracted by the previous process is input, and a prediction function is given out for epilepsy seizure type classification [6].

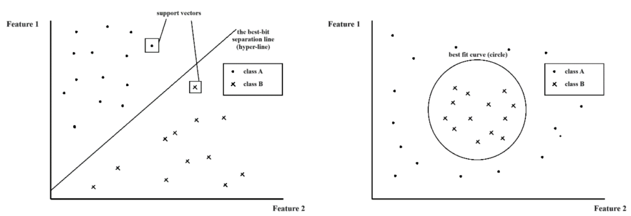
The prediction function can be either linear (Figure 2(a)) or nonlinear (Figure 2(b)), if different classes of support vectors cannot be linearly separated, we need to introduce a Kernel function that transforms the support vectors to a higher dimension and separate the vectors using a hyper-plane [2]. Choosing the appropriate Kernal function eq (1-3) for the problem can increase classification accuracy. The nonlinear function includes radial-based function (RBF), sigmoid, and grid [1].

$$Linear: K(x_i, x_j) = {x_i}^T x_j \tag{1}$$

$$RBF: K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2}, \gamma > 0 \tag{2}$$

$$Sigmoid: K(x_i, x_j) = tanh(\gamma {x_i}^T x_j + r) \tag{3}$$

$$Gird: \ determined\ by\ the\ gird\ search$$



(a) left-SVM with linear Kernal function (b) right-SVM with nonlinear Kernal function

Figure 2. Two types of SVM

Comparing those 4 types of SVM, the results found that the grid and RBF SVM have the highest average accuracy, sensitivity, and specificity, both in the inter-ictal and seizure ictal situations. According to this research, the highest average predicting accuracy for EEG signals using the grid SVM can reach 98.91%. The strengths of SVM are that the machine training process is relatively

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easy compared with other machine training and deep learning methods, such as the neural network methods [2].

2.3.2. K-Nearest Neighbour (kNN)

The K-nearest number method also classifies EEG signals by machine learning algorithm, so before the kNN can be applied in real cases, the algorithm must be trained by several samples. In original kNN methods an appropriate value of k must be selected to reach the highest accuracy of the algorithm, and researchers determine the similarity of each sample by calculating their Euclidean distance. However, ZHIPING WANG (2020) and his team [4] discussed that the Euclidean distance is limited when determining the similarity of EEG data since Euclidean distance can only deal with two low-dimensional samples. Therefore, the research used WBCKNN in his research. In this research, the EEG data are stored in high-dimensional spaces according to their feature parameters, and he introduces the Brey Curtis distance to determine the similarity of high-dimensional samples. The kNN method, evaluated by the research, is simple and effective, but is a lazy learning method.

2.4. Data processing

2.4.1. Convolutional Neural Network (CNN)

A neural network consists of an input layer, a hidden layer, and an output layer. It intends to construct a model with a series of steps to get the best fit. However, it still has some differences. So, Cross Entropy Loss is a good way to measure difference. It is used to measure the uncertainty. If one thing has a larger uncertainty, it means it contains more information. Brain signals normally between 0-30Hz. But ill part with frequency higher than 30Hz. Also, the ill part always with low entropy and high amplitude in signals. In addition, during the seizure, there is abnormal brain activity happened. Higher frequency or sharp waves, for example. When this data is collected by EEG, CNN will divide them into signals of seizure and no signals of seizure. In this process, it can be divided into four main parts, including data input, filter, convolution, and max pooling. Max pooling is a process that simplifies the calculation.

2.4.2. Recurrent Neural Network (RNN)

Kosuke [5] proposed a method that combines RNN and a Self-attention mechanism in 2022. This system consists of two long-short-term memory(LSTM) and one self-attention layer. LSTM, an average-pooling layer, will give features very quickly, and the self-attention mechanism will analyze its weights and relationship. As a result, they found that the self-attention layer has a greater response to epileptic wave peaks.

2.4.3. Transformer

Transformers are different from CNN and RNN. It contains an encoder and a decoder. This model entirely uses self-attention mechanisms. It does not use recurrence or convolution, which means it can achieve parallel programming to improve efficiency. Also, it can deal with a long data sequence to get the relationship and analyze it. Transformer segments EEG signals into several blocks and transform them into one-dimensional vectors. The results are in the attention layer. What is found is that EEG signals in each patient with epilepsy are different, so it is important to develop individual predictions as it is hard to detect.

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3. Challenge and discussion

Table 2. Comparison of different classification techniques

Classification techniques	accuracy	data weight analysis	parallel data processing	long sequence data analysis
CNN	Around 90%	Yes	Weak	No
transformer	Around 94%	No	Strong	Yes
RNN	Around 88%	Yes	Weak	No

Table 3. Comparisons of different extraction techniques

Extraction techniques	application	information	efficiency
FFT	Periodic signal	Frequency domain	high
WT	Unstable signal	Temporal domain	relatively low
CSP	filter	spatial	depends

This article compares the different methods to detect epileptic EEG signals. From Table 2, we can see that CNN and RNN act in similar functions. While a transformer is a new technique, it can process long data sequences but needs to determine the weights manually. From Table 3, these three different extraction techniques give different data. However, we found that WT is more efficient and accurate when dealing with brain signals.

4. Conclusion

This review illustrates how epileptic signals could be detected by using EEG in different methods. We reviewed the different EEG-related articles. Their methods are used in feature extraction and classification. How EEG signals are classified. Filtering the useless signals (e.g., surroundings, electromyographic signals)

We find that analyzing EEG signals using the frequency or temporal domain supports the identification of epileptic signals. Overall, EEG is a very important method of patient diagnosis. This approach may improve patients' lives by providing more valuable insights.

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