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iEEG Signal Data Augmentation in Convolutional Neural Networks for Epileptic Focus Localization

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Abstract

Epileptic focus localization plays a crucial role in the diagnosis and treatment of epilepsy. Convolutional Neural Networks (CNNs) have exhibited promising outcomes in automatically detecting epileptic focus through the analysis of intracranial electroencephalogram (iEEG) signals. However, the limited availability of labeled iEEG dataset, which require specialist annotations, has constrained the effectiveness of CNNs. In this study, data augmentation techniques, including time shifting, amplitude scaling and noise addition, were employed to enhance the diversity and information content of the data. These techniques aimed to enable machine learning models to extract features from various aspects of iEEG data, thereby improving the accuracy of the models. Three deep learning models, namely DeepConvNet, ShallowConvNet and EEGNet, were introduced for the identification of epileptic foci. To evaluate the proposed methods, the Bern-Barcelona iEEG dataset was utilized. The experimental results demonstrated that the augmented dataset, formed by applying the three data augmentation techniques, achieved higher accuracies across all three deep learning models compared to the original dataset. This finding underscores the feasibility and efficacy of the proposed data augmentation and feature extraction methods in automated epilepsy detection.

Keywords: epileptic foci, data augmentation, convolutional neural networks, k-fold cross-validation

Introduction

Epilepsy is a group of non-communicable neurological disorders characterized by recurrent epileptic seizures (Fisher et al., 2014; Ghosh et al., 2021). There are many expressions such as sudden loss of consciousness, stiff whole body, convulsions, temporary vagueness and rapid contraction of muscles in the whole body. According to the data from World Health Organization (WHO), Epilepsy is one of the most common neurological diseases in the world and there are approximately 50 million people suffering from it (World Health Organization, 2016). In alternative terms, the International League Against Epilepsy (ILAE) provides the following conditions for defining epilepsy (Fisher et al., 2014): (1) the occurrence of at least two unprovoked (or reflex) seizures with an interval of more than 24 hours, (2) a single unprovoked (or reflex) seizure with a probability of subsequent seizures similar to the general risk of recurrence (at least 60%) over the next 10 years after two unprovoked seizures and (3) the diagnosis of an epilepsy syndrome. Epileptic seizures can be classified into three general types: generalized seizures, focal seizures and unknown seizures (Fisher et al., 2017).

Electroencephalogram (EEG) is a non-invasive technique used to record and analyze the electrical activity of the brain (Niedermeyer & da Silva, 2005). It involves placing electrodes on the scalp to measure and capture the electrical signals produced by neurons in the brain. EEG plays a crucial role in the detection of epilepsy, with approximately

80% of epilepsy patients exhibiting abnormal EEG patterns. During interictal periods, characteristic waveforms such as spikes, sharp waves and spike-and-wave complexes can be observed on the EEG (Gotman & Gloor, 1976). These abnormal patterns assist in the diagnosis of epilepsy and the localization of epileptic foci. EEG is also valuable for monitoring the effectiveness of treatment and assessing the frequency and severity of seizures. In summary, EEG is a vital tool in epilepsy detection, providing valuable insights into brain activity and aiding in the diagnosis, localization and evaluation of treatment for epilepsy patients.

In epilepsy patients, up to 70% of them can be successfully treated with antiepileptic drugs (AEDs) (Organization et al., 2019). However, for those who are resistant to AEDs, surgical resection of the epileptic tissue becomes necessary to control seizures. Therefore, the automated detection and localization of epileptic foci play a crucial role in guiding surgical interventions. Currently, methods used to determine the epileptic seizure area include physical examinations, intracranial electroencephalography (iEEG), magnetoencephalography (MEG) (Baumgartner et al., 2000) and functional magnetic resonance imaging (fMRI) (Bhattacharyya et al., 2017). Unfortunately, fMRI lacks temporal resolution and cannot capture complete brain activity, while MEG is expensive and less practical for routine use. Thus, utilizing EEG for the localization of epileptic foci emerges as the optimal choice.

In clinical diagnosis, the presence or absence of epilepsy foci was determined mainly by artificially identifying characteristic waves. During the intermittent development of epilepsy, the brain will discharge abnormally. To accurately diagnose epilepsy disease, it is necessary to monitor the patient's EEG for a long time. The EEG data is a very weak unsteady signal, has strong chaos characteristics and strong background noise. Since a long time, the interpretation of EEG has been artificial. Due to the high labor intensity and large subjective factors, it is difficult to realize an EEG test of the nature of a large-scale sieving test (Xia et al., 2021). Therefore, we need a complete system for the automatic detection of epileptic foci.

An automated detection system for epileptic foci is a system that uses deep learning and artificial intelligence techniques to analyze and process EEG data to automatically detect and localize epileptic foci. Such automated detection systems typically involve multiple steps, including data pre-processing, feature extraction, model training and epilepsy detection. The automatic epilepsy detection process is shown in Fig. 1. The raw epileptic EEG data undergoes pre-processing steps such as filtering, denoising and calibration to remove noise and interference and improve signal quality. Next, features, such as time-domain, frequency-domain or time-frequency-domain features, are extracted from the processed EEG data and used to train a machine learning model. During the model training phase, supervised learning methods such as convolutional neural networks (CNN) (Zhang et al., 1988), recurrent neural networks (RNN) or support vector machines (SVM) are often used to train classifiers capable of automatically identifying epileptic lesions (Cortes & Vapnik, 1995; Jordan, 1997). The training data usually consists of already labeled EEG data containing both epileptic seizure and non-seizure samples and is used to train the classification model. During the lesion detection phase, the already trained model is used to predict and classify new EEG data to detect and localize epileptic lesions. The system typically outputs information about the location, duration and intensity of one or more lesions to assist physicians in making diagnostic and treatment decisions for epileptic lesions.

The common signal processing transforms used in the proposed methods for EEG data feature extraction in epilepsy are the Short Time Fourier Transform (STFT) and the Continuous Wavelet Transform (CWT) (Sejdić et al., 2009; Xia et al., 2021). However, in the course of actual experiments we found that these two methods consume a relatively long time and the calculated results are saved as images in the format of pictures, thus taking up a large amount of computer memory.

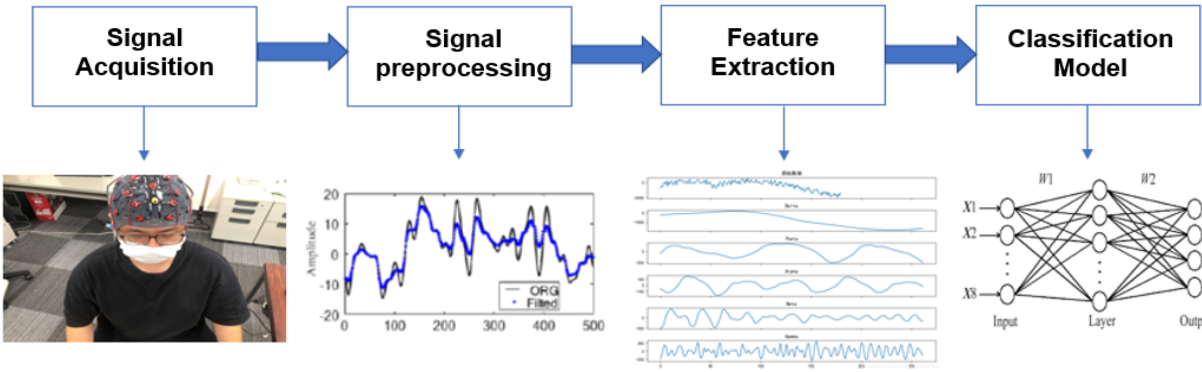

Fig. 1. Epilepsy Automatic Detection Flowchart

In this paper, we propose three data augmentation methods for feature extraction in epileptic EEG data: Time shifting (TS), Amplitude scaling (AS) and Noise addition (NA). These methods are employed to enhance the analysis of epileptic EEG data (Shorten & Khoshgoftaar, 2019). By applying certain transformations to the existing data to generate more samples. The advantage of this approach is that it helps the model learn the features of the data better and improves the generalization ability of the model. In this phase of classification grading, we propose 3 deep learning models: the DeepConvNet model (Mekruksavanich & Jitpattanakul, 2022), the ShallowConvNet model and the EEGNet model (Lawhern et al., 2018; Roots et al., 2020), which have become common tools in deep learning research. The DeepConvNet is a convolutional neural network-based model specifically designed for epileptic focus detection. DeepConvNet performs well in processing multichannel EEG data and can accurately identify and localize epileptic focus. ShallowConvNet is a shallow convolutional neural network model that is particularly suitable for processing time-domain features. It uses fewer convolutional and pooling layers with fewer parameters and faster training. EEGNet is a hybrid network model that combines CNN and Temporal Convolutional Networks (TCN) and aims to take full advantage of the spatiotemporal features of EEG data. It has a shallow network structure and local connectivity patterns, which can effectively capture the temporal information and frequency domain features in EEG data. Finally, we use the Bern-Barcelona dataset to verify that the data augmentation method is helpful in network model learning and capturing different features and patterns in the data, thus validating the feasibility and efficiency of the data augmentation feature extraction methods in epilepsy automatic detection systems.

The rest of the article is organized as follows: Section 2 describes the dataset used in the experiment and the method of data augmentation and CNN. Section 3 describes a comparison of the architecture of the three deep learning models proposed. The experimental results are presented in Section 4, and the last is the conclusion of this paper.

Data Augmentation

Data augmentation is a technique commonly used in signal feature extraction. Feature extraction involves deriving informative and non-redundant features from measured data, facilitating learning, generalization and human interpretation (Sarangi et al., 2020). This is used to improve the performance of the automatic detection system for epileptic EEG. The extracted features can be used as input to various machine learning algorithms for classification, such as support vector machines (SVM) (Cortes & Vapnik, 1995), artificial neural networks (ANN) (Guresen & Kayakutlu, 2011), or random forests (RF)(Ho et al., 1995), to achieve accurate and reliable detection of epileptic brain activity. Data augmentation generates new extended datasets by performing a series of transformations or syntheses on the original signal, thus increasing data diversity, improving model robustness, alleviating data imbalance problems and extracting richer features (Shorten & Khoshgoftaar, 2019). The following are some of the applications of using augmented data in signal feature extraction:

Time Shifting. By shifting the original EEG data along the time axis, a new time-shifted signal is generated. The EEG data can be shifted forward or backward in time by a certain number of time steps to simulate the temporal displacement of the EEG data. The shifted data will contain delayed versions of the original data in time. The purpose of this is to enable the model to capture the temporal dependencies in the data and help the model understand the variations of EEG data features at different time points, such as the changes in different frequency rhythms (α waves, β waves, etc.) over time. Time shifting can introduce the temporal relationships of the data. For EEG data, time shifting can help the model capture the correlations and dynamic changes at different time points. By introducing time shifting, the model can better adapt to slight variations and shifts in the input data, thereby improving the model's robustness. Fig. 2 is an example of EEG data after 3000 times shifting.

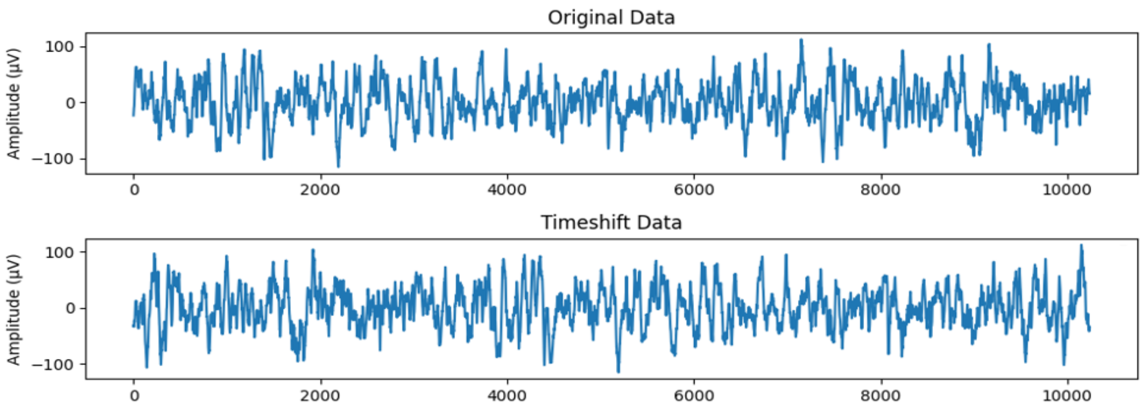

Fig. 2. Original EEG Data and Time Shifted EEG Data

Amplitude Scaling. By performing amplitude scaling on EEG data, important features in the data can be highlighted. This helps to emphasize signal patterns and variations that are relevant to epilepsy, making it easier for the model to capture key features. The original EEG data can be transformed into a lower-dimensional feature representation. This helps to reduce the complexity of the feature space and may improve the efficiency and performance of the system. By adjusting the amplitude range of EEG data, the influence of noise signals can be minimized, thereby enhancing the accuracy and stability of the epilepsy model. Amplitude scaling ensures that data remains consistent across different ranges, allowing effective comparison and analysis of data from different sources, sampling rates, or EEG devices acquisition. This is crucial for building a universal epilepsy model. Assuming that the original EEG data is $x(t)$, the amplitude scaled signal can be expressed as $ax(t)$, where a is the scaling factor, which can be a positive value greater than 1 for amplification or less than 1 for reduction. Fig. 3 is an example of an EEG data that has undergone amplitude scaling.

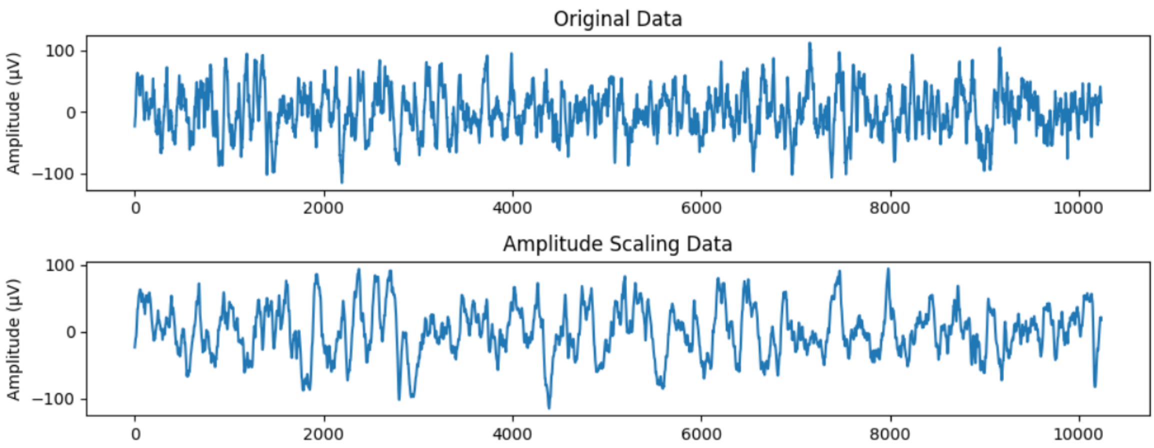

Fig. 3. Original EEG Data and Amplitude scaled EEG Data

Noise Addition. Noise addition is a commonly used data augmentation technique that enhances data diversity by introducing randomness and variation. By adding different types and intensities of noise to the original data, it simulates a wider range of data variations and noise scenarios found in the real world, enabling the model to better handle various inputs. This method helps improve the model's robustness and generalization, especially when dealing with small or imbalanced datasets. By introducing moderate levels of noise, the model becomes more adaptable to real-world data variations and noise scenarios. In this article, we employed the Gaussian noise method for noise addition. Gaussian noise involves generating random numbers that follow a Gaussian distribution with a mean of 0 and a certain variance, and adding them to each feature of the original data. Fig. 4 is an example of an EEG data after noise addition.

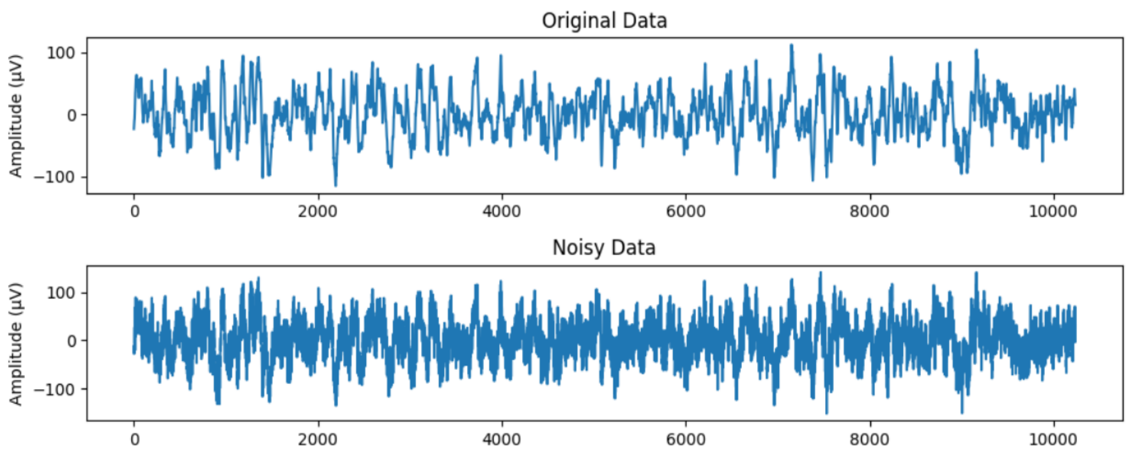

Fig. 4. Original EEG Data and Noise Addition EEG data

Convolutional Neural Networks

In this paper, we introduce three deep learning models: DeepConvNet, ShallowConvNet and EEGNet. All three models employ convolutional neural network (CNN) architectures. DeepConvNet is a 1D-CNN-based model designed for processing one-dimensional sequential data, such as iEEG data (Eren et al., 2019). While 2D and 3D models have been widely used for complex tasks like image processing and shape recognition, we leverage the power of 1D-CNN models to detect epileptic foci given the symbolic nature of our time-series data. The ShallowConvNet model has fewer parameters and a shallow architecture, making it suitable for handling simpler classification tasks (Roots et al., 2020). It also offers faster training and inference speeds. The EEGNet model offers several advantages as it is specifically designed for EEG data, considering both temporal and spatial correlations, as well as spectral features (Lawhern et al., 2018). It exhibits lightweight architecture, robustness and interpretability, making it an effective tool for tasks such as automated detection of epileptic foci in EEG data analysis.

DeepConvNet Model. The DeepConvNet model, which utilizes 1D-CNN, allows direct classification of raw EEG data. The 1D-Convolutional layer is capable of extracting features from the EEG data. The developed DeepConvNet model incorporates five different types of layers: Convolutional layer, Max Pooling layer, Dropout layer, Batch Normalization (BN) layer and Fully Connected (FC) Layer. The architecture of the DeepConvNet model is illustrated in Fig. 5.

We use convolutional kernels with a size of 3 × 1 in each layer to make the feature extraction stage not have too much computation. In order not to miss features, we set the stride of the convolutional kernel to 1. All the convolutional layers are followed by the rectified linear unit (Relu) activation function. To reduce the computational burden of the whole model and not to miss critical features, we set the max-pooling layers with pooling kernels size of 2 × 1 and stride as 2 after every convolutional layer. All the feature maps obtained from the convolutional layer and pooling layer are flattened into a one-dimensional feature vector as the input of the first fully connected layer. The output obtained from the first fully connected layer is nonlinearized by the Relu activation function and dropout with a rate of 0.3, and then as the input of the second fully connected layer. In this layer, input EEG data are classified as focus and non-focus. The dropout was added in various locations to reduce the effect of overfitting.

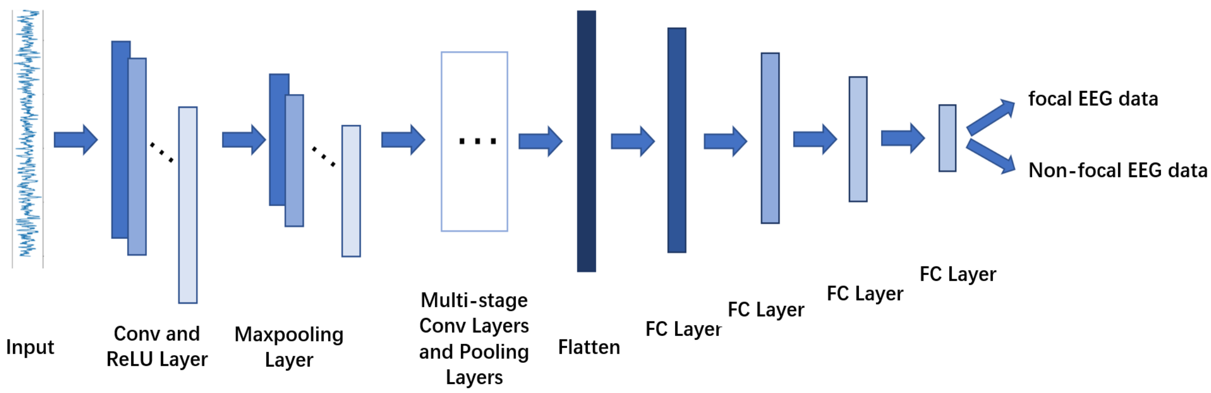

Fig. 5. Structure of DeepConvNet model

ShallowConvNet Model. The ShallowConvNet is a convolutional neural network (CNN) architecture designed for processing EEG data. It is specifically designed for the classification of EEG data in tasks such as brain-computer interfaces (BCIs) and cognitive state analysis.

The ShallowConvNet consists of two main blocks. The first block applies a series of convolutional layers to extract spatial and temporal features from the input EEG data. It includes a 1D convolutional layer followed by batch normalization, ReLU activation and average pooling. This block captures local patterns and spatial correlations in the EEG data. The second block of the ShallowConvNet flattens the output from the previous block and connects it to a fully connected layer. This layer is mapped to the target class. It is followed by a softmax activation function, which produces the probability distribution over the classes. The architecture of the ShallowConvNet model is illustrated in Fig. 6.

The ShallowConvNet architecture has several advantages. It has a compact structure with a smaller number of layers and parameters compared to deeper CNN architectures. This makes it computationally efficient and suitable for real-time applications. The architecture is designed to capture both spatial and temporal dependencies in the EEG data, allowing it to effectively discriminate between different brain states or classes. The model can be trained with relatively small amounts of labeled data, making it applicable in scenarios with limited training samples. Overall, the ShallowConvNet is a lightweight and efficient model that can achieve good performance in EEG classification tasks. Its simplicity and effectiveness make it a popular choice for analyzing EEG data in various neuroscientific and clinical applications.

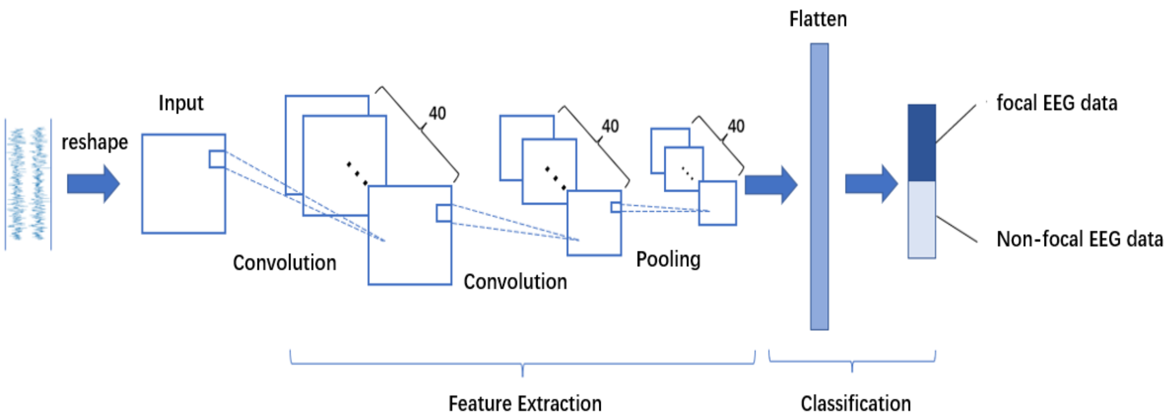

Fig. 6. Structure of ShallowConvNet Model

EEGNet Model. EEGNet is one of the most popular deep learning models in EEG classification (Lawhern et al., 2018). Due to being a relatively large network while limiting the number of parameters, EEGNet has been widely used in recent studies.

An EEGNet consists of 2 convolution stages, one fully connected stage, a dropout layer and a final output layer, which the structure of the EEGNet model is shown in Fig. 7. In the first convolution stage the raw EEG data is reshaped as input with size 1×3000 is firstly convoluted by a 1×64 filter and slide with the stride of 8, which is then followed by a BN layer. After that, we use every pooling layer and BN layer with a kernel size of a 1×4 average. We apply batch normalization along the feature map dimension before applying the exponential linear unit (ELU). To help regularize the model, we use the dropout technique and we set the dropout for within-subject classification to help prevent over-fitting.

In the second convolution stage, we use a separable convolution, which is a depthwise convolution layer with a kernel size of 1×16. The main benefits of separable convolutions are reducing the number of parameters to fit and explicitly decoupling the relationship within and across feature maps by first learning a kernel summarizing each feature map individually, then optimally merging the outputs afterward. An Average Pooling layer with a kernel size of 1×8 is used for dimension reduction. We fit the model using the Adam optimizer, minimizing the categorical cross-entropy loss function. In the classification block, the features are passed directly to a SoftMax classification with 2 units. We omit the use of a dense layer for feature aggregation before the SoftMax classification layer to reduce the number of free parameters in the model.

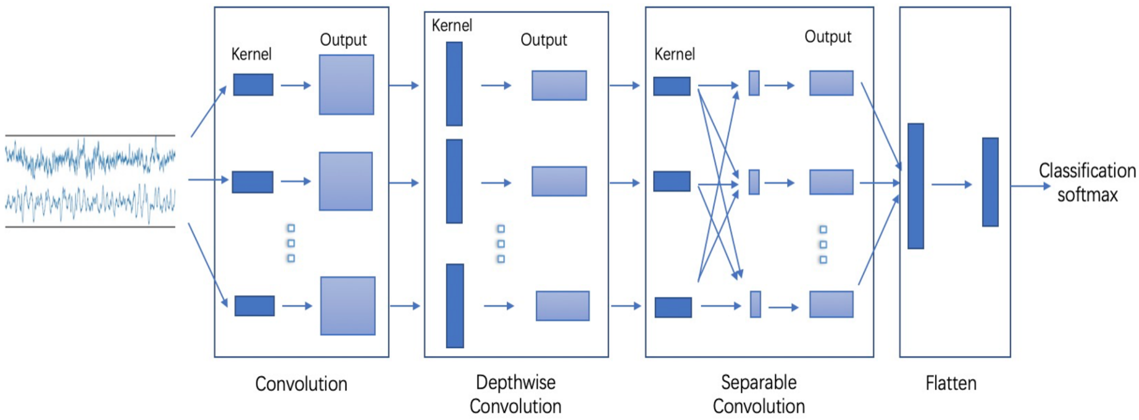

Fig. 7. Structure of EEGNet Model

K-fold Cross-validation

In the machine learning modelling process, it is common practice to divide the data into a training set and a test set. The test set consists of data that is independent of the training process and is not used in any way during training. It is specifically used to evaluate the performance of the final model. During the training process, there is often an overfitting problem, where the model can match the training data well, but cannot predict the data outside the training set very well. Using the test data to adjust the model parameters at this point would be equivalent to knowing some of the information from the test data at the time of training, which would affect the accuracy of the final evaluation results. It is common practice to use a portion of the training data as validation data to evaluate the training effect of the model.

The validation data is taken from the training data but is not involved in the training so that the model can be evaluated objectively on how well it matches the data outside the training set. The evaluation of the model in the validation data is commonly done by cross-validation, also known as round-robin validation. It divides the original data into K groups (K-Fold) and makes a separate validation set for each subset of data, with the remaining K-1 subsets of data serving as the training set, resulting in K models. These K models are evaluated separately in the validation set and the final error Mean Squared Error (MSE) is summed and averaged to obtain the cross-validation error. Cross-validation makes efficient use of the limited data available and the evaluation results are as close as possible to the performance of the model on the test set, which can be used as a metric for model optimization (Rodriguez et al., 2009).

In practical application. Firstly, divide the entire sample into k subsets of equal size. Secondly, iterate through these k subsets in turn, each time taking the current subset as the validation set and all the remaining samples as the training set, for training and evaluation of the model. Finally, the average of the k evaluation metrics is taken as the final evaluation metric. Such as k=10 becoming 10-fold cross-validation.

The original data set is divided into 10 parts; each part is used as the test set and the remaining 9 (k-1) are used as the training set, which becomes k * D (D denotes the number of data samples contained in each part); finally, the average of the classification rates obtained k times is calculated as the true classification rate of the model or hypothesis function. As shown in Fig. 8.

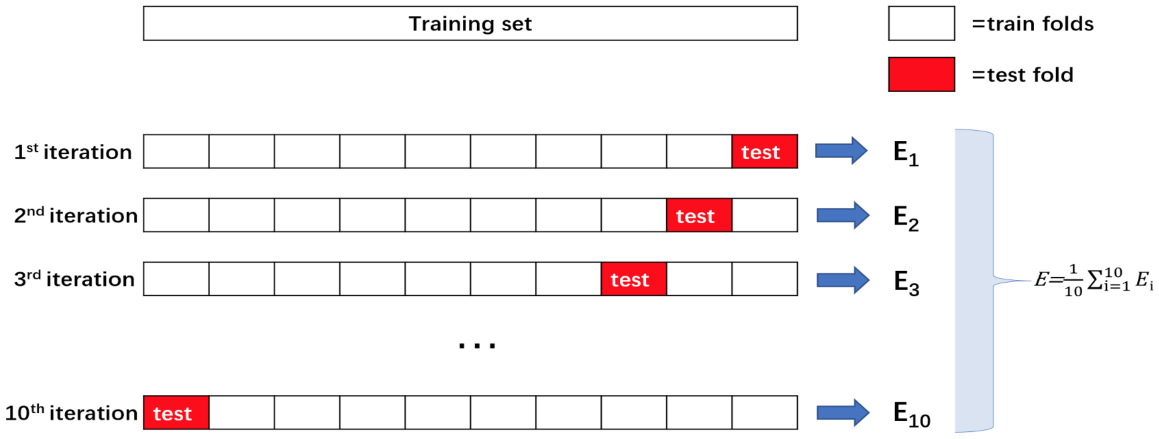

Fig. 8. K-fold cross validation (K = 10)

Cross-validation is primarily used in applied machine learning to estimate the skill of machine learning models on unseen data and it uses a limited number of samples to estimate how well the model generally performs when used to make predictions on data that was not used during the training of the model. K-fold cross-validation is popular because its principles are simple to understand and it generally provides models with less bias in their outcome estimates.

Experimental Results and Discussions

Dataset. The EEG data used in this paper were obtained from a publicly available EEG dataset called the Bern-Barcelona iEEG database provided by Andrzeja et al. from the Department of Neurology at the University of Bern (Andrzejak et al., 2012). iEEG is a measurement of EEG data and involves implanting electrodes directly under the patient's scalp and skull to obtain signals by measuring the activity of neurons inside the brain. Compared to conventional EEG, iEEG has several advantages, including higher spatial resolution, better signal quality and the ability to record from deeper areas of the cerebral cortex. This allows for more precise localization of the source of seizures and better identification of specific areas of the brain involved in different cognitive processes. The data were collected from five patients with epilepsy who underwent long-term intracranial EEG recordings. All patients had long-term drug-resistant temporal lobe epilepsy and were candidates for surgery (Sui et al., 2019). Signals recorded in the epileptogenic and non-epileptogenic regions were labeled as focal and non-focal, respectively. Each category included 3750 pairs of signals collected from adjacent channels in the same region. All signals were collected during seizures and each signal was sampled at 512 Hz for 20 seconds, which resulted in one-dimensional data consisting of 10240 elements. In addition, the signals were denoised and normalized, which makes the Bern-Barcelona EEG dataset an ideal training and testing dataset for machine learning.

In this paper, we use the Bern-Barcelona Dataset, which is publicly available on the web, to evaluate the practicality of signal feature extraction for data augmentation and the performance of these three models. All proposed models were implemented using Python programming language on PyTorch framework on a workstation with 12 Intel Core i7 3.50 GHz (5930K), a GeForce RTX 2080 Ti graphics processing unit (GPU) and 128 GB of random access memory (RAM).

Ten-fold cross-validation is used in the training, the dataset is randomly divided into 10 equal parts, 9 of them are used as training sets and 1 as test set. We perform data augmentation on the EEG data in the training set to generate new data. These augmented data are then combined with the original training set data to create the new training set. We run 400 training epochs with a batch size of 512 and perform validation stops, saving the model weights that produce the lowest validation set loss. We use 10-fold cross-validation to ensure more reliable results. Main methodology of classification is shown in Fig. 9.

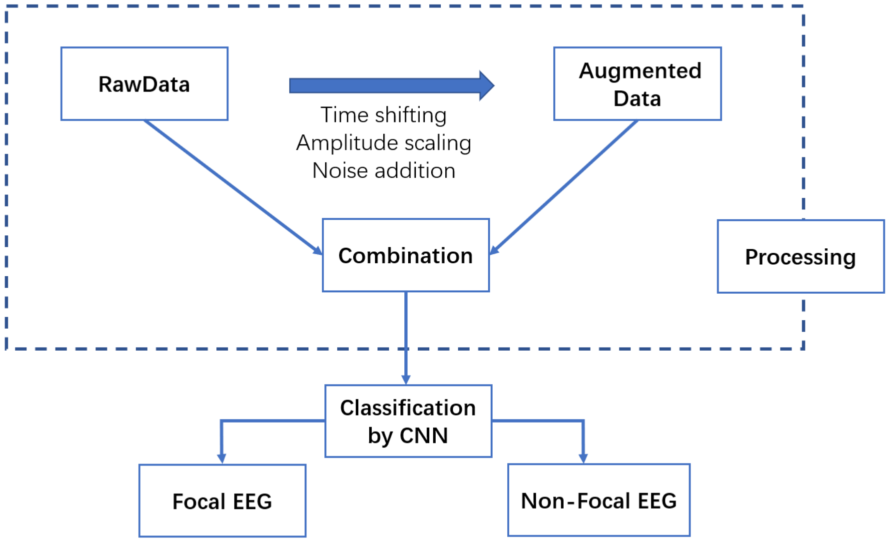

Fig. 9. Main methodology of classification

In this paper, a total of 15 experiments were conducted. Firstly, we separately input the raw data into the DeepConvNet, ShallowConvNet and EEGNet models for classification learning and obtain the corresponding model accuracies. Secondly, we applied three data augmentation techniques: Time Shifting, Amplitude Scaling and Noise Addition as feature extraction methods. The data generated by these three methods were combined with the raw data to form three new datasets. Subsequently, these datasets were used to train the DeepConvNet, ShallowConvNet and EEGNet models, the corresponding model accuracies were obtained. Finally, the raw data and the data obtained by combining the three augmentation techniques were combined to form a new dataset, which was then used to train the three different deep learning models for classification, resulting in the corresponding model accuracies. The accuracy of raw data and data augmented with three different deep learning models are shown in Table 1.

Table 1. Accuracy of raw data and augmented data with three different deep learning models

	DeepConvNet	ShallowConvNet	EEGNet
RawData	90.9%	81.7%	85.5%
RawData + TS Data	92.3%	82.4%	87.2%
RawData + AS Data	91.4%	82.8%	86.5%
RawData + NA Data	91.3%	82.2%	87.4%
RawData + TS Data + AS Data + NA Data	92.4%	82.9%	87.5%

Although the results did not reach the highest accuracy for epileptic seizure localization, the experiments demonstrate that when several different data augmentation techniques are used in multiple deep learning models, the accuracy of the models is higher than the accuracy of the raw data in the models. The principle of pre-processing implementation of data augmentation is simpler and takes less time to complete than other methods such as EMD or entropy (Itakura & Tanaka, 2017).

The experimental results show that the three data augmented feature extraction methods are able to improve the accuracy of the model on all three deep learning networks. In the case where all three methods were used, the most improvement in accuracy was achieved compared to the model that used the raw data. There is still a large gap compared to other better experimental results, however there are a large number of tunable parameters in the feature extraction process for signal data augmentation, as well as in the structure of the CNN. It is hoped that the details of each parameter can be optimised to further improve the accuracy.

Conclusions

As the rapid development of machine learning has attracted attention in recent years, its efficiency and accuracy have been improving, which is gradually opening up new possibilities for signal recognition. Recognition based on epileptic foci is essentially the recognition of two different signals and relying on machine learning for the recognition task is promising research. In this paper a new approach is devised in which a feature extraction algorithm using data augmentation is used to provide more information to the CNN, resulting in a more accurate model. The performance of three different models (DeepConvNet, ShallowConvNet and EEGNet) in EEG data classification is also presented and compared. Based on the experimental results, we found that the three feature extraction methods without data augmentation in time shifting, amplitude scaling and noise addition have good model accuracy improvement over the raw data in different deep learning models. Finally, the most significant improvement in model accuracy was achieved when all three data augmentation directions were used collectively. Compared to the state-of-the-art classification results, these networks fall significantly behind in terms of accuracy. With further tuning of the parameters and optimization of the CNN structure, the accuracy should improve to an even higher level. In addition, it is worthwhile to try to improve the accuracy by combining more channels from other transform or feature extraction methods in further experiments.

Previous research has demonstrated the effectiveness of deep learning methods for classification of iEEG data in achieving accurate and stable automated diagnosis of epileptic foci in clinical practice. Future work will focus on two main areas. Firstly, based on the accuracy of the validation set, it is easy to estimate the presence of overfitting during model training. By continuously adjusting and optimizing the parameters of the neural network, higher accuracy can be achieved. Secondly, results have shown that combining multiple feature maps provides the neural network with informative and discriminative feature representations, leading to improved accuracy. In future work, it is worth exploring additional feature extraction methods for a given signal and integrating two or more feature maps to further improve accuracy and achieve higher levels of performance.

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Conflicts of Interest

The author has no conflict of interest about anything in this article.

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