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Research Article

Detection and Prediction of Epileptic Seizures using Convolutional Neural Network

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Abstract

Epilepsy is one of the most common neurological disorders. Approximately 50 million of the population is affected by epileptic seizures worldwide. The diagnosis of epileptic seizure is a time consuming process. Moreover 75% of the epilepsy patients cannot even afford the expenses of the treatment of the epilepsy. An automatic approach is proposed for the detection of the epileptic seizures using the EEG signals. The detection of epilepsy requires potential features to be extracted from the EEG signal. The proposed approach will help the neurologists to detect the epileptic seizures with higher accuracy. In our approach we have used the power of convolutional neural network to extract robust features and have achieved an accuracy of 90%.

Keywords: *Epilepsy; deep learning, convolutional neural network; Preictal; ictal*

Introduction

Epileptic seizure is a neurological condition that may arise due to malfunctioning of brain's electrical system [4]. It is caused to approximately 1% of the population [14]. Epilepsy has a risk of premature death as well [13]. Epileptic seizures are caused due to abnormal activities of neuron in the brain [3]. It epileptic seizures are kept untreated, then they may degrade the life of the patients as well [2]. Loss of consciousness, abnormal movements is some of the side effects of seizure [6]. Epilepsy can affect anyone and at any age [18]. The traditional approach followed by neurologists for the diagnosis of epileptic seizures is time consuming. The average time that is required for the long term monitoring is between 4.8 and 7.6 days [8]. Due to this a limitation exists that it takes time to analyze the recordings of patients. This puts a decrease in the number of diagnosis that can be performed in a day by the neurologists [9]. To improve over this, an automated approach is required that can detect the presence of epileptic seizures and predict them as well. Prediction of epileptic seizures is equally important because if they are predicted at an early stage, then they can be suppressed. Electroencephalography plays an important role in the diagnosis of the epileptic seizures. It records the electrical brain activity by measuring the differences in the voltages between electrodes [7]. It is recorded by placing the electrodes on the scalp of epilepsy patient [17]. Epilepsy detection is considered as a classification problem [10]. Seizure activities can be used for the identification of the epilepsy, which results from the imbalance of neuron's excitation and inhibition [11] detection and prediction over existing system by using 13 layers CNN architecture capable of extracting robust features from the EEG signals. In section II we elaborate on the related work performed, section III illustrates the methodology followed, the EEG dataset used in the system, architecture of CNN used for the study and training, testing details of the CNN model. In section IV we discuss the result and discussions. In Section V, we discuss the conclusion of the work.

Literature Survey

Different approach has been studied for the diagnosis of epileptic seizures. It was observed that machine learning techniques cannot handle multichannel EEG signals well. Deep learning techniques can accommodate multichannel EEG signals and can be used in such cases. Epileptic seizures can be detected from videos as well. In the approach proposed by Achilles et al., they have used videos for the detection of epilepsy and have designed a system that is generalized to different types of seizures [2]. In the approach proposed by Boonyakitanont et al., they have used artificial neural network (ANN) and convolutional neural network (CNN) as classifiers. It was observed that CNN provided better accuracy results as compared to ANN [3]. In the approach proposed by Page et al., they have used max pooling convolutional neural network. Moreover ANN required extraction of distinguishing feature while CNN doesn't manual feature extraction [1].

In the approach proposed by Priyanka et al., after the feature extraction they have performed feature ranking for the dimensionality reduction and they have used neural network was used for the classification task [4]. In the approach proposed by Birjandtalab et al., multilayer perceptron has been used to classify the seizure and non seizure EEG signals [5]. In the approach proposed by Zhou et al., they have analyzed time domain and frequency domain EEG signals [7]. In the approach proposed by Emami et al., they have used images as the input to the convolutional neural network. The EEG signal was segmented into segments and images were constructed using it. It was observed that image based representation is more useful in assisting the neurologists for the diagnosis of epileptic seizures [8]. Instead of examining the complete EEG signal, it was observed that a system is required that will extract segments from EEG signals that needs to be analyzed by the neurologists for the diagnosis of epileptic seizures. A channel restricted CNN was used for the classification of EEG signals in the approach proposed. The goal of this research is to improve the accuracy of performed into seizure and non seizure classes [10].

Table I. Related work

Ref	Features	Dataset	Accuracy
[1]	Automatic features extraction	CHB-MIT	100 %
[2]	Automatic features extraction	Adult patients admitted to an EMU	-
[3]	Time – frequency, time, frequency	CHB-MIT	99.07%
[4]	Kurtosis, Variance, Mean, Maximum, Standard deviation, minimum, skewness, entropy	Neurology and sleep center, New Delhi	96.90%
[5]	Frequency domain	CHB-MIT	-
[7]	Frequency, time domain	Intracranial Freiburg and scalp CHB MIT	97.5%
[8]	Spectro – temporal features	NTT Medical Center Tokyo and University of Tokyo Hospital	-
[9]	Spectral, temporal, spatial	CHB-MIT	-
[10]	Binary patterns of brainwave activity	CHB-MIT	-
[11]	Closed neighbourhood gradient pattern, combined texture pattern	Diagnostic centre located in Coimbatore	-
[12]	Spectral, temporal	First Affiliated Hospital of Xinjiang Medical University	-
[14]	Frequency, temporal and spatial features	TUH EEG Seizure corpus	-
[16]	Frequency and time	CHB MIT, Freiburg Hospital intracranial EEG dataset, Kaggle American Epilepsy Society Seizure Prediction Challenge's dataset	-
[17]	Temporal, spectral features	CHB MIT	99.65%
[18]	Automatic feature extraction	Bon university database	88.67%
[19]	Interictal epileptoform discharges	MGH Boston	83.86%

The novelty in the approach proposed by Jothiraj et al. is that, they have used artefact brain maps for the automatic detection of epileptic brain maps. They have performed the classification of epileptic brain maps from the artefact brain maps. It is difficult to handle multichannel EEG signal data using machine learning approach [11]. In the approach proposed by Wei et al., they have used 3D kernel for the extraction of robust featured from the EEG signal. They have observed that machine learning techniques are not effective for handling multichannel EEG signals. But deep learning techniques can handle multichannel EEG signals effectively [12]. The main challenge in the work done by Asif et al., was the cross patient approach. The novelty of this paper is, they have used CNN classifier for the classification of seizure type in a cross patient approach. 2D CNN filter can also be used for the extraction of features from EEG signal [14]. In the approach proposed by Truong et al., a 2D convolutional filter was convolved for the extraction of both time and frequency [16]. CNN was used by Hossain et al., for the extraction of spectral, temporal and spatial features for the classification of the EEG signals. Brain mapping images were also generated in this approach, which can be used for the diagnosis purpose by the neurologists [17]. In the methodology proposed by Acharya et al., they have used a 13 layer convolutional neural network to perform the classification task for the detection of epileptic seizures. The CNN extracted robust features and an average accuracy achieved was 88.7 % [18]. In the proposed approach by Thomas et al., interictal epileptoform discharges (IEDs) are considered as the feature for the detection of epilepsy. Using pre-processing, waveform level classification and EEG level classification they have achieved an accuracy of 83.86 % [19]. In the approach proposed by Alkanhal et al., they have learnt robust feature from the EEG signal data, and have generated image representation of the EEG signal. They have extracted spectral, spatial and temporal featured from the EEG signal. CNN classifier was used for the classification [6].

Proposed Methodology

In the proposed approach convolution neural network model is used for the detection and prediction of epileptic seizure. Epileptic EEG signals vary more than normal EEG signals. Neural patterns generated by the EEG signals can be used for the detection and prediction of epileptic seizures. Three classes have been used in this approach: "healthy", "ictal" and "Preictal". For detection and prediction of seizure, "seizure" and "preictal" class has been used respectively.

A. Convolutional neural network

Convolutional neural network has 3 layers: convolution layer, pooling layer and fully connected layer. Convolution layer is responsible for the extraction of features. The kernels or filters convolve over the input and generate feature maps. Pooling layer is used to reduce the feature dimension. Max pooling has been used in our approach. Fully connected layer is responsible to flatten the input vector and the activation function gives the final output results. 2D convolution operation can be given by —(1).

$$G_i = f(W_i * X_{i-1}) + b_i \quad (1)$$

Where, "i" is the i^{th} layer of CNN, f is the activation function, "*" denotes the convolution operation, b denotes bias, X denotes the input signal, W is the weight and G is the 2D convolution operation.

B. Activation function

Activation function is used to determine the output at a particular node which has been provided with some input value. We have used Relu and softmax activation functions in our proposed approach.

C. Relu:

Relu is a one of the most common activation function, especially in the convolutional neural network. The Relu activation function is given by —(2).

$$Y(x) = \max(0, x) \quad (2)$$

Relu activation function has certain advantages. Since, it performs max operation; it is not much computationally intensive. It converges faster. Moreover it is sparsely as it assigns zero value to all negative input values.

D. Softmax:

The softmax activation function normalized the input values into a vector that follows a probability distribution. The values in the vector sum up to 1. The class having the highest value of probability is predicted as the output class. The probability distribution output value is given by — (3).

$$P_{yi} = \frac{e^{zi}}{\sum_{k=1}^{n} e^{-zi}} \quad (3)$$

Where P_{yi} is the i^{th} probability distribution output.

E. Regularization

In order to improve over the prediction results, prediction model should not undergo overfitting. Regularization is used to reduce overfitting. L1 regularization has been used in this approach. L1 regularization is also known as lasso regression. Lasso regression turns the coefficient of less important features to zero. The cost is given by —(4):

$$\sum_{I=1}^{N}\left(Yij - \sum_{j=1}^{P} Xij * Wj\right)^2 + \lambda \sum_{j=1}^{P}|Wj| \quad (4)$$

F. Architecure

A 13 layer convolution neural network has been used in this approach. Deep learning technique is considered as the most powerful technique among the others [9]. Deep learning techniques can accommodate multichannel EEG signals easily. Convolution neural network extracts robust features and perform automatic feature extraction. TABLE II shows the activation functions used in the respective layers. Relu and softmax activation functions have been in this approach. We adapted to the network used in the approach proposed by [18]. To overcome the problem of overfitting, we have used L1 regularization. We have used 0.01 as the regularization parameter. Adam optimizer has been used to perform the optimization. The learning rate used was 0.001.

Table III shows the detailed architecture of the proposed Convolutional neural network with 13 layers. The proposed CNN architecture consists of 5 convolution layers, 5 max pooling layers and 3 fully connected layers.

E. Dataset

Bonn university database collected by Andrzejak et al. [15] at Bonn university, Germany is used in the proposed approach. It consists of 5 sets: Set A, B, C, D, E. In our approach, we have used 3 sets : set B, D, E having EEG signals corresponding to normal, preictal and seizure class respectively. Each set consists of 100 EEG signal samples. In our approach we are using 300 EEG signals each having a duration of 23.6 seconds.

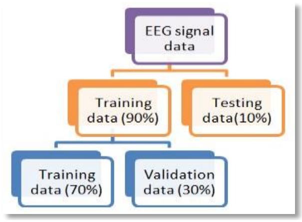

Fig. 1 Splitting criterion of training, testing and validation data

F. Training

The model is trained using a batch size of 3. Adam optimizer has been used for the optimization. The values of weight corresponding to the minimum error value are selected as the solution. Lasso regression is used to reduce the problem of overfitting of model.

Table II. Activation functions

Layer	Activation function
1	Relu
2	-
3	Relu
4	-
5	Relu
6	-
7	Relu
8	-
9	Relu
10	-
11	Relu
12	Relu
13	Softmax

G. Testing and validation

Validation has been performed to reduce the problem of overfitting of model. From 300 signals EEG data, 10 % of the data was used as the testing data. The splitting criterion of training, testing and validation has been shown in Fig. 1.

Result and Discussions

The proposed methodology was implemented using a system with following configurations: Intel(R) Core(TM) i5-8250U CPU with 2GB graphics card and a RAM of 8GB. Table IV shows the confusion matrix obtained using our approach. It can be observed that, 2 instances of Preictal class were misclassified whereas 1 instance of seizure class was misclassified.

Table III. System architecture

Layers	Number of kernels	Kernel size	Output
Convolution	4	(1,6)	(4, 1, 4092)
Max pooling	-	(1,2)	(4, 1, 2046)
Convolution	64	(1,5)	(64, 1, 2042)
Max pooling	-	(1,2)	(64, 1, 1021)
Convolution	128	(1,4)	(128, 1, 1018)
Max pooling	-	(1,2)	(128, 1, 509)
Convolution	128	(1,4)	(128, 1, 506)
Max pooling	-	(1,2)	(128, 1, 253)
Convolution	128	(1,4)	(128, 1, 253)
Max pooling	-	(1,2)	(128, 1, 125)
Fully connected	-	-	(50)
Fully connected	-	-	(20)
Fully connected	-	-	(3)

Table IV. Confusion matrix

Actual class	Predicted cla		ss
	Normal	***Preictal***	***Seizure***
Normal	9	0	0
Preictal	2	10	0
Seizure	0	1	8

Table V shows the accuracy, sensitivity, specificity and precision obtained after 150 epochs. It can be observed that the specificity and precision of ictal class is 100%.

Table v. Results

Class	Accuracy	Sensitivity	Specificity	Precision
Normal	93.33%	100%	90.48%	81.82%
Preictal	90.00%	83.33%	94.44%	90.90%
Ictal	96.67%	88.89%	100%	100%

Table VI shows the overall accuracy obtained across all classes is 90%.

Table vi. Overall accuracy

Overall accuracy across all classes
90.00%

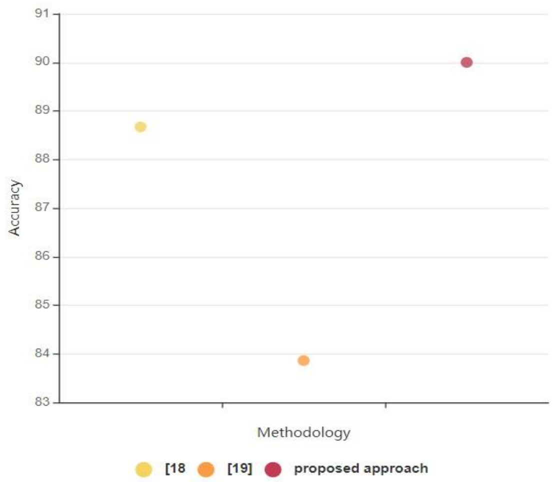

Fig. 2 Accuracy obtained by other approached

Conclusions

For accurate predictions feature extraction is very important. Robust features should be extracted in order to make correct predictions. Convolutional neural networks used in the approach perform automatic feature extraction. This system may assist the neurologist in performing diagnosis. Moreover this system can be used in the places where immediate access to the neurologist in not possible. Neural patterns of EEG signals can be analyzed for the prediction and detection of epileptic seizures. Our proposed approach has achieved an overall accuracy of 90% across 3 classes. In healthcare domain, accuracy cannot be compromised and hence a system is required that will make predictions with maximum accuracy. Hence the accuracy can be improved further by making use of ensemble techniques or increasing the size of the dataset.

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