

Deep Neural Network for the Automated Detection and Diagnosis of Seizure using EEG Signals

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Abstract - An encephalogram (EEG) is generally used ancillary test for the diagnosis of epilepsy. The EEG signal contains information about brain electrical activity. Neurologists employ direct visual inspection to identify epileptiform abnormalities and this technique can be time-consuming which provides variable results secondary to reader expertise level and is limited to identify the abnormalities. Since it is essential to develop a computer-aided diagnosis (CAD) system to automatically distinguish the classes of EEG signals using machine learning techniques. This is the first time to study the convolutional neural network (CNN) for analysis of EEG signals. In this work, 11-layer deep convolutional neural network (CNN) algorithm is implemented to detect normal, preictal, and seizure classes. This technique achieved an accuracy as high as possible with 99%.

Key Words: epilepsy, convolutional neural network, encephalogram signals, deep learning, seizure.

1. INTRODUCTION

According to the World Health Organization (WHO), nearly 60 million people suffer from epilepsy worldwide. It is estimated that 2.5 million people are diagnosed with epilepsy annually. Seizures are due to the uncontrolled electrical discharges in a group of neurons. Epilepsy is diagnosed when there is the recurrence of at least two unprovoked seizures. It can act on anyone at any age. A timely and accurate diagnosis of epilepsy is essential for patients in order to initiate anti-epileptic drug therapy and subsequently reduce the risk of future seizures and seizure-related complications. Currently, the diagnosis of epilepsy is made by obtaining a detailed history, performing a neurological exam, and ancillary testing such as neuroimaging and EEG. The EEG signals can identify interictal means between seizures and ictal means during seizure epileptiform abnormalities. Figure 1 shows a graphical representation of the brain electrical activity of healthy subjects and seizure patients. Neurons are communicated through electrical signals. Therefore, activities of the regular brain, electrical signals are normally regulated. However, during a seizure, there is an abnormally increased hyper-synchronous electrical activity of the epileptogenic neural network. This activity may remain localized to some part of

the brain or spread to the entire brain. Neurologists inspect the EEG via direct visual inspection to investigate for epileptiform abnormalities that may provide valuable information on the type and etiology of a patient's epilepsy [1].

However, the judgment of the EEG signals by visual assessment is time-consuming particularly with the increased use of out-patient static EEG's and in-patient continuous video EEG recordings, where there are many of EEG data that needs to be reviewed manually. The majority of EEG software includes some form of automated seizure detection; however, due to the poor sensitivity and specificity of the pre-determined seizure detection algorithms, the current forms of automated seizure detection are rarely used in clinical practice. Additionally, the natural nature of visual inspection results in varying clinical clarification based on the EEG reader's level of expertise in electroencephalography. Complicating matters, the quality of the study may be confounded by interfering artefactual signal limiting the reader's ability to accurately identify abnormalities. Moreover, the low yield of routine out-patient studies poses another problem. A patient with epilepsy can go for an outpatient EEG and the study may be completely normal. This is because the brains of patients with epilepsy are generally not continually firing off epileptic discharges. An EEG is simply a "snapshot" of the brain at the moment of recording. The sensitivity of identifying epileptic discharges can be increased by having the patient come back for repeated outpatient studies or recording them for longer periods of time, either via a home ambulatory study or an inpatient continuous video EEG monitoring study, which are both costly and time-consuming for the patient and for the physician reading the EEG. A trained neurologist analyzes the clinical characteristics of the event in conjunction with a visual inspection of the EEG to determine whether the patient has epilepsy or not. The increased amount of data also allows the neurologist to look for inter-ictal abnormalities. Seizures can be partial and exist in one part of the brain only, or they can be general and affect both halves of the brain. During a focal seizure, the person may be conscious and unaware that a seizure is taking place, or they may have uncontrollable movements or unusual feelings and sensations [3]. A diagnosis of epilepsy is made with the help of an electroencephalogram (EEG). EEG recordings are

commonly visualized as charts of electrical energy produced by the brain and plotted against time. The visual interpretation of these signals is prone to inter-observer variabilities. Therefore, for an accurate, fast, and objective diagnosis a computer-aided diagnosis (CAD) system is advocated. Since the seminal article by Adeli et al., automated EEG-based seizure detection and epilepsy diagnosis has been the subject of significant research. Many researchers have proposed different approaches to automatically detect epileptic seizure using EEG signals. For reviews of this literature, see Acharya et al. and Faust et al. where different approaches, namely, time, frequency, time-frequency, and nonlinear methods are discussed. Acharya et al. also review the application of entropies for automated EEG-based diagnosis of epilepsy. The EEG signal is nonlinear and nonstationary in nature thus; the signal is highly complex and is difficult to visually interpret the signals (see Figure 1). Based on the reviews, it can be observed that the researchers have extracted features, performed statistical analysis, ranked the features, and classified the best classifier by comparing the performance of different classifiers [1].

Deep learning is a type of machine learning in which a model learns to perform classification tasks directly from images, text, or sound. Deep learning is usually implemented using neural network architecture. The term “deep” refers to the number of layers in the network the more layers, the deeper the network. Traditional neural networks contain only 2 or 3 layers, while deep networks can have hundreds. A deep neural network combines multiple nonlinear processing layers, using simple elements operating in parallel and inspired by biological nervous systems. It consists of an input layer, several hidden layers, and an output layer. The layers are interconnected via nodes, or neurons, with each hidden layer using the output of the previous layer as its input. In this study, a deep learning method is employed to automatically identify the three classes of EEG signals. To the best of the authors' knowledge, this is the first EEG study to employ a deep learning algorithm for the automated classification of three EEG classes [1]. An 11-layer deep convolutional neural network (CNN) is developed to categorize the normal, preictal, and seizure class.

The structure, of the remainder, of this paper, is as follows. Section 2 describes the methodology included the flow of the system, preprocessing and neural networks. Section 3 discusses deep learning and its use in seizure and non-seizure classification, next describes the evaluation and the results are discussed in Section 4 and the paper is concluded in Section 5.

2. METHODOLOGY

2.1. The flow of the proposed system

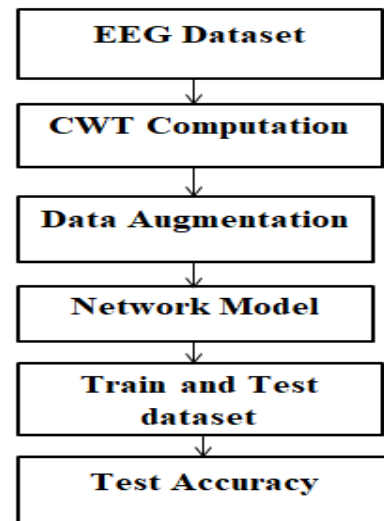


Fig -1: Flow of the System

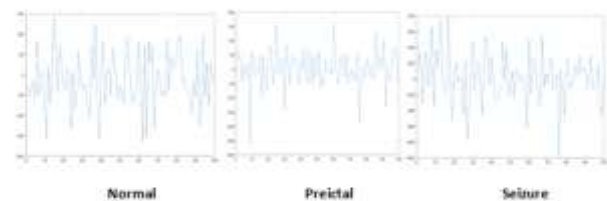


Fig -2: Sample normal, preictal, and seizure EEG signals from the Bonn University database.

Figure 1 displays sample normal, interictal, and seizure EEG signals from the Bonn University database. EEG segments used in this research are those collected by Andrzejak et al. [7] at Bonn University, Germany (<http://epilepsy.uni-freiburg.de/database>). The dataset obtained from 5 patients contains three classes of data, namely, Set B as normal, Set D as preictal, and Set E as a seizure. There is a total of 100 EEG signals in each dataset. Each record is a single channel EEG signal with a duration of 23.6 seconds. The normal dataset comprises of EEG signals obtained from 5 healthy subjects, each containing 100 cases. Likewise, the preictal class contains 100 data from 5 epileptic patients, when they did not undergo seizure during the time of acquisition. The seizure class consists of 100 cases with the same subjects when they were having epilepsy during the time of signals acquisition [22].

2.2. Preprocessing:

Each EEG signal 1D waveform converted to 2D image by using CWT. The EEG signal is sampled at 173.61 Hz. The data augmentation of dataset take place that means image rotate

(-5 to 5). We got 5100 images per class. Total images were 15300. The deep convolutional neural network (CNN) for training and testing. We trained 90% data and tested 10% data. Total 13770 images were trained. Remaining 1530 images were tested.

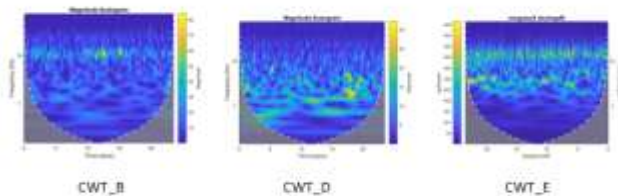


Fig -3: CWT of EEG Signals

2.3. Artificial Neural Network (ANN):

Artificial neural networks are computational systems originally inspired by the human brain. They consist of many computational units, called neurons, which perform a basic operation and pass the information of that operation to further neurons. The operation is generally a summation of the information received by the neuron followed by the application of a simple, non-linear function. In most neural networks, these neurons are then organized into units called layers. The processing of neurons in one layer usually feeds into the calculations of the next, though certain types of networks will allow for information to pass within layers or even to previous layers. The final layer of a neural network outputs a result, which is interpreted for classification [5].

2.4. Convolution Neural Network (CNN):

An improved and recently-developed neural network, known as Convolutional Neural Network (CNN) is employed in this research. The improved ANN is both shift and translational invariance. The convolution operation in CNN is a subset of deep learning which has attracted a lot of attention in recent year and used in image recognition such as analysis of x-ray medical images, magnetic resonance images, and computed tomography images.

A convolutional neural network (CNN) is one of the most popular algorithms for deep learning with images and videos. Like other neural networks, CNN is composed of an input layer, an output layer, and many hidden layers in between [4].

- A. **Feature Detection Layers:** These layers perform one of three types of operations on the data: convolution, pooling, or rectified linear unit (ReLU).
 1. **Convolution** puts the input images through a set of convolutional filters, each of which activates certain features from the images.

$$y_k = \sum_{n=0}^{N-1} x_n h_{k-n} \dots\dots\dots(1)$$

Where x is signal, h is filtered, and N is the number of elements in x. The output vector is y. The subscripts denote the nth element of the vector.

2. **Pooling** simplifies the output by performing nonlinear downsampling, reducing the number of parameters that the network needs to learn about. [2]
3. **Rectified linear unit (ReLU)** allows for faster and more effective training by mapping negative values to zero and maintaining positive values.

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0.01x & \text{otherwise} \end{cases} \dots\dots\dots(2)$$

These three operations are repeated over tens or hundreds of layers, with each layer learning to detect different features.

B. **Classification Layers**

After feature detection, the architecture of CNN shifts to classification. [2]

1. The next-to-last layer is a **fully connected layer (FC)** that outputs a vector of K dimensions where K is the number of classes that the network will be able to predict. This vector contains the probabilities for each class of any image being classified.
2. The final layer of the CNN architecture uses a **softmax** function to provide the classification output.

$$p_j = \frac{e^{x_j}}{\sum_{k=1}^k e^{x_k}} \text{ for } j = 1, \dots, k. \dots\dots\dots(3)$$

Where x is the net input. Output values of p are between 0 and 1 and their sum equals to 1.

3. ARCHITECTURE

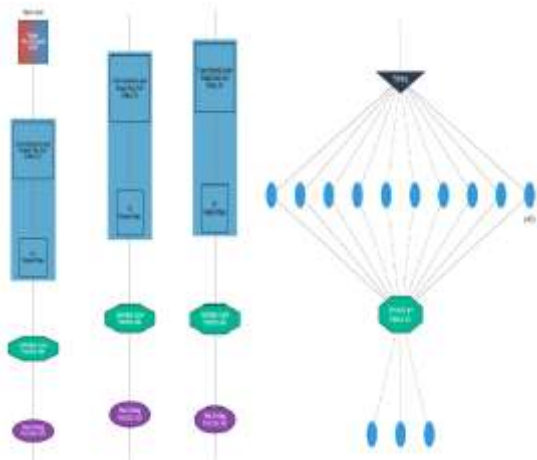


Fig -4: Layer Architecture of the system

The input layer (in Figure 4) is convolved using equation (1) with 64x64 pixel RGB images to produce the next layer with kernel size 5x5. Then, a max-pooling of size 2 is applied to 20 feature map. Layer activated with Relu function. After the max-pooling operation, the number of neurons is reduced. Again, the 30 feature map in the previous layer is convolved with a kernel of size 5 to produce the next layer. A max-pooling operation of size 2 is applied to feature map, reducing the number of neurons with Relu activation function. Then, 50 feature map from this layer is convolved with a kernel of size 5 to produce the next Layer. Again, a max-pooling of size 2 is applied to reduce the number of neurons in the output layer with an activation layer used Relu function. Flattening the samples then dense with activation function Relu. Finally, the last layer (Output Layer) with 3 output neurons (representing normal, preictal, and seizure classes) using softmax function.

4. EVALUATION and RESULTS

4.1. Training and Testing of Data:

A total of 150 epochs of training were run in this work. An epoch refers to one iteration of the full training set. After every iteration of an epoch, our algorithm validates the CNN model by using 90% of the total training dataset and 10% of the testing dataset in the model. This is to prevent overfitting of the CNN model during training because Early Stopping imported in the model [19]. A total number of samples of all dataset for training was 13770 and testing 1530. From these samples, the evaluation took place and test accuracy evaluated. The performance (accuracy) of the proposed model with respect to training and testing is summarized in the following Table.

Table -1: Performance of the proposed model

Number of Trained samples	Number of Test samples	Accuracy
13770	1530	99.47
13770	1530	99.21
13770	1530	97.64
13770	1530	97.38

```
[26] from matplotlib import pyplot
# evaluate the model
_, train_acc = model.evaluate(Training_Data, Training_labels, verbose=1)
_, test_acc = model.evaluate(Test_Data, Test_labels, verbose=1)
print('Train: %.3f, Test: %.3f' % (train_acc, test_acc))

13770/13770 [-----] - 2s 138us/step
1530/1530 [-----] - 8s 138us/step
Train: 1.000, Test: 0.995

[27] scores = model.evaluate(Test_Data, Test_labels, verbose=1)
print('Test accuracy:', scores[1]*100)

1530/1530 [-----] - 8s 166us/step
Test accuracy: 99.47712418380654
```

Fig -5: Snapshot of the performance evaluation

5. CONCLUSION

The proposed model works with a small training set and aimed for low-resolution images with high accuracy. We were able to achieve competitive classification rate with the help of deep learning based EEG classification system. The model can be deployed on any embedded system in the future.

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