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Prediction of Epileptic Seizure Using CNN

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Abstract: *Epilepsy is one of the world's most common neurological diseases. Early prediction of the incoming seizures has a great influence on epileptic patients' life. In this, a seizure prediction technique based on CNN and applied to long-term scalp EEG recordings is proposed. The goal is to accurately detect the preictal brain state and differentiate it from the prevailing interictal state as early as possible and make it suitable for real-time. The raw EEG signals instead of manual feature extraction was used to distinguish ictal, preictal, and interictal segments for epileptic seizure detection. . In our model, we used time or frequency domain signals as inputs for classification. The frequency domain is a coordinate system that describes the frequency features of the signals. A frequency spectrogram reflects the relationship between the frequency and amplitude of a signal and is often used to analyze signal features. We compared the performances of time and frequency domain signals in the detection of epileptic signals. In our study, we used a very simple CNN structure. the CNN included only three main layers, and the network was very simple compared with the deep network. Meanwhile, satisfactory results were obtained. The achieved highest accuracy over 90% and the algorithm can be modified in a way that it works online and alerts in real time.*
Keywords*— Epilepsy, CNN*

I. INTRODUCTION

Epilepsy is defined according to the International League Against Epilepsy (ILAE), as a neurological brain disorder identified by the frequent occurrence of symptoms called epileptic seizure due to abnormal brain activities.

Seizure's characteristics include loss of awareness or consciousness and disturbances of movement, sensation or other cognitive functions. Electroencephalogram (EEG) is the electrical recording of the brain activities and is considered the most powerful diagnostic and analytical tool of epilepsy. There are various methods proposed to address the seizure prediction problem trying to reach high classification accuracy with early prediction. Since EEG signals are different across patients due to the variations in seizure type and location, most seizure prediction methods are patient specific. In these methods, supervised learning techniques are used through two main stages which are feature extraction and classification between preictal states and interictal states. Most of the previous work proposed machine learning based prediction schemes like Support Vector Machine (SVM). SVM classifier is used in numerous studies to predict the epileptic seizures. SVMs achieved outstanding results over other types of classifiers in terms of specificity and sensitivity. In proposed model, we used time or frequency domain signals as inputs for classification. The frequency domain is a coordinate system that describes the frequency features of the signals. A frequency spectrogram reflects the relationship between the frequency and amplitude of a signal and is often used to analyze signal features. , Here used a very simple CNN structure .the CNN included only three main layers, and the network was very simple compared with the deep network. Meanwhile, satisfactory results were obtained. The algorithm can be modified in a way that it works online and alerts in real time.

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II. LITERATURE SURVEY

The task of epileptic focus localization receives great attention [1] due to its role in an effective epileptic surgery. This surgery usually aims to remove the epileptogenic region which requires precise characterization of that area using the EEG recordings. In this paper, we propose two methods based on deep learning targeting accurate automatic epileptic focus localization using the non-stationary EEG recordings. The results of our experiments demonstrate high classification accuracy and clustering performance in localizing the epileptic focus compared with the state of the art.

Seizure prediction can allow timely preventive measures for patients with epilepsy. In this study, we propose a hybrid model consisting of convolutional neural networks (CNNs) and an extreme learning machine (ELM) to predict seizures using scalp EEG [2]. Here covert the EEG time series on 30-s windows into 2D spectrograms using the short-time Fourier transform. Then we apply CNNs to these images to extract features automatically. Finally, we use the ELM to classify preictal and interictal segments. The proposed method achieves sensitivity of 95.85% and a false prediction rate of 0.045/h on the Boston Children's Hospital-MIT scalp EEG dataset.

Epilepsy is a disorder in the electrical activity of the brain that occurs in a specific area or even the entire brain. These changes are visible through the acquisition of electroencephalogram (EEG) brain signals. EEG signals are important tools in predicting epilepsy because they are noninvasive measurement and display electrical activity at different external nodes at human brain [3]. Here used the CHB-MIT EEG Database in this study to develop an artificial model to predict epileptic seizures.

Thus, applied a one-dimensional convolutional neural network (CNN) to investigate raw EEG signals as an important indicator for starting time of a seizure. The seven-layer CNN was used to detect Preictal and Interictal states of brain where the performance of the proposed model was evaluated in terms of accuracy, specificity, and sensitivity which resulted in 97%, 98.47%, and 98.5%, respectively.

III. PROPOSED SYSTEM

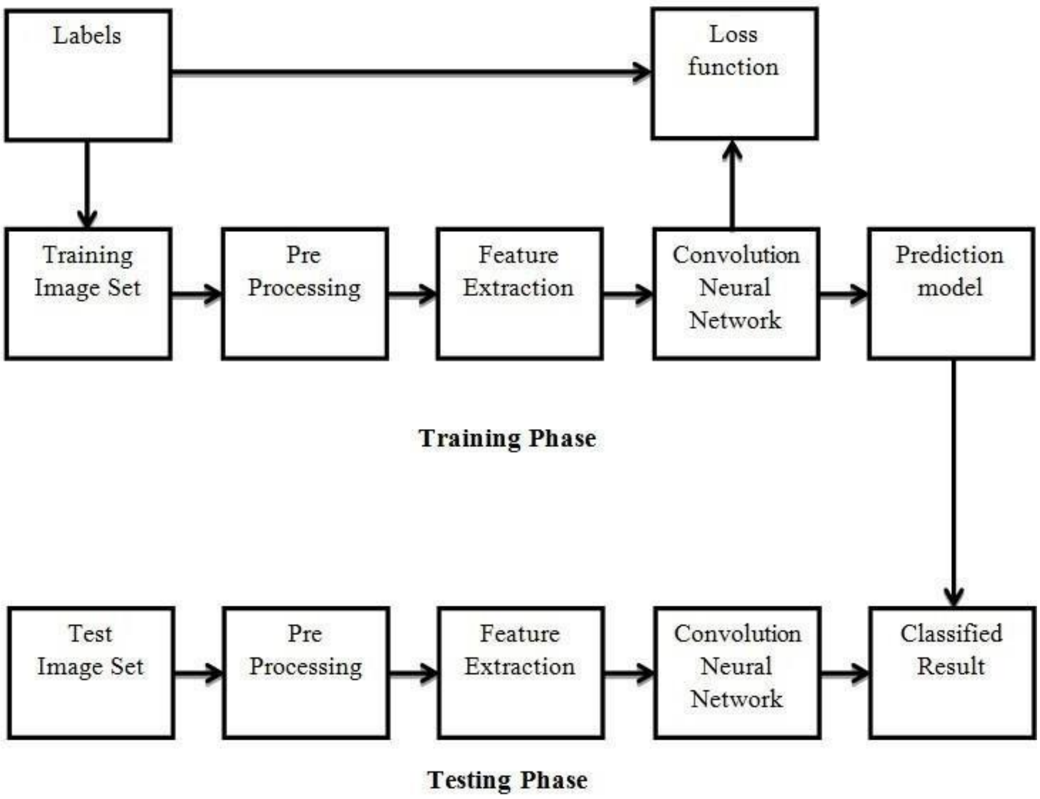

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Fig. 1 Proposed block diagram

IV. METHODOLOGY

Data Set for Seizure Event Detection. Bonn University data is used for the study of seizure event detection. The recording was done using standard 10-20 electrode placement system. The complete data sets consist of five sets each containing 100 channels which is named from A to E. Sets A and B consist of EEG segments taken from surface EEG recording carried out on five healthy volunteers. Volunteers were relaxed in an awaken state with eyes open (A) and eyes closed (B), respectively. Sets C, D, and E were taken from EEG archive of presurgical diagnosis. Segments in set D were recorded from the epileptogenic zone. Set C is recorded from hippocampal formation of opposite hemisphere of brain. Sets C and D contain only activity measured during seizure-free intervals. Set E contains only seizure activity [24]. Data is recorded within 128-channel amplifier system and digitized at 173.61 Hz sampling rate and 12-bit A/D resolution. To select the EEG signal of desired band a band-pass filter having a pass band of 0.53–40 Hz (12 dB/oct) was used. It was cut out from continuous multichannel EEG recordings after visual inspection for artifacts due to muscle activity or eye movement.

Tools and Technologies Used:

Python 3.8.0 Installation Get started working with Python 3.8.0, you'll need to have access to the Python interpreter. There are several common ways to accomplish this:

Python can be obtained from the Python Software Foundation website at python.org. Typically, that involves downloading the appropriate installer for your operating system and running it on your machine. Some operating systems, notably Linux, pro- video a package manager that can be run to install Python. On macOS, the best way to install Python 3 involves installing a package manager called Homebrew. You will see how to do this in the relevant section in the tutorial. On mobile operating systems like Android and iOS, you can install apps that provide a Python programming environment. This can be a great way to practice your coding skills on the go. Alternatively, there are several websites that allow you to access a Python interpreter online without installing anything on your computer at all.

Windows It is highly unlikely that your Windows system shipped with Python already installed. Windows systems typically do not. Fortunately, installing does not involve much more than downloading the Python installer from the python.org website and running it.

Networks Used:

A CNN consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, pooling layers and fully connected layers. Convolutional layers apply a convolution operation to the input, transferring the result to the next layer. The convolution emulates the response of an individual neuron to visual stimuli. Convolutional networks may include local or global pooling layers that combine the outputs of neuron clusters in one layer into a single neuron in the next layer. Mean pooling uses the average value from each cluster of neurons in the previous layer. Fully connected layers connect every neuron in one layer to every neuron in another layer.

V.RESULTS

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Epileptic

The above result is of Epileptic patient which is different from the normal readings.

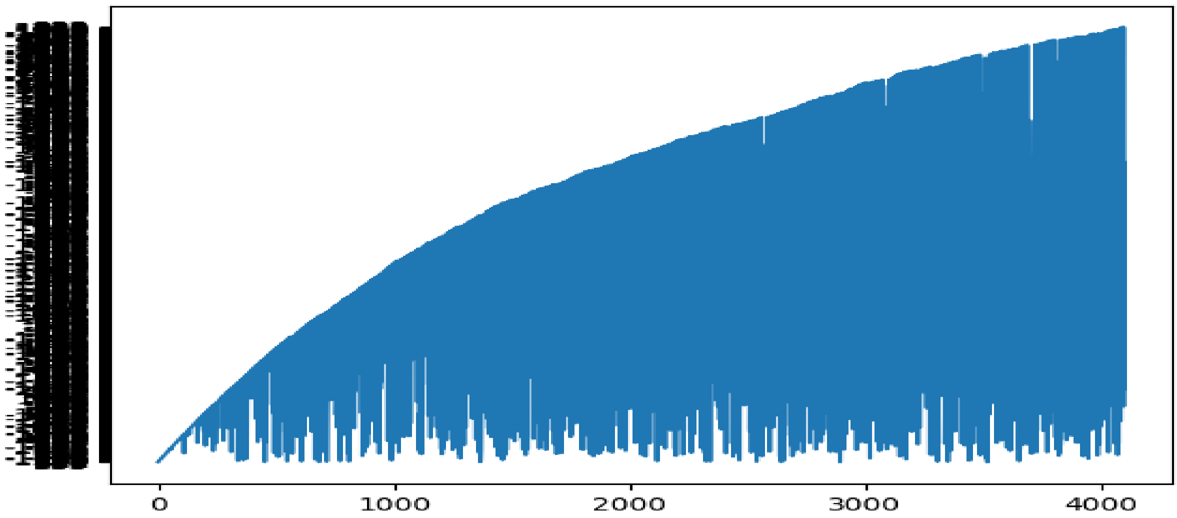

Fig.2 Epileptic patient

Normal

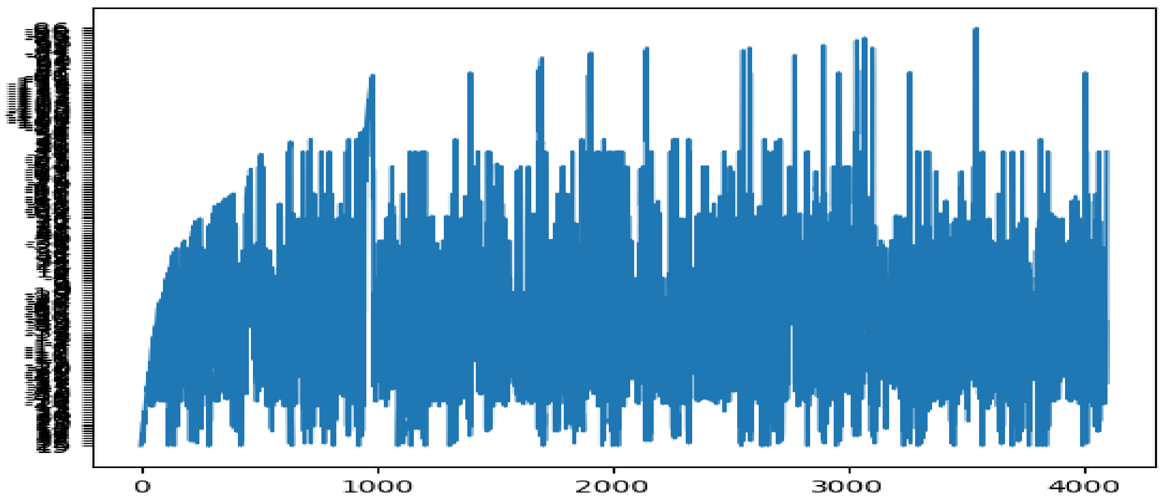

Fig. 3 Normal person

The above result is of Normal person.

In this way the results will be classified into NORMAL and EPILEPTIC sample

1) Train loss vs validation loss:

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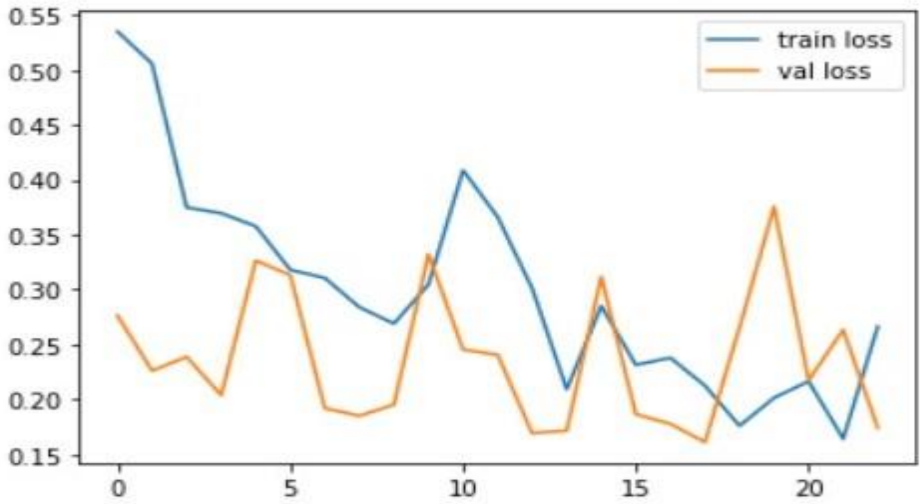

Fig 4.Train accuracy vs validation accuracy:

V. CONCLUSION

The proposed method may achieve a higher prediction accuracy and sensitivity A modified architecture is not necessary when a simple architecture gives satisfactory results. Furthermore, the architecture involving frequency domain signals outperforms the ones involving time domain. The objective of training a CNN to detect various phases of an elliptic seizure using EEG data was achieved quite successfully. The algorithm can be modified in a way that it works online and alerts in real time whether the person is approaching a seizure hence saving the patient from a potential fatal injury and alerting nearest medical facility at the earliest.

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