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Detection of Epileptic Seizures Using Hybrid Deep Learning Approaches

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Abstract: Epilepsy is a brain disorder that results in abnormal electrical activity in the brain. Epilepsy is also called a seizure disorder. The diagnosis of epilepsy can be made if the person suffers from two or more seizures. Seizures are the main symptom of epilepsy. Different models are introduced to diagnose epileptic seizures with the help of electroencephalography (EEG). EEG are wavelet signals that are most widely used to find the abnormal events identified in the brain. Deep Learning (DL) algorithms can efficiently discover epileptic seizures based on their features. In this paper, an automated epilepsy seizure detection system (AESD) is developed to diagnose and detect epilepsy seizures from the human brain. The existing models analyze many challenges to seeing this disease. The dataset attributes include patient family history, age, and information about patient medicines that have been used for a long time. The performance is analyzed based on the parameters.

Keywords: *Epilepsy, electroencephalography (EEG), Deep Learning (DL), epileptic seizures.*

1. Introduction

Epilepsy is a common brain disorder that causes sudden and spontaneous seizures [1]. Brain disorders may occur the patients with the age of above 70 years, and it is hard to recover after 70+ ages. In many countries, the Epilepsy patients count is increasing daily based on human habits and activities [2]. In India, 10 million people suffer from a brain disorder, rising from 0.5 to 1 million yearly [3]. The symptoms of this disease are based on patient behavior, cramps in muscles, abnormal sensations and lack of awareness, etc.; these symptoms lead to significant injuries, damage in the brain, or deaths of the patients caused by road accidents. These seizures are to be controlled by several prevention methods to improve the lifestyle of epileptic patients [4].

Epileptic seizures generate rapid fluctuations in the human brain, which are calculated using the EEG method [5]. Generally, experts analyze EEG samples and specify the stage of the seizures [6]. Thus, this process is manual and takes more time to know the status of the disease. Deep Learning (DL) plays a significant role in finding accurate patterns in complex conditions like alzheimer's, mild cognitive impairment (MCI), and Epileptic seizures. DL provides a better solution for various health-related issues, especially the diseases like brain disorders. DL models automatically analyze the differential EEG features from the given input signals. From the input EEG signals this process extracts the relationships. The EEG data is segmented into a pattern of non-overlapping epochs. Long Short-Term Memory (LSTM) is the DL model utilized to analyze the high-level analysis of standard and EEG patterns. Finally, the Softmax technique is used to train and classification. Thus, the proposed model can work efficiently in real-time conditions also.

Epilepsy is a neurological disorder that affects millions of people worldwide. One of the most common symptoms of epilepsy is seizures, which can be disruptive to daily life and potentially life-threatening if not managed properly. Seizures are caused by abnormal electrical activity in the brain, which can lead to a variety of physical symptoms such as convulsions, loss of consciousness, and involuntary movements. Deep learning is a powerful tool that has shown promising results in various medical applications, including the detection and classification of epileptic seizures. Deep learning algorithms can learn to identify patterns in large amounts of data, making them well-suited for tasks such as image recognition and signal processing. In the context of epilepsy, deep learning can be used to analyze electroencephalogram (EEG) recordings, which measure the electrical activity in the brain. By training a deep learning model on a large dataset of EEG recordings, the model can learn to recognize the patterns associated with epileptic seizures and automatically detect when a seizure is occurring. The ability to automatically detect

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seizures using deep learning has the potential to improve the accuracy and speed of diagnosis, reduce the risk of misdiagnosis, and allow for earlier intervention and treatment. However, there are still challenges to be addressed, such as the need for large, diverse datasets, and the potential for false positives and false negatives. Nonetheless, deep learning has shown promise as a tool for improving the detection and management of epileptic seizures.

2. Literature Survey

Epileptic seizures are sudden and recurrent bursts of electrical activity in the brain that can cause convulsions, loss of consciousness, and other symptoms. Detecting and predicting seizures is an essential task for epileptic patients to manage their conditions and improve their quality of life. DL techniques have shown promising results in the detection and prediction of epileptic seizures from EEG signals. In this literature survey, we will explore some of the recent works in this field.

Y. Li et al. [7] introduced a combined model called as spectral-temporal squeeze-and-excitation network (CE-stSENet). CE-stSENet combines both multi-level and multi-scale parallel. Each model represents the different types of patterns used to find the features. CE-stSENet helps to detect the Epileptic Seizure from the EEG signals. The proposed model obtained better accuracy compared with several models. Z. Song et al. [8] proposed single-channel seizure detection using brain-rhythmic recurrence biomarkers (BRRM) combined with the optimized model (ONASNet). BRRM is the most widely used method to find brain rhythms obtained from EEG signals. The two models, BRRM and ONASNet, are used to extract the accurate features for detecting Epileptic Seizures.

M. A. Sayeed et al. [9] proposed the EEG-based seizure detection approach with various mathematical models integrated with the ML classifier. Detection of seizures can be done in two stages; in the first stage, the EEG signal is divide into two sub-parts, and impact-based features are extracted from every sub-part. Finally, the DNN is used to classify EEG samples based on the disease affected. Y. Liu et al. [10] developed the novel Deep C-LSTM to detect seizures and the tumor present in the human brain, which is identified at the time of eye status. The result obtained for every 0.006 seconds is a concise detection rate.

J. Saini et al. [11] discussed several DL models used to detect epilepsy using EEG signals. The proposed approach in this paper uses the accurate feature extraction method that extracts the complex information present in the EEG signal. The proposed approach obtains better results compared with existing models. I. L. Olokodana et al. [12] developed an enhanced approach that detects and diagnoses seizures from the EEG signals. The proposed approach is connected with wearable devices and shows a better detection rate. A. Anuragi et al. [13] proposed the hybrid classifier with the integration of advanced feature extraction methods to extract significant features from epilepsy datasets. The empirical wavelet transform (EWT) divides the EEG signals into two parts and extracts their features. The proposed approach, FBSE, is used to classify the EEG samples after feature extraction. Thus, the classification gives better accuracy compared with previous models. N. Verma et al. [14] proposed a new epilepsy detection model based on EEG signals using the low-energy SoC. Based on the patient, the SoC belongs to the single EEG channel, and it is up to 18 channels used to detect abnormalities for chronic disease treatment. Here the ADC amplifier is combined with SoC to achieve better results than existing models. L. S. Vidyaratne et al. [15] introduced a variety approach for detection of automatic epileptic detection using input samples. The proposed model is an automated system that decomposes the EEG signal using fast wavelet decomposition and measures based on Fourier transform to find the abnormal frequency measures. Thus the novel approach achieves an accuracy of 99.8%. S. P. Burns et al. [16] proposed the dynamic epileptic detection system using epileptic seizures from the (ECoG) recordings.

3. Types of Epilepsy Detection Models:

There are several types of epilepsy detection models that have been developed to identify and diagnose epilepsy in patients. Here are some of the most commonly used types:

EEG-based detection models: These models analyze electroencephalogram (EEG) signals to identify abnormal brain activity that is characteristic of epilepsy. EEG-based models can be used for both seizure detection and seizure prediction.

Machine learning models: These models use algorithms to analyze patient data, including EEG signals, video recordings, and other clinical information, to identify patterns that are indicative of epilepsy.

Deep learning models: These models are a type of machine learning that use artificial neural networks to analyze patient data and identify patterns that are indicative of epilepsy.

Wearable device-based detection models: These models use wearable devices such as smartwatches, wristbands, and patches to monitor a patient's physiological signals, including heart rate, breathing rate, and movement, to detect seizures.

Video-based detection models: These models use video recordings of patients to detect seizure activity based on visible symptoms such as jerking movements, loss of consciousness, and changes in facial expressions.

Hybrid models: These models combine multiple detection methods, such as EEG-based and machine learning-based approaches, to improve the accuracy of epilepsy diagnosis and prediction.

Role of EEG signals for Epileptic Seizure Detection

EEG (electroencephalogram) signals play a crucial role in the detection of epileptic seizures. *Epilepsy* is a neurological disorder that causes abnormal electrical activity in the brain, which can result in seizures. EEG is a non-invasive technique that uses electrodes placed on the scalp to record the brain's electrical activity. EEG signals can detect the onset of an epileptic seizure, distinguished by an abrupt increase in the frequency and amplitude of electrical activity in the brain. These changes in the EEG signal are often accompanied by other physiological changes, such as changes in heart rate, respiration, and blood pressure. Machine learning (ML) algorithms can be trained on EEG signals to detect patterns associated with epileptic seizures.

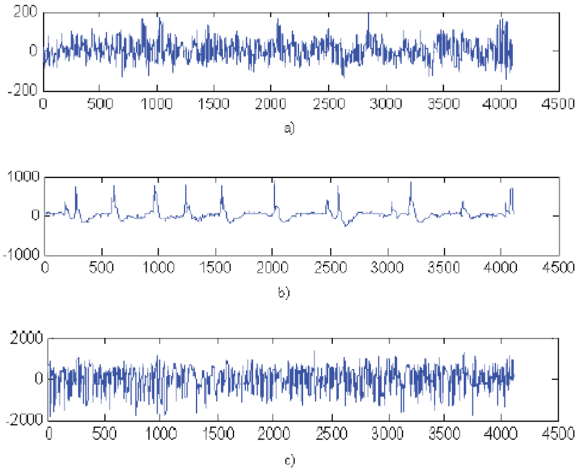

Fig 1: EEG signals: a) Normal; b) Pre-ictal; c) Epilepsy.

These algorithms can then be used to develop automated systems that can detect seizures in real-time. This can be particularly helpful for people with epilepsy who may not be able to recognize the onset of a seizure themselves. Additionally, EEG signals can be used to localize the source of epileptic activity in the brain, which can be helpful in determining the best treatment approach for a person with epilepsy. For example, if the source of epileptic activity is localized to a specific region of the brain, surgical intervention may be considered to remove that region. Overall, EEG signals play a critical role in the detection and management of epilepsy, and ongoing research in this area is helping to improve our understanding of the disorder and develop new approaches for treatment and care.

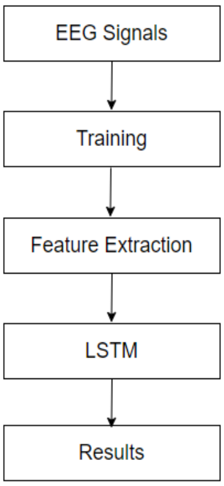

Fig 2: System Architecture

Proposed Methodology: Automated Epilepsy Seizure Detection System (AESD)

Deep Learning (DL) is the domain that can process complex datasets in academic research. Detection and diagnosis of epileptic seizures using the proposed system called DRNN, specifically the LSTM model. This study's proposed analysis was carried out with input EEG signals belongs to time-series.

These EEG signals are divided into small non-occupying segments and are sent into the LSTM that are used to learn the superior level rendering of EEG samples. The result of the LSTM forwarded to the time-based dense layer to identify the most relevant features of the epileptic seizures. The estimations of the labels are extracted from the softmax layers. Figure 1 shows the three gates: input, forget, and output, and it also contains the block input, activation function, and keyhole connectivity.

$$x_t = \sigma(w_x[h_{t-1}, a_t] + y_x \quad (1)$$

$$z_t = \sigma(w_z[h_{t-1}, a_t] + y_x \quad (2)$$

$$l_t = \sigma(w_l[h_{t-1}, a_t] + l_x \quad (3)$$

$$x_t \rightarrow initializesaninputport$$

$$z_t \rightarrow initializesanforgetport$$

$$l_t \rightarrow initializesanoutputport$$

$$\sigma \rightarrow initializessigmoidfunction$$

$$h_{t-1} \rightarrow resultofpreviousLSTMblock$$

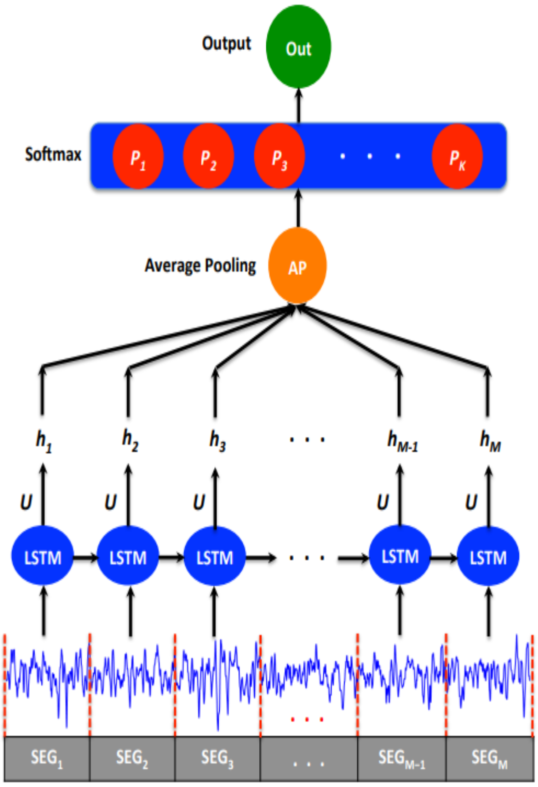

Fig 3: Proposed System Architecture

To learn the suggestive features of the seizure properties from EEG samples, DL extracts the parametric features more appropriate to seizures. The proposed DNN model contains three layers, and the softmax layer is on the top. The input samples are first sent to a fully connected LSTM layer of more than 100 neurons. The proposed model also learns the short and long differences among the EEG segments in every signal and over the similar class. The default behavior of the LSTMs is based on the data processing for input signals. In the next step, the dense layer is adapted to convert the data understood by the LSTM layer into meaningful seizure-connected features. Thus, the proposed model solves the sequence labeling issues. Finally, a time-distributed dense layer is utilized to measure the cost function on all the EEG time steps. This study used 50 units of a fully-connected thick layer based on the 1D average pooling layer.

Dataset Description

The dataset was collected from "Klinik fur Epileptologie, Universitat Bonn" repository. Totally 500 EEG signal samples are present with single-channel EEG signals with a sampling rate of 173.64 Hz with a processing time of 23.7 seconds. All these samples are collected from various patients based on their eye movements and muscle activities.

Performance Analysis

The performance of the model is analyzed by using the confusion matrix. The count values of the model are measured by using the true positive (TP), true negative (TN), false positive (FP) and false negative (FN). The classification of proposed model shows the two classes predicted and actual. Based on the above count values the performance is analyzed by using the accuracy, sensitivity, specificity and F1-score.

Sensitivity: From all the actual positives (normal) calculates the sensitivity.

$$\text{Sesitivity} = \frac{\text{No. of TP}}{\text{No. of TP} + \text{No. of TN}}$$

Specificity: From all the actual negatives (abnormal) calculates the specificity.

$$\text{Specificity} = \frac{\text{No. of TN}}{\text{No. of TN} + \text{No. of FP}}$$

Accuracy: This will calculate the overall accuracy of the overall normal and abnormal effected area.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

F1-Score (F): This measures the consonant of precision and recall values.

$$F = \frac{2 \times \; presicion \; \times recall}{presicion + recall}$$

Table 1: Performance of Algorithms

Algorithms	Sensitivity	Specificity	Accuracy	F1-Score
SVM	85.67	86.89	87.12	86.34
RF	90.12	90.78	89.78	90.67
AESD	95.67	96.76	97.12	97.67

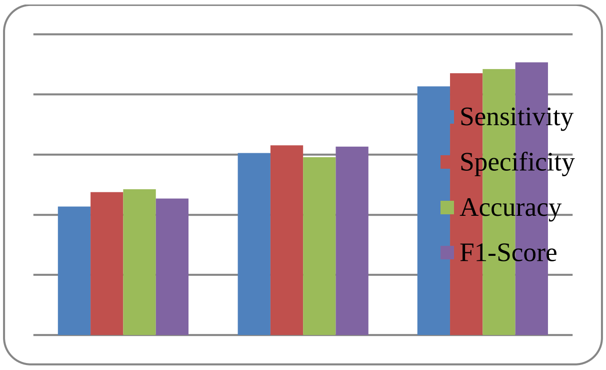

Fig 4: Performance of Existing and Proposed Algorithms

4. Conclusion

The proposed approach AESD in this paper provides accurate detection of epileptic seizures from EEG signal data. The proposed method employs a sequential and automated process to detect abnormalities in EEG signal samples. To detect epileptic patients, AESD extracts incorporeal features from EEG signal segments. These features include the several segments of EEG sample with few measurements. The proposed model outperforms the input EEG signals in terms of accuracy, and the processing time ranges from 5 to 50 seconds. The AESD achieved the accuracy of 97.12%, sensitivity of 85.67%, Specificity of 96.76% and F1-score of 97.67%.

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