Automatic Seizure Detection Using EEG Reports

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Abstract

Seizures are a result of abnormal electrical activity in the brain, and they can lead to hazardous physical injuries if not detected and treated promptly. EEG reports are the most used reports to detect epilepsy or seizures. The advantages and limitations of the currently employed techniques for epileptic seizures diagnosis are presented along with a new proposed architecture solution. This paper proposes a model that used a much smaller architecture and provides the same accuracy. It involves preprocessing of the EEG signals to remove any noise or artifacts before applying feature extraction and classification algorithms, which are then used to classify the seizure patterns. The classification algorithm used in the proposed model is BLSTM which has been shown to provide high accuracy in seizure detection.

Keywords— seizure, EEG report, architecture, feature extraction, BLSTM, and accuracy

I. INTRODUCTION

In Elliptical Seizure or commonly known as seizure or epilepsy is a neurological disorder that is found in almost 50 million people worldwide according to WHO or in simple terms, we can say almost 6 people in every 100 people are affected with it.

Seizures can vary from person to person and the intensity will vary again, it may be possible that the person may not be able to experience any significant change, say maybe has blanked out for a while which may seem a minor thing that can be ignored but later on may result in a big attack or in other cases patients may experience a sense of jerk in some part of the body. Since it is a neurological disorder, the sudden abnormality in the electrical activity of the body may lead to disruption of a part or the whole body due to the sudden change. Thus, we can say it may also result in a possible physical injury if no proper action is taken in the proper time frame.

Currently there are many ways of detecting the possibility of a seizure occurring in humans using EEG (Electroencephalogram) scanning, MRI (Magnetic Resonance Imaging), CT, PET, SPECT and EEG scanning remains the most common and important form of detection amongst many physicians, the main reasons being that it is quite economical as compared to a MRI scan and also its quite portable.

What exactly happens in an EEG scanning is that the persons are connected with electrodes, we can consider it to be like a skull cap with electrodes associated on it and these electrodes cover the entire cerebrum of the brain. The electrical activities that are associated with the neurons are then captured using these electrodes and the neuroimaging is done, the spikes that are detected in 4 different phases namely - Ictal, Preictal, Postictal, Interictal. The spikes are first normalized using a mean filter and then the maximum spike is used as an indicator for prediction.

II. LITERATURE SURVEY

Kamel, Mahmoud, and Hassanien proposed an EEG-based seizure detection system using multi-domain feature extraction and support vector machine (SVM) classification. They extracted statistical, frequency and entropy features from the EEG signal and used SVM for classification. The proposed method achieved high accuracy in detecting seizures and could be useful in clinical settings.

Manimegalai and Duraiswamy conducted a review on EEG signal analysis for seizure detection. They analyzed the different methods and techniques used for feature extraction, feature selection, and classification of EEG signals. They also discussed the limitations and challenges of EEG-based seizure detection and suggested possible solutions for overcoming them.

Homayoun et al. proposed a novel method for automatic seizure detection based on wavelet transform and artificial neural networks (ANNs). They extracted features from the EEG signal using wavelet transform and used ANNs for classification.

Sharma and Pachori proposed a method for seizure detection using an adaptive neuro-fuzzy inference system (ANFIS). They extracted features from EEG signals using a combination of discrete wavelet transform (DWT) and empirical mode decomposition (EMD) and used ANFIS for classification.

Chua et al. proposed a method for seizure detection using a combination of wavelet transform, independent component analysis (ICA), and machine learning techniques. They extracted features from EEG signals using wavelet transform and ICA and used a random forest classifier for seizure detection

The system proposed in this project is novel and unique in the sense that most systems are developed to with very large models and combinations of them. This leads to a large architecture and takes a lot of processing time. Using this project, we can achieve the same accuracy with a much smaller architecture.

III. System Architecture and working

Electroencephalography (EEG) is a valuable tool for monitoring brain activity, but automated EEG processing poses several challenges, such as high dimensionality, artifacts, and real-time processing requirements. Deep learning has shown promise in addressing these challenges and has been applied in various EEG processing tasks, such as brain-computer interfaces, sleep scoring, and epileptic seizure prediction. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been used for feature extraction and classification from raw EEG signals. Additionally, deep learning has been used for other applications, such as event-related potential detection, emotion recognition, and cognitive workload assessment.

A. *BLSTM*

Bidirectional Long Short-Term Memory (BLSTM) is a type of recurrent neural network that has gained popularity for its ability to process sequential data in both forward and backward directions. In an BLSTM, the input sequence is fed into two separate LSTM networks, one in the forward direction and one in the backward direction. The outputs from these two networks are then concatenated to form the final output sequence, which can capture dependencies in both past and future contexts. BLSTM has been applied in various applications such as speech recognition, natural language processing, and image captioning, where it has shown significant improvements in accuracy over traditional neural networks.

B. *Proposed Model*

The proposed model is designed to take in EEG signals as inputs with 178 data points and 1 channel. EEG data can be thought of as a time series of electrical signals that are generated by the brain. These signals can provide valuable insights into brain function and are commonly used in the diagnosis and treatment of neurological disorders.

The first layer in the model is a dense layer with 32 units and an Exponential Linear Unit (ELU) activation function. The purpose of this layer is to transform the input data into a more expressive feature representation that can be better understood by the subsequent layers in the network. The ELU activation function has been shown to outperform other activation functions, such as ReLU, in terms of learning complex representations and preventing the vanishing gradient problem.

The next layer in the model is a BLSTM layer with 128 units. A BLSTM layer is a type of recurrent neural network that is capable of processing sequential data in both forward and backward directions. This allows the model to capture dependencies in both past and future contexts, which can be important in understanding the underlying patterns in the EEG signals. The output of the BLSTM layer is then passed through a dropout layer with a dropout rate of 0.3. The purpose of the dropout layer is to randomly drop out some of the nodes in the network during training, which can help prevent overfitting and improve generalization performance.

A batch normalization layer is then added to normalize the output of the previous layer. Batch normalization is a technique that can improve the stability and convergence of deep neural networks. It works by normalizing the output of each layer to have zero mean and unit variance. This can help prevent the activation functions in the subsequent layers from saturating, which can improve the overall performance of the network. Another dense layer with 64 units and a Rectified Linear Unit (ReLU) activation function is added next. Another dropout layer with a dropout rate of 0.3 is added after the dense layer to further prevent overfitting. Another batch normalization layer is added after the dropout layer to further improve the stability and convergence of the network.

Finally, a dense output layer with 2 units and a softmax activation function is added for binary classification. The softmax activation function is commonly used in multi-class classification tasks and outputs a probability distribution over the possible classes. The loss function used for training the model is sparse categorical cross-entropy.

C. *Training*

The proposed neural network model underwent a training process consisting of 70 epochs with a batch size of 32. This process involved iteratively updating the model's weights based on the error between the predicted output and the actual output. The choice of 70 epochs was determined based on empirical evaluation, and it indicates the number of times the model was exposed to the entire training dataset during the training process. On the other hand, the batch size of 32 refers to the number of training examples processed in each iteration of the weight updates. This value was chosen to balance the trade-off between memory usage and computational efficiency. By training the model for 70 epochs with a batch size of 32, we aimed to optimize the model's performance on the given task while preventing overfitting or underfitting due to the hyperparameter choices.

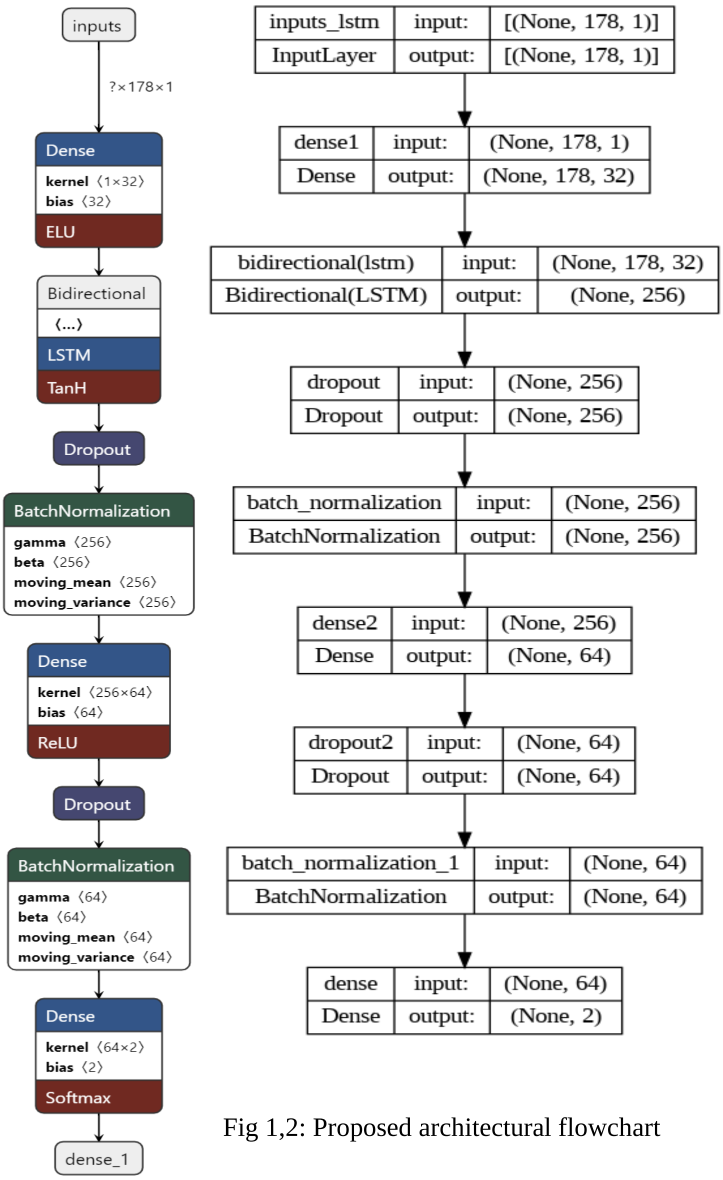

Fig 1,2: Proposed architectural flowchart

IV. Approach

Before reaching the final conclusion, we had to test through different ML models and deep learning models. Initially, starting with the ML models, we tried using the following models in order to check if the performance of our model could be improvised in any aspect

1. Logistic Regression
2. ANN
3. K Means Clustering
4. SVM

On the implementation of logistic regression, we could classify the given dataset in terms of 2 things that is 0's and 1's, if it has seizure or not.
Based on the model applied we could achieve the accuracy of 83.5% which results to be better than the results achieved in the paper but still not the best

ANN: is basically a replica of our brain in the manner of the entire nervous system of a human body, neural networks deliver two important functions as pattern classifiers and as non-linear adaptive filters. ANN is many aspects is better for computation of the complex problems but becomes cumbersome in the case of any image analysis. Thus, it is best to use CNN in these cases. Since we have broken the image into several data points, we are able to achieve an accuracy of 95.7% here.

K mean Clustering: It is an unsupervised learning model where we will be able to form clusters based on the various data points that are given to us. The major drawback that remains here is that we have to initially mention the value of the number of clusters that we plan on to take, i.e., the value of K. By simply taking the value of the clusters as 2 we are able to achieve an accuracy of 93.9%.
The other drawback that can be classified in taking such a small value of K in our case is that we are again simply classifying the data into 2 clusters - as seizure detected or seizure not detected. There may be a case where the neural activity may be not so strong to be classified as a seizure but there may be a possibility of it happening but will be classified as a non-seizure patient.

The **SVM model** is better than the logistic regression model as it is able to classify even those points which are not linearly separable, thus can be used for regression and classification, since it has a better functionality as compared to the other ML and we are able to achieve a good accuracy of 97.7% in it, the drawback that remains in using this algorithm is that SVM requires large number of parameters and takes larger computation time too

Based on the above analysis we can thus claim that since we have a large amount of data that is being created everyday it won't be an optimal approach if the analysis takes a large amount of time for computation despite of achieving a good accuracy, thus we require the need to use Deep Learning which is able to incorporate large amount of data in a limited time frame.

V. Assumptions and Dependencies

A. *Device Specifications*

Since, the model needs to be trained and tested on a large dataset, it cannot run on small storage devices or devices with low computational power. This seizure detection paper using EEG reports model was built, trained and tested on Windows Intel(R) Core(TM) i7-10510U processor with x64 processors.

B. *Dataset*

The dataset from Kaggle used is mentioned in the references for this project which has been collected from the UCI Machine Learning Repository. The dataset is a recording of the brain activity for 23.6 seconds which gives us a total of 4097 data points that depict the different functioning of the neurons in different parts of the brain. Over here we have a total of 500 patients whose scanning has been considered and each of these data points are divided in 23 chunks with each chunk having 178 (4097/23) data points corresponding to each second. The response variable is y in column 179, the Explanatory variables X1, X2, X178 and y contains the category of the 178-dimensional input vector. Specifically, y in {1, 2, 3, 4, 5}:

i. The point y=5 detects eyes open, means when they were recording the EEG signal of the brain the patient had their eyes open

ii. The point y=4 detects eyes closed, means when they were recording the EEG signal the patient had their eyes closed

iii. The point y=3 detects they identify where the region of the tumor was in the brain and recording the EEG activity from the healthy brain area

iv. The point y=2 records the EEG from the area where the tumor was located

v. The point y=5 is the recording of seizure activity

All subjects falling in classes 2, 3, 4, and 5 are subjects who did not have epileptic seizure. Only subjects in class 1 have epileptic seizure. Our motivation for creating this version of the data was to simplify access to the data via the creation of a .csv version of it. Although there are 5 classes most authors have done binary classification, namely class 1 (Epileptic seizure) against the rest.

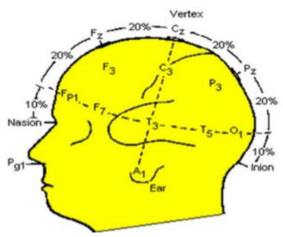

Fig: Datapoints for dataset

VI. PERFORMANCE ANALYSIS

A. *MODEL 1 – using Convolutional Neural Network*

Convolutional Neural Networks (CNNs) are a class of deep neural networks that are particularly suited for image classification and object detection tasks in computer vision. CNNs were inspired by the visual cortex in the brain, which is responsible for processing visual information. We ran a CNN model for image classification and trained it for two different numbers of epochs. The accuracy obtained for the two different epochs are 91.30% for 100 epochs and 93.48% for 120 epochs.

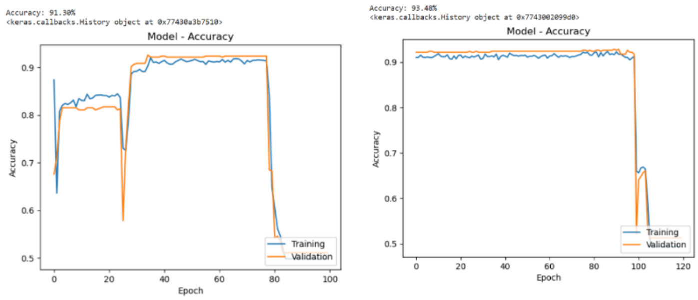

Fig: Accuracy model for a) 1oo epochs b) 12o epochs

B. *MODEL 2a – using BLSTM*

To increase the model's accuracy, we used a second model. It is a variety of recurrent neural networks (RNNs) that are capable of learning long-term dependencies, especially in sequence prediction problems. LSTM has feedback connections, i.e., it is capable of processing the entire sequence of data, apart from single data points such as images. This finds application in speech recognition, machine translation, etc. LSTM is a special kind of RNN, which shows outstanding performance on a large variety of problems. On running BLSTM with

Activation Function at layer 1: relu

Activation Function at layer 2: relu

Activation Function at main_output: softmax

Epochs: 100 ; Accuracy Achieved: 97.83%

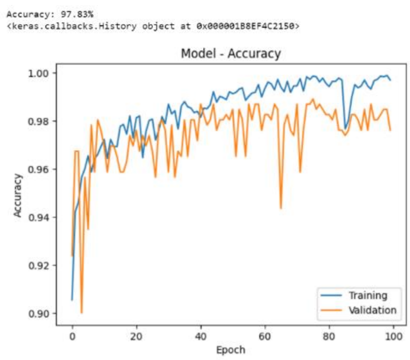

Fig: 97.83% accuracy

C. *MODEL 2b – using BLSTM*

On running BLSTM with

Activation Function at layer 1: relu

Activation Function at layer 2: relu

Activation Function at main_output: softmax

Epochs: 70 ; Accuracy Achieved: 98.4%

Fig: 98.4% accuracy

Based on all the above-mentioned models we achieved the highest accuracy by using the three layered Bidirectional Long Short-Term Memory Networks having activation functions at three different layers as elu, relu and softmax (at main output) and number of epochs as 70 achieving the accuracy of 98.04%.

VII. Conclusion

The use of EEG report analysis for seizure detection has proven to be an effective and reliable method for diagnosing and treating epilepsy. While there are still challenges to be addressed, such as the need for standardization of EEG analysis methods and the integration of EEG monitoring into routine clinical practice, the potential benefits of using EEG reports for seizure detection cannot be overlooked. The ability to detect seizures in a timely and accurate manner can greatly improve the quality of life for those living with epilepsy and their families, as well as reduce the risk of seizure-related injuries and deaths. Continued research and development in this area will undoubtedly lead to further improvements in diagnosis and treatment of epilepsy.

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[10] Dataset: Click here to view the dataset