Unveiling Epilepsy: Machine Learning and Deep Learning Approaches for EEG Signal-Based Patient Detection

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Abstract

The intricate neurological condition known as epilepsy, which is common across the world, presents considerable difficulties in accurately identifying and differentiating between non-epileptic and epileptic activity using electroencephalograms (EEGs). To customize successful therapies, it is essential to accurately identify the kinds of epileptic activity. Since epilepsy affects about 50 million people worldwide according to latest update of WHO and is typified by spontaneous seizures, early identification and prediction are vital in enabling people to minimize possible harm. Therefore, use of machine learning, which includes various machine learning algorithms such as K-Nearest Neighbor (KNN), Logistic Regression, Naive Bayes, Random Forest, Support Vector Machine (SVM) and Decision Trees. This report explores the evolving field of epilepsy diagnosis and reviews the various machine learning algorithms, datasets, and computational techniques currently in use. To identify small patterns in EEG data, this study combines cutting edge technologies, like Long Short-Term Memory (LSTM) and 1D-CNN (Convolutional Neural Network) leveraging data from five hundred patients acquired from the UCI Machine Learning Repository. To optimize the 1D-CNN LSTM architecture and hyper-parameters, Bayesian optimization is employed, allowing for efficient exploration of the parameter space. Its effectiveness is not only limited to enhancing the performance metrics of a particular model but also minimizing the computing power required for fine tuning. The research evaluates the effectiveness of the 1D-CNN LSTM-based model, showcasing its potential as a reliable tool for automated epilepsy detection with accuracy of 99.47% (≈ 100%), average sensitivity of 99.45%, and average specificity of 99.57%. This approach, emphasizes the significance of anticipating seizures in advance, attempts to provide epileptics the tools they need to control and avoid seizures in advance, so ultimately enhancing their quality of life for patients.

Proposed Technique

1D CNN LSTM: This model combines the temporal modelling or complementing skills of LSTMs with the spatial feature extraction capabilities of CNNs to produce a potent framework for the analysis of sequential and temporal data.

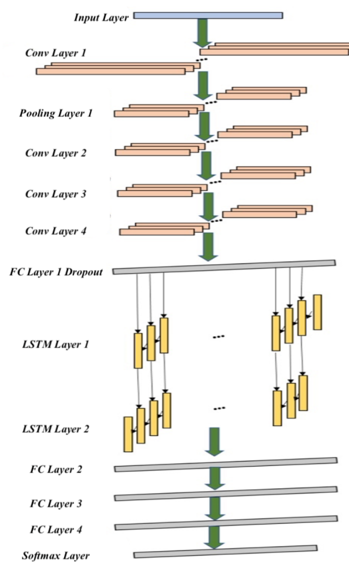

Fig.1. 1D CNN LSTM Model

4 convolutional layers, 2 LSTM layers, 1 input layer, 1 pooling layer, 4 fully connected (FC) layers, and a SoftMax output layer make up the suggested ensemble model. First, as the data source for the proposed model, the 45 X 1 form of the one-dimensional EEG signal data is used after that, to extract abstraction features from the raw signal data, input data is transmitted through an initial convolution layer composed of 64 one dimensional convolution kernels with a shape of 3 X 1 and a length of 1, respectively. A ReLU (Rectified Linear Unit) activation layer comes after this convolutional layer, which adds non-linearity to the suggested model.

A. UCI DATASET:

Each of the five folders in the original dataset [3] has one hundred files, each of which represents a particular topic or individual. Every file contains a 23.6-second observation of neural activity. Data points totalling 4097 are collected from the related time-series. The value of the EEG recording at a particular moment in time is represented by each data point. There are five hundred distinct individuals in all, and every one of them having 4097 data points for 23.5 seconds.

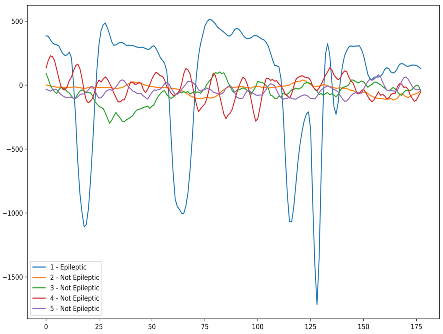

Fig.2: The Raw EEG Signal Waveform of Four Healthy Subjects And One Epileptic Subject

C. 10-20 Electrode System

A 10-20 electrode arrangement serves as a standardized technique for the strategic placement of electrodes on the human scalp, primarily for electroencephalography (EEG) measurements as shown in Fig 3. the 10–20 electrode system is a standard approach which is used widely across the world for recording the EEG signals of a brain that also have medical support and proves. The guaranteed and the uniform placement makes it easier to read the data of any patient from various sources.

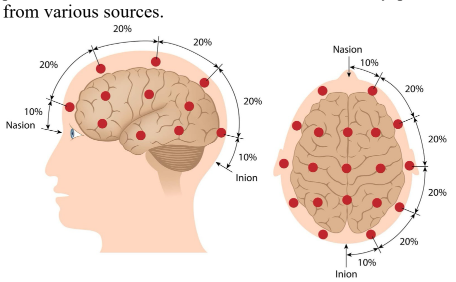

Fig.3: Electrode Placement

B.1D Convolution operation (1D CNN):

In order to obtain representations and effective features from 1D time series convolution sequence data, a 1D-CNN may perform 1D operations with different filters. Fig 3 shows the technicalities of the 1D-CNN process. To confirm to the single dimensional nature of the raw EEG signal data, the feature maps and convolutional filters of the 1DCNNs used in this work are entirely one dimensional. By increasing the number of convolutional layers, CNN is capable of progressively generating higher level features for epileptic seizure detection tasks which are resistant and discriminable.

C. LSTM:

The standard LSTM block structure is shown in Fig 4 The LSTM block consists of four gates: input gate z_i, here, a sigmoid function receives the input states the previous hidden state and the current input state and determines which values should be updated by converting them to a range of 0 to 1. One indicates importance, whereas zero indicates not much; forget gate z_f, this gate determines what data should be retained or discarded. The sigmoid function processes data from the present input as well as data from the prior hidden state; gate z in the cell state that retains the data throughout time; and output gate z_o, which determines the value of the subsequent hidden state keeping in mind that information about prior inputs is contained in the concealed state and predictions are also made using the concealed state.

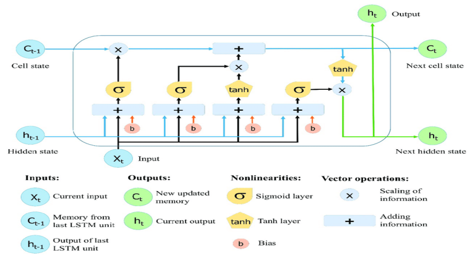

Fig. 4: LSTM Block Structure

Experimental Results

A 90-10 train test split on the data is performed throughout the experiment. The number of training epochs for the CNN, 1D convolutional LSTM, and deep neural network (DNN) models is 100. The suggested method also employs the dropout strategy to enhance the generalization performance and prevent the issue of overfitting. Distribution of the data in a random manner is done before training, and then subsequently forwarded to the network.

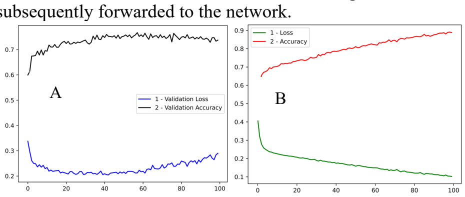

Fig.5: Training and Validation Accuracies (A) Validation Loss and Accuracy (B) Training Loss and Accuracy

Model	Accuracy	Precesion	Recall	F1-Score
CNN	*97.13%*	*94.24%*	*92.34%*	*0.9328*
DNN	*96.35%*	*95.18%*	*87.50%*	*0.9118*
Suggested 1D CNN LSTM	*99.47%*	*99%*	*99%*	*0.9959*

Table 1: Performance Metric of Deep Learning Models

Conclusions

With a 99.47% accuracy rate, the suggested model outperforms KNN by 7.7%, SVM by 5%, and DT by 2.27% as compared to the machine learning algorithms applied. This drives to the fact that suggested 1D-CNN LSTM ensemble model has great potential in the field of epileptic seizure detection research through EEG signals, as demonstrated by all these results. Table 1 shows dominance of suggested deep learning algorithm over the best performing Machine learning algorithm though the suggested model used an extensive hardware and overloaded it, but it also provides a significant rise in the results.

Acknowledgement

[1] P.Hospitals,"Internationalepilepsyday12feb,2024:Themeandimportance."https://www.pacehospital.com/international-epilepsy- day. Accessed: Feb 12, 2024

[2] [WHO, "World health organization 2024." https://www.who.int/ news-room/fact-sheets/detail/epilepsy. Accessed: Feb 12, 2024

[3] Q. Wu and E. Fokoue, "Epileptic Seizure Recognition." UCI Machine Learning Repository, 2017