# Epilepsy Prediction using a Combined LSTM - XGBoost System on EEG Signals

**Shanmuga Skandh Vinayak E, Shahina A, Nayeemulla Khan A**

***Abstract—Ranking 4th in the list of most common neurological diseases, Epilepsy – a severe chronic disorder that causes recurrent and unprovoked seizures, affects over 1% of the world population. One of the most preliminary and commonly used mechanisms to test the presence of epilepsy in patients is the electroencephalogram (EEG). EEG – an instrument capable of recording the electrical activity in the brain. The EEG data are capable of revealing information, unique to a patient with episodes of seizure. In this article a system capable of detecting such information is proposed, using neural networks and machine learning algorithms, which can be utilized in the automation process of epilepsy detection. The proposed system utilizes the Long Short-Term Memory (LSTM) neural network algorithm and the eXtreme Gradient Boosting (XGB) algorithm, to classify the channels of the EEG data. The system produces an average accuracy of 96.2% in the LSTM channel classification models and an ensemble classification of the LSTM classifications using XGB, producing an average accuracy of 98.5%. Data encoding is employed in the system, which improves the efficiency and performance of the system by exhibiting a classification duration of 31s/sample.***

***Keywords—Epilepsy, Detection, EEG, Sliding Window, Encoder, Neural Network, Machine Learning, LSTM, XGB.***

## I. INTRODUCTION

Epilepsy – A severe neurological disorder, caused by a wide range of possible factors, ranging from a mere bacterial infection or stress to more acute factors such as genetic causes or even trauma to the brain. Around 50 million people around the world are affected by epilepsy, according to the World Health Organization (WHO), and 80% of the affected live in low-income and middle-income countries [1]. According to the paper published by Eugen Trinka et al., in 2018 [2] that focuses on the study of epilepsy in the Asian continent reveals that approximately 23 million people in Asia are affected by epilepsy, making Asia the continent with the highest number of epileptic patients. Although the tally is high, it is estimated that up to 70% of the affected can be cured with proper diagnosis and treatment, according to the World Health Organization (WHO) [1]. One of the most preliminary and commonly used mechanisms to test the presence of epilepsy is the electroencephalogram (EEG) that measures and records the electrical activity in the brain.

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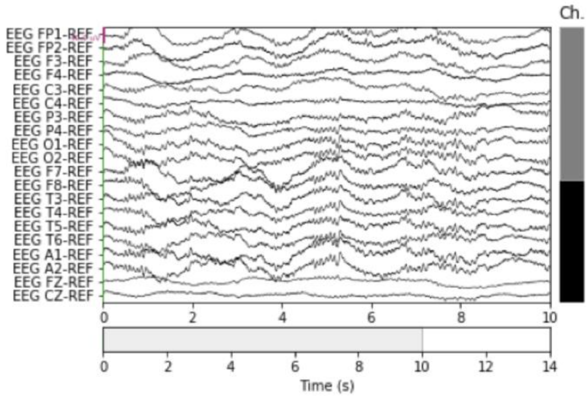



**Fig. 1. Electroencephalogram (EEG) signals**

The data obtained from EEG tests show the possible presence of epilepsy in the test subject, by revealing the presence of periodic lateralized epileptiform discharges (PLED) in the brain electrical activity, caused by seizures. In the Asian subcontinent such as India, where, epilepsy affects 3-12 in every 1000 people and EEG tests are relatively cheap, a system capable of detecting the presence of epilepsy can be effective in providing diagnosis for people with income ranging closer to the average income of the country. The proposed system utilizes and classifies the EEG data, based on the presence of epilepsy. The proposed system utilizes machine learning algorithms such as, Neural networks (NN) and Decision trees to classify the EEG data. This paper is organized as follows. Section II reviews the contemporary studies carried out on the detection of epilepsy using EEG analysis and machine learning techniques. The Experimental setup and results are discussed in section III. The limitation of this work, along with further directions are discussed in the concluding section IV.

## II. RELATED WORKS ON EPILEPSYPREDICTION

A sliding window approach, combined with a deep learning algorithm is implemented by Xuelin Ma et al., in their work [6] to predict epileptic seizures from intracranial EEG data. A Long Short-Term Memory (LSTM) based multi-task learning (MTL) model is proposed, to be trained using the data and perform prediction with latency regression simultaneously. The dataset is fed into the model using a sliding window with window sizes of equal length, to perform the learning process. The model predicts and classifies the preictal (before seizure) state of the brain EEG as epileptic. 3 models, k-nearest neighbour (KNN), XGB, and an LSTM-STL (Single-Task Learning model, that does not perform latency regression) is implemented, to compare the accuracy with the LSTM-MTL model. The LSTM-MTL model performs with the highest accuracy of 89.39%, 3.41% higher than the state-of-the-art detection model, and 2.5% higher than the LSTM-STL model.

The authors David Ahmedt-Aristizabal et al., propose a light-weight deep learning neural network model to classify epilepsy EEG signals in their work [7]. A public dataset of size 100, each of sample size 4096, sectioned into sets, A, B, C, D, and E is used to train and validate the classification models. The authors utilize the LSTM algorithm variant of the Recurrent neural network (RNN) architecture to develop 2 LSTM models, model 1 and model 2, to compare their performances, based on the set combination utilized to train and validate the model. Model 1 is a simple one-to-one LSTM neural network model with 1 hidden layer having 64 neural units. Model 2 is a many-to-one architecture having two consecutive hidden layers of size 64 units and 128 units respectively. The models are compared based on the validation accuracy and the area-under-curve (AUC). Model 1 performs with an average of 95.50% validation accuracy and an AUC – 98%, while model 2 performs with an average of 86.42% validation accuracy and an AUC – 93%.

An artificial Neural Network (ANN) based approach is proposed by the authors Vairavan Srinivasan et al., in their work, to detect epilepsy in EEG signals using approximate entropy (ApEn) based epilepsy detection technique [8]. ApEn is a statistical parameter to quantify the regularity of the time series in EEG data, which measures the predictability of the current amplitude values of the EEG signals, based on its previous amplitude values. ApEn is dependent on 3 features of the EEG signal namely, the number of samples used for the prediction (m), the noise filter level (r), and the number of data points in a given signal (N). The calculated ApEn is used as the input parameter to the ANN. 2 types of the ANNs, Elman (EN) and probabilistic neural network (PNN) are tested in their works. The EN is a two-layered backpropagation network with a feedback connection from the output of the hidden layer to its inputs. The PNN is a feedforward neural network with two middle layers (radial basis and competitive layers). The EN model performs with an accuracy range 95.45% - 100% for a higher number of combinations of the input parameters (m, r, and N), while the PNN performs with an accuracy range 98%-100% for fewer combinations.

The proposed system in this article utilizes the sliding window technique proposed in [6] and LSTM-based machine learning models to classify each EEG channel as either epileptic or non-epileptic. Although the solution proposed in [8] produces the highest accuracy, the utilization of the parameter r is eliminated in the proposed solution by removing the noise in the EEG signal before prediction. The RNN model proposed in [7] is efficient and performs with high accuracy. However, the solution can be extended for EEG systems with a greater number of channels such as the 10-20 system, as done in the proposed system using LSTM models. The LSTM models also have encoded EEG signals as input, thereby reducing the network learning duration. The LSTM models are simple, with 2 hidden layers and 1 dense layer. This allows the system to learn more quickly than a deep network. In addition to these methods, the system also utilizes an ensemble classification model (using XGB) for the collective signal classifications, to provide higher average accuracy of 98.5%.

## III. EXPERIMENT AND RESULTS

All the data are obtained from the Temple University Hospital (TUH, Philadelphia, Pennsylvania) EEG Epilepsy Corpus, version 1.0.0 [3], a publicly available dataset published to develop automated epilepsy detection solutions. The dataset contains recordings of EEG samples from epileptic and non-epileptic patients. The experiment is conducted in a HP Z4 G6 Tower workstation, having a 2.1 GHz octa-core Xeon Haswell – EP processor, that a 64 GB DDR4 DRAM utilizes, with an NVIDIA GeForce GeForce® GTX 1080 Ti consisting of 3584 CUDA cores, clocking at 1.5 GHz. The modules and packages used in this experiment are utilized in the Python 3.6.1 environment, to develop the EEG classification system.

### A. *Dataset Analysis*

All the EEG data collected are in raw European Data Format (EDF) files, recorded using 36 electrode channels that includes EKG, EEG and EOG electrodes. This experiment is aimed at providing automation solution for EEG procedure following the international 10-20 electrode placement system [4] (figure 2). Hence, out of the 36 channels, 21 EEG channels that include, the frontal ($F_p1$, $F_p2$, F7, F3, Fz, F4 and F8), temporal (T3, T4, T5 and T6), parietal (P3, Pz and P4), occipital (O1 and O2), central (C3, Cz and C4) and the preauricular (A1 and A2), are utilized in the prediction model. The sample frequency of the data is 250Hz. The dataset consists of 149 EEG files of epileptic subjects, with an average recording duration of 18 minutes ± 9 minutes and 153 EEG files of non-epileptic subjects, with an average recording duration of 13 minutes ± 19 minutes.

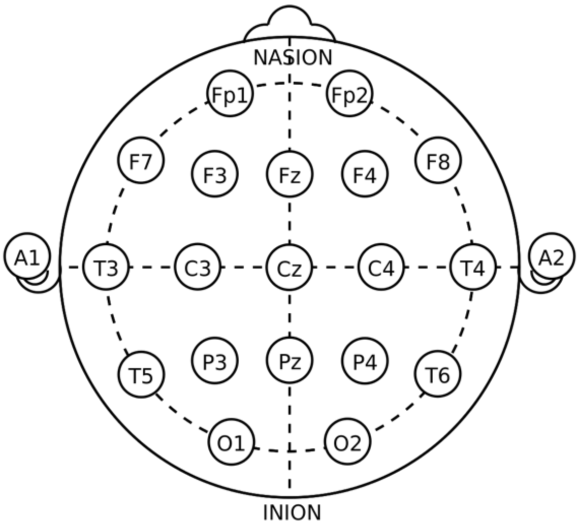



**Fig. 2. International 10-20 EEG electrode system (top view of the head)**

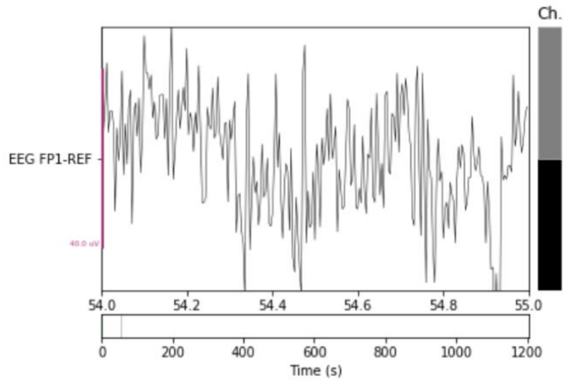



**Fig. 3. $F_p1$ channel of epileptic EEG**

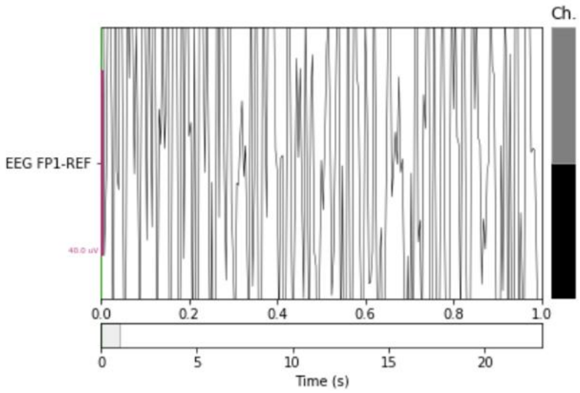



**Fig. 4. $F_p1$ channel of non-epileptic EEG**

### *B. Metadata Analysis*

The metadata (provided as text files) of the EEG data, contains demographic information on the recorded subjects, to lay out the background statistics of the data used to train and validate the classification system. This section provides a summary of both the longitudinal and short-term EEG recordings performed on the test subjects. The number of sessions specified in the table 1, is the selected EEG data from a cumulative total of 561 sessions data and the age specified is for the selected sessions.

**TABLE I. METADATA SUMMARY OF TEST SUBJECTS**

| Group | Subjects | Sessions | Age (years) |
|---|---|---|---|
| **Epileptic** | 133 | 149 | 55.33±15.6 |
| **Non-Epileptic** | 104 | 153 | 60.0±17.4 |

### *C. Data preprocessing*

**1. Eye Movement Removal -** In the data collection process, the subjects are prone to eye movement during the recording procedure. The EEG instruments are capable of recording these movements in all the channels and are observed to be significant in the pre-frontal (Fp1 and Fp2) region of the electrodes. These recordings are considered as noise, as they do not provide any significant difference between an epileptic and a non-epileptic subject. The eye movements are detected between the range of 10Hz and 15Hz (α region). For this experiment, the eye movement is removed using Independent Component Analysis (ICA), an analysis algorithm capable of minimizing the statistical dependence between the components using a linear transformation.

Initially, the data are filtered using a high pass Finite Impulse Response (FIR) filter, with a lower passband edge of 1Hz and a Hamming stopband attenuation of 53dB, to remove low frequency drifts [5]. The data are then added with white noise to preserve the amplitude as much as possible using Principle Component Analysis (PCA) method.

The whitening matrix W is defined using equation 1.

$$\boldsymbol{W} = \boldsymbol{\Lambda}^{-1/2}\boldsymbol{U}^{\boldsymbol{T}} \quad \textbf{(1)}$$

Where,$\Lambda$ is the Eigenvalues of the data matrix and $U$ is the Eigenvector of the data matrix.

The whitened data are obtained by combining the original data with the whitening matrix.

$$\boldsymbol{z} = \boldsymbol{W} \times \boldsymbol{x} \quad \textbf{(2)}$$

Where,$x$ is the original dataset.The ICA is applied on $z$ to obtain $S$, by rotating each channel projected in a new subspace, with minimal noise in the projected space of all the channels.

$$\boldsymbol{S} = \boldsymbol{Tz} \quad \textbf{(3)}$$

Where,$T$ is the weighted matrix of the data for the rotation. This results in the minimization of the Gaussian noise in the data.

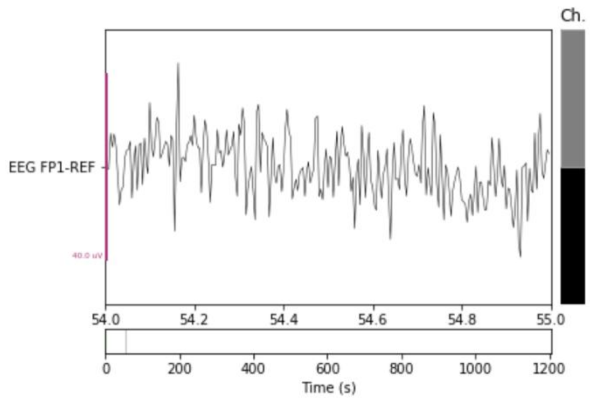



**Fig. 5. Eye movement removed EEG signal**

**2. Signal Padding -** The prediction model requires the input size of the data to be constant in the input layer of the neural network. Hence, the input size of each neuron must be standardized. An arbitrary window size of 100 data points, is selected for this experiment. Considering the variable sizes of each EEG recording, the data points may not fit in the window of size 100. Hence, the signals are padded with the value 0, such that all data points fit exactly in a window after splitting the dataset into several windows.

**3. Dataset Normalization -** The EEG signal in each channel is normalized to improve the learning efficiency and duration. The new data point $D^{'}$ in an EEG channel can be defined using the following equation.

$$\boldsymbol{D}^{'} = \frac{\boldsymbol{D}-\boldsymbol{D_m}}{\boldsymbol{D_M}-\boldsymbol{D_m}} \quad \textbf{(4)}$$

Where, $D_m$ and $D_M$ are the minimum data point and the maximum data point values in the channel, respectively.

### D. *Epilepsy Classification System*

The system consists of 4 sections to classify the input data as either epileptic or non-epileptic. The 4 sections are as follows:

1. Sliding Window
2. Encoding
3. Signal Classification
4. Ensemble Classification

**1. Sliding Window -** The EEG dataset with the padded zeros, is divided into multiple windows, each of size 100. These windows are slid from one window to another, while overlapping 50 data points from the previous window (50% overlapping in each window). Let the EEG signal $(x)$ be defined as the following form, $x = \{D_1, D_2, D_3 ... D_n, ... D_N\}$.The window $(C_i)$ for an EEG signal$x$, having $N$ data points after padding can be denoted by the following equation.

$$\boldsymbol{C_i = [D_{i-1} + 50, D_{i-1} + 100]} \qquad \boldsymbol{1 < i < \frac{2N}{100} - 1} \quad \textbf{(5)}$$

Where, $D_i$ denotes the first value of the window $C_i$. The slid windows with the overlapping data points are the input to be encoded before it is fed into the neural network.

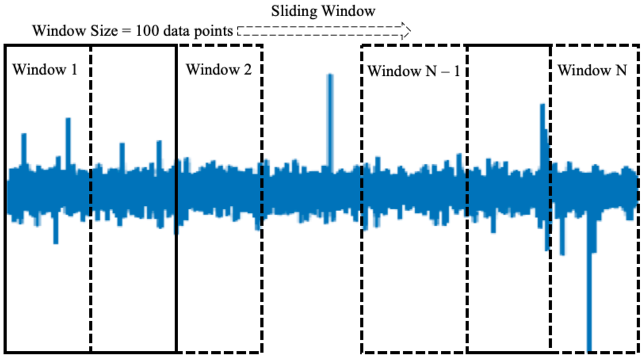



**Fig. 6. Sliding Window mechanism**

**2. Encoding-** An encoder is an algorithm, that is capable of converting an input data to another form of representation. The encoder used in this experiment is an artificial neural network (ANN), that takes a vector input and produces a feature vector output. This feature vector retains information with features, that represents the input. The encoder is trained to represent the input as a feature vector with lower dimensions. i.e. compressed. Each window of size 100, is encoded using the Dense auto-encoder. In the auto-encoder, the vector map obtained from the encoder section is utilized for the system (figure 7). The auto-encoder takes an input vector$x\epsilon[0,1]^d$and maps it to a representation$y\epsilon[0,1]^d$ through a deterministic mapping, which can be characterized by the following equation.

$$\boldsymbol{y = f_\theta(x) = s(Wx + b)} \qquad \textbf{(6)}$$

The equation is parameterized by$\theta = W, b$. where, $W$ is the $d' \times d$ weight matrix, $b$ is the bias vector and $s$ is the sigmoid activation function,$s(x) = \frac{1}{1+e^{-x}}$. The encoded data is used in the system to efficiently train the neural network utilizing reduced amount of data thereby improve training and classification performance.

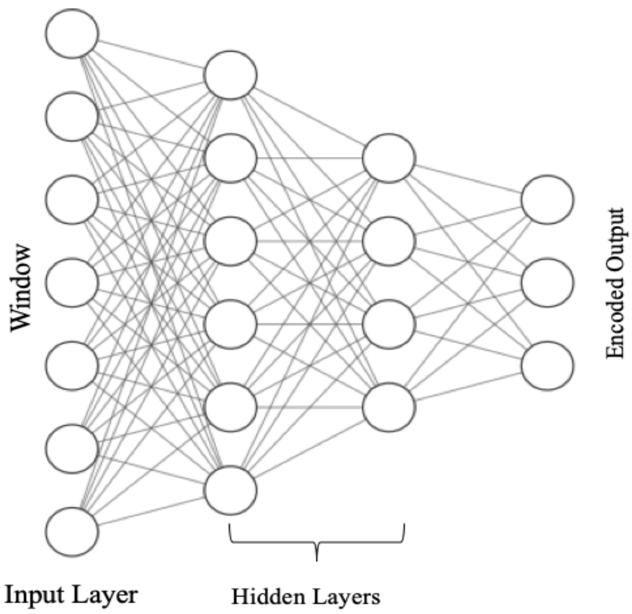



**Fig. 7. Auto-encoder (Encoding operation)**

The compressed windows are fed into the system. The training performance and the validation accuracy is compared between non-encoded and encoded data. A sample size of 202 EEG recordings are utilized to train and validate the system.

**TABLE II. COMPARISON OF PERFORMANCE AND ACCURACY BETWEEN ENCODED AND NON-ENCODED DATA**

| Metrics | Encoded | Non-encoded |
|---|---|---|
| **Performance (Training duration in minutes)** | 113 | 194 |
| **Accuracy** | 98 | 98 |

Although the accuracy is the same, the encoding process has significantly reduced the training duration, thereby increasing the efficiency of the system.

**3. Signal Classification -** The signal classification system utilizes the Long Short-Term Memory (LSTM) algorithm, an extension of the recurrent neural network (RNN), to classify the EEG signals of each channel.

An RNN is a class of neural networks, that models the dynamic temporal behavior of sequences, through directed cyclic connections between its units, by maintaining the internal hidden states. The RNN stores the states of the previous inputs and combines the past states with the current input, thereby maintaining the relationship of the current input with the previous inputs. The weights and the bias of the network are updated through back-propagation and unlike the conventional feed-forward of the convolution neural network (CNN), the RNN feeds back the state information from one layer to back to the previous layer (figure 8).

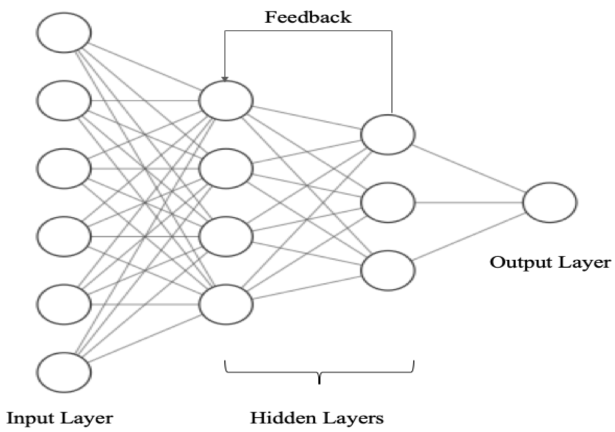



**Fig. 8. Recurrent Neural Network**

An RNN for the time $t$ can be visualized with the state $h_t$, utilizing the input $x_t$ and producing an output $y_t$, as shown in figure 9. The weights are represented as$W$, for the respective parameters ($h$, $x$ and $y$).

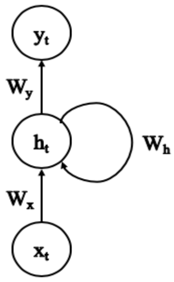



**Fig. 9. Recurrent Neural Network for time step (t)**

The current state ($h_t$) and the output ($y_t$) of the RNN, with an activation function $\theta$, can be defined as

$$\boldsymbol{h_t = \theta(W_{hh}h_{t-1} + W_{xh}x_t)} \quad (7)$$

$$\boldsymbol{y_t = W_{hy}h_{t-1}} \quad (8)$$

The LSTM is a supervised algorithm and an extension of the RNN, as it adds 3 gates, namely input ($i$), forget ($f$), and output ($o$) gates to an RNN neuron. This enables the LSTM algorithm to learn long-term dependency on a sequential method. The equations that define the 3 gates for a time $t$ with the recurrent connection $U$, can be expressed as follows.

$$\boldsymbol{i_t = \sigma(x_t W^i + h_{t-1}U^i)} \quad (9)$$

$$\boldsymbol{f_t = \sigma(x_t W^f + h_{t-1}U^f)} \quad (10)$$

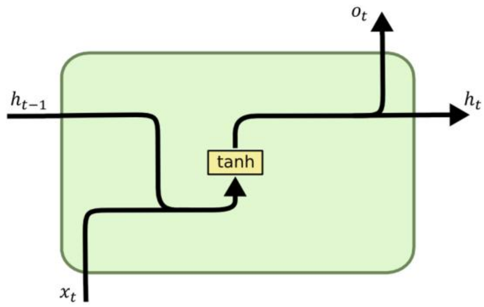
$$\boldsymbol{o_t = \sigma(x_t W^o + h_{t-1}U^o)} \quad (11)$$

Similar to the RNN, the LSTM depends on the past states but additionally, also utilizes the 3 gates. The current state $h_t$ can be defined using the following equations for the LSTM network.

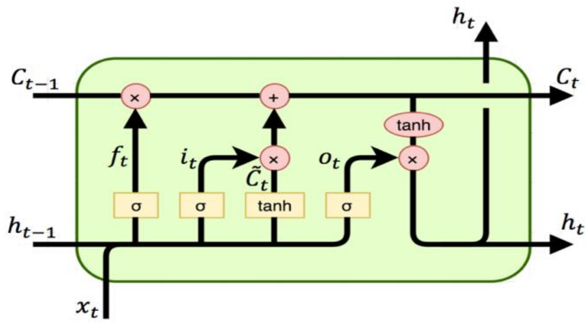
$$\boldsymbol{\widetilde{C}_t = \tanh(x_t W^g + h_{t-1}U^o)} \quad (12)$$

$$\boldsymbol{C_t = \theta(f_t * C_{t-1} + i_t * \widetilde{C}_t)} \quad (13)$$

$$\boldsymbol{h_t = \tanh(C_t * o_t)} \quad (14)$$




**(a). RNN neuron**




**(b). LSTM neuron**

**Fig. 10. A comparison between RNN neuron and an LSTM neuron**

The signal classification system consists of 21 LSTM models, to predict the classification of the EEG signal sequence for each channel in an EEG data. The models consist of 2 hidden layers with 128 units and 100 units, respectively. The Sigmoid activation function is realized in the Dense layer. The model is trained for 100 epochs with a batch size of 10 samples.

The initialized configuration of the model is given in the following table.

TABLE III. LSTM MODEL CONFIGURATION

| Parameter | Configuration |
|---|---|
| **Hidden Layers** | 2 |
| **Activation Function** | Sigmoid |
| **Optimizer** | Adam |
| **Learning Rate** | 0.001 |
| **Loss function** | Binary cross entropy |

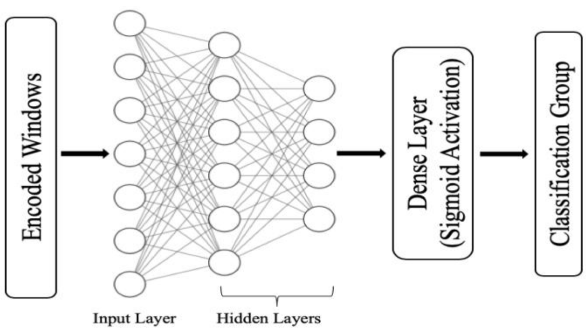



**Fig. 11. Architecture of the LSTM model**

4. **Ensemble Classification** - This section of the classification system, utilizes the combined predictions of the 21-channel LSTM models, to provide an ensembled classification of the test data. A dataset created by the classification results of the LSTM models serves as the training and testing data for the ensemble classifier. The ensemble is a type of classification where, the final classification model depends on the results of several classification models and combines the results of those classification models, to give the final results. But unlike the conventional voting-based ensemble classification, that considers the best results or the most probable results, the proposed classifier uses machine learning methods to identify the pattern of the results produced by the neural network models and provides the final classification group. This method is followed since the voting-based approach of choosing the most common classification, resulted in a lower validation accuracy of 73.5%. The XGB algorithm (a) is considered as the ensemble classifier. The validation accuracy is compared with 2 other existing machine learning algorithms, Random Forest, and Support Vector Machine (SVM) for 10-fold cross-validation.

a. **EXtreme Gradient Boosting** - The eXtreme Gradient Boosting (XGB) is a decision tree ensemble technique, that parallelizes and performs greedily in the tree pruning process. Using more complex models such as the least absolute shrinkage and selection operator (LASSO) and Ridge regularization, the XBG algorithm prevents overfitting. XGB utilizes the distributed weighted Quantile Sketch algorithm, to effectively find the optimal split points amongst weighted datasets.

TABLE IV. COMPARISON OF CLASSIFICATION ALGORITHMS

| Algorithm | Accuracy (%) |
|---|---|
| **XGB** | 98.5 |
| **Random Forest** | 96 |
| **SVM** | 87.5 |

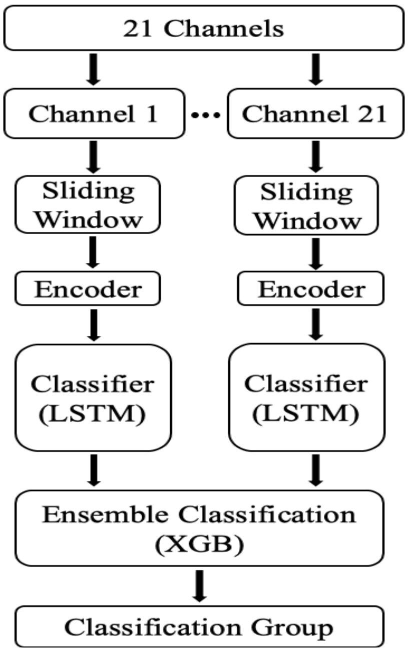



**Fig. 12. Epilepsy classification system**

### *E. Results*

The 21 LSTM classifiers, provide an average accuracy of 96.2% in the classification process of the input EEG signals. The XGB model-based ensemble classifier produces the highest accuracy with an average accuracy of 98.5% amongst the tested machine learning algorithms. The accuracy reports for the XGB model when trained with 55 EEG classification results and tested with 45 EEG classification results are given as follows.

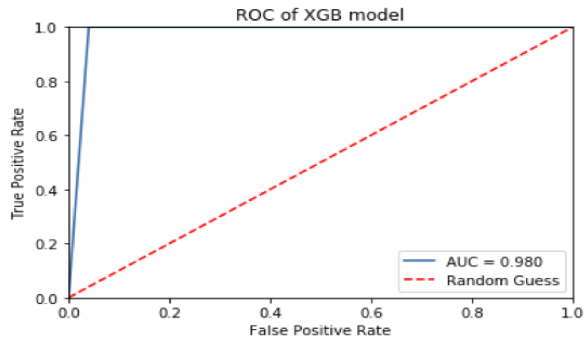



**Fig. 13. AUC – ROC of XGB model**

TABLE V. CONFUSION MATRIX OF XGB CLASSIFICATION

| Group | Epileptic | Non-Epileptic |
|---|---|---|
| **Epileptic** | 20 | 0 |
| **Non-Epileptic** | 1 | 24 |

TABLE VI. ACCURACY REPORT OF XGB CLASSIFICATION

| Group | precision | recall | f1-score | support |
|---|---|---|---|---|
| **Epileptic** | 0.95 | 1.0 | 0.98 | 20 |
| **Non-Epileptic** | 1 | 0.96 | 0.98 | 25 |

The proposed system is capable of classifying a test dataset of 100 samples, in an average duration of 51 minutes and 40 seconds. This shows that the processing and prediction duration of the system is 31s/sample. Although this duration appears to be high, the light-weight neural network and the XGB algorithm only utilize approximately 54% of the total CPU cycles and 37% of the RAM to perform the tasks, making it effective to be utilized in countries with lower Gross Domestic Product (GDP) and thereby, having hardware with minimal configurations for the system.

## IV. CONCLUSION

A system that classifies the EEG dataset, based on the presence of epileptic features, is proposed in this article. The model utilizes the combination of the LSTM-RNN model and the XGB machine learning model, to classify the EEG data. From the proposed work, the following conclusions can be drawn

1. The EEG data proves to provide significant information such that, an automated Epilepsy detection system will be able to detect the presence epilepsy from it.
2. The encoding of data improves efficiency, by increasing the performance of the models. Thereby, reducing computation duration.

3. The LSTM model with a minimal number of layers is sufficient in providing high accuracy. The light-weight system provides a computationally simple architecture, hence hardware with mid-range configurations is sufficient.
4. An ensemble-based machine learning system, that classifies the 21-channel classification, proves to produce a higher accuracy than a majority decision-based approach.

### *A. Limitations:*

The epilepsy classification system can be utilized by medical professionals, to aid the initial assessments in detecting the presence of epilepsy in patients. Although, the but may not be used to finalize or arrive at any decision without consultation. The medical professionals must proceed with further tests such as blood tests (to measure the amount of prolactin hormone that influences epilepsy disorder), analyse magnetic resonance imaging (MRI) scans, perform infection tests, assess ancestral demographics, etc., before drawing any conclusions.

### *B. Future Works:*

The epilepsy detection system, using EEG can be combined with an MRI epilepsy detection system, that uses image processing techniques, to identify epilepsy. Thereby, improving the pace of the diagnosis. The detection system can be improved through retraining the system, to detect and classify seizures frequencies, that may occur during the EEG recordings, to provide an insight into the brain activities during seizure episodes.

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