Epilepsy Detection Using Bi-LSTM Integrated with Decision Tree

Kiranpreet Kaur[1], Richa Sharma[1], Abhinav Kumar[2,3,4], and Sachin Kumar Gupta[5,*]

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ABSTRACT

Epilepsy is a dangerous disorder after Alzheimer's. Around 50 – 70 million people around the world are affected by this disease. It happens due to the disturbance in the motor nerves of the brain which results in epileptic seizures. A seizure is a state, in which it has misbalancing or breaks out of electrical movement in the brain having properties like time frequent and unpredictable. This neurological illness is transient, chronic, and recurrent. An epileptic seizure occurs when neurons suddenly misfire and synchronize; mimicking the brain's excessive and hyper-synchronous neural activity. It causes sudden fainting, uncontrollable motion of upper and lower limbs, and anxiety. The seizures are measured by the process of electroencephalogram (EEG). Using EEG records from the CHB-MIT scalp EEG collection, we compare how well deep learning and traditional machine learning models predict seizures. The data set, which includes preprocessed EEG data from pediatric individuals with spontaneous seizures, enables a thorough assessment of the model's effectiveness. Traditional machine learning models like Artificial Neural Networks (ANN) and Decision Trees are combined with Bidirectional LSTM (deep learning technique). The model aims to classify epileptic seizures from non-epileptic seizures. The total accuracy obtained by the model is 99.99%.

1. INTRODUCTION

Epilepsy is a disease that is caused by a disturbance of the electrical activity in the brain. In every 100,000 people, the 48th individual has epilepsy. It is the third most occurred type of seizure after stroke and Alzheimer's disease. The World Health Organization reports that most of the patients are from underdeveloped countries, and from rural areas. Even the likelihood of dying young people is higher in epilepsy. Epilepsy is defined by the brief episodes of uncontrolled movement that may impact only a specific area of the body (partial) or the entire body (generalized). There are situations when these seizures are followed by unconsciousness. Every year, between 100,000 and 120,000 children are hospitalized due to being epileptic. When an adult (over 18) is having epilepsy experiences two or more times within a year, their condition is considered active. Low blood sugar, low oxygen levels, or a severe electrolyte imbalance are the symptoms that children usually experience at a very young age. Consequently, having seizures does not automatically indicate that a person has epilepsy. Seizures caused by anomalies throughout the body are not taken into consideration for inclusion in the diagnosis of epilepsy. If a patient has a seizure that lasts more than 1-2 minutes, they should get medical attention right away. Electroencephalography is a technique used to detect epileptic symptoms [1]. The procedure involves applying electrodes, which are tiny metal discs with thin wires, to the patient's scalp. The electrodes capture electrical charges generated by brain cell activity. The charges are amplified and shown in the Fig. 1 (EEG amplitude of the channel).

There are many kinds of epileptic seizures depending on the features of the seizure [2]-[3]. EEG uses the principle of differential amplification. It diagnosed brain disorders like stroke and epilepsy. However, EEG recorded from the cortex surface or the scalp cannot record short-term changes in local field potential caused by action potentials in neurons. Moreover [1], motion errors in the EEG traces are mostly caused by the lengthy wires that are used to link several electrodes. As a result, wearable EEG solutions with few electrodes are highly desired by patients because they enable continuous monitoring throughout the day [4], [5]. EEG

[1]Bachelor of Computer Applications Department, Eternal University, Himachal Pradesh, India.
[2]School of Computer Science and Engineering, Lovely Professional University, Phagwara-144411, Punjab, India.
[3]Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, 140401, Punjab, India.
[4]Department of Mechanical Engineering and Renewable Energy, Technical Engineering College, The Islamic University, Najaf, Iraq.
[5]Department of Electronics and Communication Engineering, Central University of Jammu, Samba-181143, Jammu, (UT of J&K), India.
*Corresponding author: Sachin Kumar Gupta; Email: sachin.ece@cujammu.ac.in.

signal collection is not simple, and even in the absence of lengthy wires, data can get tainted with artifacts. In real, physiological variables are irrelevant to the brain and can produce artifacts (eye blinks, muscle movement). Because of their structural similarities in amplitude and frequency, these EEG artifacts are misinterpreted as seizures, which cause problems for the algorithms used for epilepsy detection. Therefore, it is crucial to identify EEG abnormalities accurately to prevent false alarms in epilepsy detection systems. The epilepsy detection system then decides whether to extract elements that can help in the system's classification of seizures. Accurate seizure detection is essential for automated detection systems when a seizure is identified based on the characteristics taken from the epileptic EEG signals that describe the patient's state. During neurological surgery, precise seizure detection can be applied to evaluate the state of the patient. It takes a lot of time for EEG specialists to observe EEG readings since they must evaluate each patient's whole 45 min to 1-hour recording period. We provide machine learning (Decision tree) and deep learning (Bi-LSTM) models to reduce the time required for epilepsy detection. It involves extracting complex characteristics out of the EEG signals and categorizing them. It is crucial to choose the relevant characteristic from the data for accurate detection.

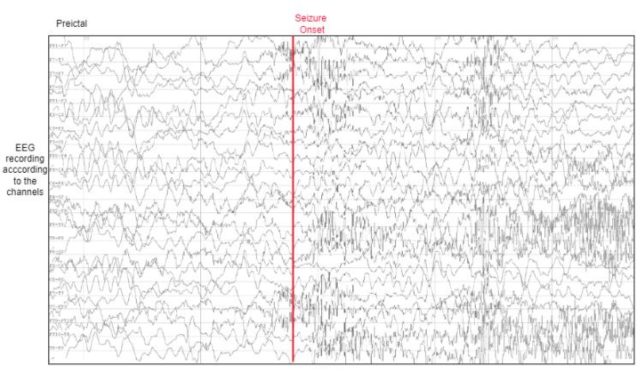

Fig. 1. EEG amplitude of the channel.

2. RELATED WORK

EEG signals are widely used in epilepsy research, especially for seizure detection, as they represent brain cell activity. EEG data is analyzed by automatic algorithms in a fast and precise manner, transforming the information into discrete outputs that allow the determination of various epileptic states, including post-seizure and seizure occurrences. Improving the model's accuracy and speed is the foremost purpose. Numerous methods for detecting epilepsy have been proposed and most of which include machine-learning approaches and deep learning algorithms, which also employ multi-view learning techniques, and have demonstrated remarkable potential in this field by effectively diagnosing the condition of epilepsy based on EEG readings.

2.1 Epilepsy detection using Machine Learning

The author [1] outlines the automatic identification of epileptic seizures through the use of a multi-layer network built using the mutual information (MI), permutation dis-alignment index (PDI), and Pearson correlation coefficient (PCC) as three distinct correlation measures. The method utilizes an improved genetic algorithm (IGA) for the optimization of features and network weights within the multi-layer network. PCC measures linear relationships, MI measures nonlinear relationships, and PDI is introduced as a permutation-based correlation index. For seizure detection, three classifiers are employed: K-nearest neighbor (KNN), Support Vector Machine (SVM), and Random Forest (RF). Random Forest (RF) has better model accuracy, generalization capacity, and training speed. The suggested approach outperforms single-layer networks in terms of performance. The author [2] demonstrates that the Electroencephalogram (EEG) has the data required to identify brain activity in humans, making scans helpful for diagnosing and treating epileptic seizures. However, it requires time to visually identify seizures from EEG images. Thus, a fast and accurate method is needed to diagnose more patients in less time. An auto-regressive moving average (ARMA) model is introduced for the dynamic and varying nature of EEG time series data. The further step is to classify suspicious elements together by using pattern recognition and later deducting them. As the data contains other seizures too so to solve this issue the paper has proposed the method of one class SVM for diagnosis. During the training phase, the EEG samples are used to train one-class SVM (RBF kernel), and the normal epilepsy EEG records to train the other one. The author [3] proposed a 54-DWT mother wavelet analysis for EEG segments, which employs four machine learning algorithms: SVM (support vector machine), KNN (k-nearest neighbors), Naïve Bayes, and ANN (artificial neural network). It employs an optimal technique using a genetic algorithm. It is observed that compared to others ANN gives more accurate predictions than others. After optimization (GA) the accuracy of ANN improves to 99.6%. But machine learning models are less efficient to work with complex time-series data due to its varying nature. Further, Table 1 presents the various ml techniques for epilepsy.

Table 1. ML techniques for epilepsy

Sr.	Methodology	Feature Extraction	Accuracy
[4]	Single-Channel and Multichannel Embedding Module:	DWT	86.68%
[6]	ARMA, SVM	SVD, EMD	93-94%
[5]	MLP	DWT	97.26%

2.2 Epilepsy detection using Deep Learning

The paper [7] describes the automated identification of epilepsy using electroencephalogram (EEG) data with deep learning techniques. The goal is to identify epilepsy so that it can be treated quickly and the probability of further seizures and the problems related to them can be decreased. This approach uses the chronological correlations between several EEG channels to identify epilepsy, in contrast to other current EEG-based methods that rely on deep learning models. A Bidirectional Long Short-Term Memory (Bi-LSTM) neural network with an attention mechanism is used in the process. Based on weight distribution, the attention mechanism brings key features from sequences. Following the input of these characteristics, a Bi-LSTM model evaluates the intrinsic temporal correlations concealed in EEG signal features, generating high accuracies on various datasets with an accuracy range of 95.60% to 99.87. The research [8]-[12] demonstrates how multiple deep learning (DL) model architectures can be employed for epilepsy detection by using transfer learning (TL) approaches. It also introduces a Transformer-based algorithm and investigates its performance in comparison to pure Convolutional Neural Networks (CNNs). A customized Convolutional Neural Network (CCNN) architecture is designed for extracting features from preprocessed EEG data. Convolutional layers with ReLU activation, max-pooling layers, and fully linked layers with a Softmax activation function are incorporated into the design. The design of the CCNN attempts to increase spatial invariance, and it is trained using the Adam optimizer. It performs better than current technologies, as evidenced by its high values for accuracy (95%) specificity, sensitivity, F1-Score, precision, and specificity. The automated feature extraction and real-time detection capabilities of machine learning (ML) classifiers are limited when it comes to doing multiple-class categorization. So, a deep Convolutional LSTM neural network model was suggested in the study [12]-[18]. The C-LSTM model predicts results at a fast rate, with short detection duration time. The paper addresses the challenges of establishing a multiple-class model for epileptic seizure detection and the requirement for predicting seizures within short-time segments.

The C-LSTM network has a short detection period and predicts outcomes quickly. To distinguish between epileptic seizure activity and those of other classes, a sliding window approach is used. Logical values are obtained by converting the likelihood of events using the Softmax activation function, once the FC layer's output is obtained. The final classification results are determined by selecting the highest values obtained from the likelihood of each node's input in the softmax layer. Manual feature extraction was necessary for ML approaches, which limited their versatility. DL allows for the complete automation of feature extraction and classification. A recurrent neural network (RNN) model [19]-[22] called long short-term memory is suggested as the basis for automated epileptic seizure detection. Because of its memory capacities and suitability for sequence data, LSTMs are useful for evaluating time-series data, such as EEG signals. For seizure detection, normal in comparison to ictal and normal in comparison to pre-ictal are the two classes in the two-class categorization in this study [23]-[34]. Using spectrograms of EEG signal segments, the Convolutional Neural Network (CNN) with residual blocks is the baseline model. The second model employs a three-layer CNN that processes spectrograms as well. The third model uses a five-layer CNN and Phase Space Reconstruction (PSR) to get over spectrogram restrictions. The primary pattern of various signal activity is captured by PSR, which offers a direct projection from the time domain. Moreover, Table 2 shows the various deep learning techniques for epilepsy used in the state of the art.

Table 2. Deep learning techniques for epilepsy

Sr.	Methodology	Feature Extraction	Performance
[2]	MDCNN	_	Accuracy of 99.56%
[1]	Bi-LSTM	_	Accuracy of 95.6%
[14]	DCNN, LSTM, D-LSTM	DWT	Accuracy of 98.80%
[16]	CNN	FFT, ICA, PCA	AUC values are 0.82 and 0.89
[22]	C-LSTM	Softmax activation function	Accuracy of 98.8%

3. MATERIALS AND METHODS

This section presents the major techniques that are taken in this study, which started with the dataset's extraction and resampling and ended with the model selection and pre-processing. Three classifiers are used for model evaluation (Decision tree, ANN, and Bi-LSTM). A workflow chart is shown in Fig. 2.

3.1 Dataset Description

For algorithm evaluation, the Children's Hospital Boston's CHB-MIT scalp EEG database has been used. The Children's Hospital Boston gathered the EEG recordings from young patients who had spontaneous seizures. The patients were monitored for a few days at most after stopping anti-seizure medication to figure out if they were suitable candidates for surgery and to characterize their seizures. 24 instances (Chb01–Chb24) from 23 pediatric patients with uncontrolled epilepsy are included in the database. The worldwide 10-20 system standard is followed for electrode locations, and 256 Hz sampling is used for

EEG readings. The 661 recordings from 23 individuals in the CHB-MIT dataset include 158 seizures across 958 hours of EEG data. Band pass filter is applied to the EEG signals at 0 Hz and 128 Hz after being captured at 256 training on overlapping 1-, 2-, and 4-second EEG segment segment. Analysis of 6000 examples of 1-second normalized data, 3000 examples of 2-second data, and 1500 examples of 4-second data was done. Preictal and ictal data that are balanced in the dataset provide a thorough assessment of the model's performance. The EEG (electroencephalogram) datasets from the "CHB-MIT Scalp EEG Database" are in open source. The dataset contains the following files.

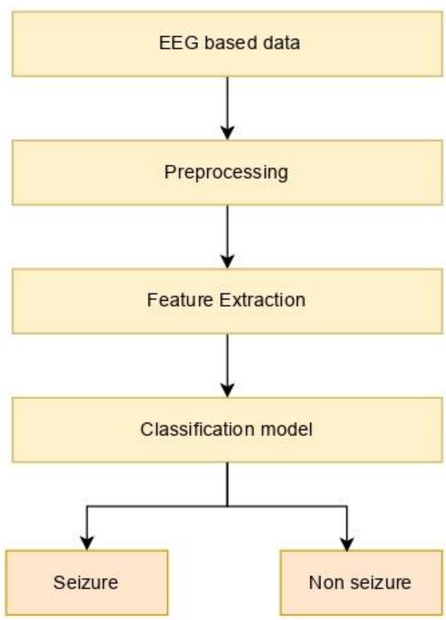

Fig. 2. Workflow of the model.

Only preictal data from all 24 patients that is contained in the Chbmit preictal channels data file, and only ictal data from all 24 patients contained in the Chbmit ictal channels data file. The balanced pre-ictal and ictal data files from all 24 patients are included in the chbmit preprocessed data file. There are 24 columns in this file; however, only 23 columns represent the channels, and last column is the label column. '0' in the label column denotes the absence of seizures, whereas '1' denotes the presence of seizures.

3.2 Preprocessing

Normalization is a preprocessing method applied to the dataset to standardize the data and ensure that it is consistent across different features and variables. Normalization plays a significant role in preparing the data for analysis and model training for epilepsy detection using EEG data. The CHB-MIT dataset consists of EEG recordings obtained from patients, which include both preictal (before seizure) and ictal (during seizure) data. It's essential to ensure that the dataset is balanced, meaning that there is an equal representation of both preictal and ictal samples. This balance helps prevent bias in the model and ensures that it can effectively learn patterns associated with seizure activity. The dataset is initially loaded from a file named 'chbmit_preprocessed_data.csv'. This file contains a structured format where each row represents a sample (a time series segment of EEG data), and each column represents a feature or channel (EEG readings from specific electrodes).

After loading the dataset, the next step is featuring scaling, where the features are normalized using standard scaling techniques. Standard scaling, also known as z-score normalization, involves transforming the data such that it has a mean of zero and a standard deviation of one. This transformation ensures that all features have similar dimensions, preventing features with high magnitudes from controlling the model training process. Then the data is reshaped to fit the proper format for input into a Bidirectional Long Short-Term Memory (Bi-LSTM) neural network. Bi-LSTM is a type of recurrent neural network (RNN) that is well-suited for sequential data, such as time series data like EEG recordings. Bi-LSTM networks require three-dimensional input data, typically in the form of (batch size, timesteps, features), where batch size represents the number of samples, timesteps represent the length of each sequence, and features represent the number of input features at each timestep. Here no explicit feature extraction is performed. Instead, the EEG data, after normalization and reshaping, serves as input to the Bi-LSTM model, which learns to extract relevant features and patterns associated with seizure activity during the training process. This approach leverages the representational power of Deep Learning models to handle complex, high-dimensional data like EEG recordings effectively.

3.3 Methodology

Deep learning models, including Bidirectional LSTM and Dense Neural Networks, are compared against classical machine learning model Artificial Neural Networks (ANN). The objective is to develop a model that accurately predicts binary outcomes based on various features.

ANN: The term Artificial Neural Network refers to a computational model whose architecture is modelled after biological neural networks present in the brain. An artificial neural network (ANN) is made up of layers of network processing units, known as neurons or nodes. It consists of an input layer, one or more hidden layers, and an output layer. After receiving input signals, it applies an activation function, and each neuron transmits the outcome to the neurons in the subsequent layer. To enable the network to learn from input data and provide the desired output, weights connected to the neurons are altered during the training phase.

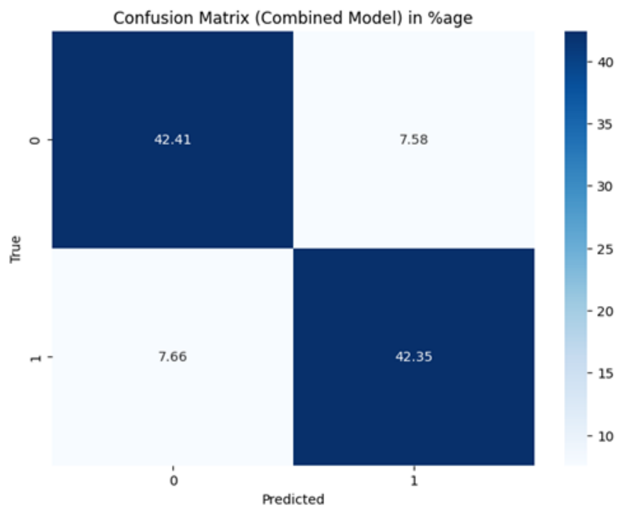

Fig. 3: Confusion matrix for ANN.

The training progresses over 20 epochs, with improvements observed in the both training and validation accuracy. The model shows a consistent decrease in loss over epochs. After training, the model is evaluated on the test set, achieving a test accuracy of 84.75%, indicating its efficiency in extracting information well on unseen data. The blue area indicates the correct prediction in the confusion matrix. Confusion matrix: It is the matrix made by the predicted variables, having four terminologies in the Fig. 3:

- **True positive** (TP): True positives are instances where seizure is detected and in actuality, seizure is also present. Here the percentage of TP is 42.41%.
- **True negative** (TN): True negatives are instances where seizure is not detected and in actuality, seizure is also absent. Here the percentage of TN is 42.35%.
- **False positive** (FP): False positives are instances where seizure is detected but in actual seizure is not present. Here the percentage of FP is 7.58%.
- **False negative** (FN): False negatives are instances where seizure is not detected but in actuality, seizure is present. Here the percentage of FN is 7.66%.

The accuracy and loss evaluated during the training phase in the ANN model are described in Fig. 4 and Fig. 5.

The following Table 3 shows the accuracy, precision, recall, and F-1 score of the ANN model. Fig. 6 show the workflow of combine model.

Table 3: Performance evaluation of ANN

Performance metrics	ANN model
Accuracy	84.75%
Precision	84.82%
Recall	84.67%
F-1 Score	84.74%

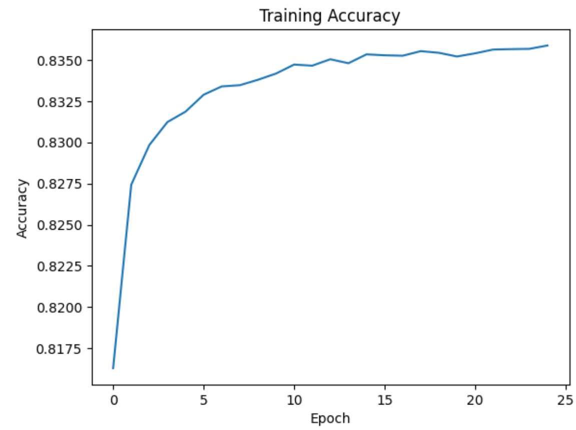

Fig. 4: Graph between epoch and model accuracy

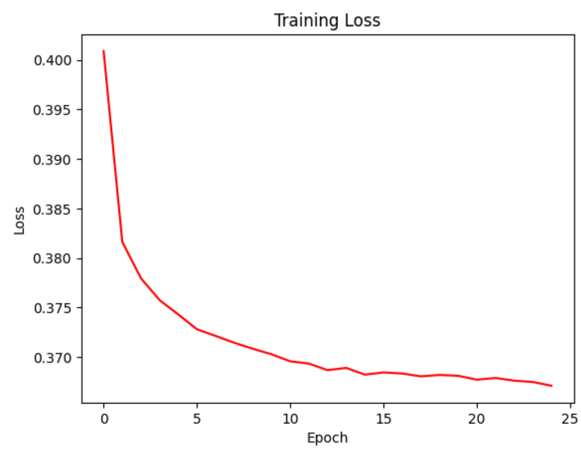

Fig. 5. Loss evaluated during each epoch.

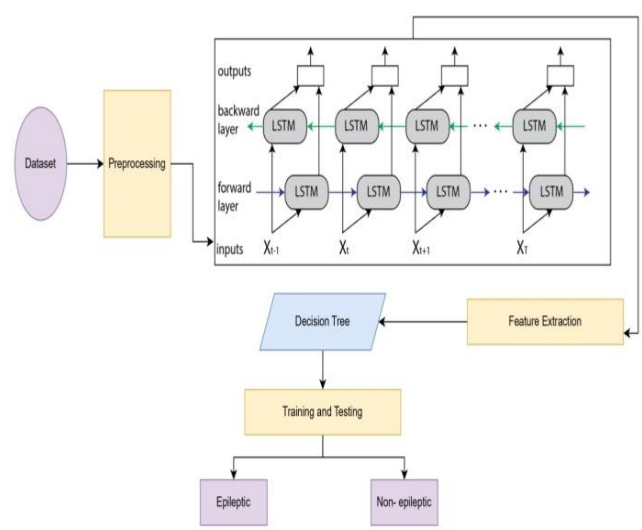

Fig. 6. Workflow of combined model.

Bi-LSTM: LSTM is an extended RNN designed to address the issue of gradient disappearance and explosion during back-propagation. It is appropriate for classifying EEG signals and effectively captures long-term dependent information from time-series data. The information propagates along with the LSTM units in the hidden layer of the LSTM network in a temporal order. We used forward and backward propagated information to build a Bi-LSTM-based neural network model, which helps to better capture long-term dependent aspects in EEG signals.

Proposed Methodology

1. Start
2. Input EEG Data and apply preprocessing: filtering and feature extraction.

$$X_{\text{preprocessed}} = \text{filter}(X_{\text{raw}})$$

3. Split EEG data into training and testing sets:

$$X_{\text{train}}, X_{\text{test}} \leftarrow \text{split}(X_{\text{preprocessed}})$$

4. Define Bi-LSTM architecture:

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$$

Compile and train the Bi-LSTM model:

$$\hat{y}_{\text{Bi-LSTM}} = \text{BiLSTM}(X_{\text{train}})$$

Evaluate on test data:

$$\hat{y}_{\text{test}} = \text{BiLSTM}(X_{\text{test}})$$

5. Input Bi-LSTM Predictions into Decision Tree
Concatenate Bi-LSTM predictions:

$$F = \text{concat}(\hat{y}_{\text{Bi-LSTM}})$$

6. Train the Decision Tree model with Gini impurity:

$$G(\mathcal{D}) = 1 - \sum_{k=1}^{K} p_k^2$$

Final decision:

$$\hat{y} = \text{DecisionTree}(F)$$

7. End

Forward LSTM:

$$\overrightarrow{h_t} = \text{LSTM}(x_t, \overrightarrow{h_{t-1}}) \tag{1}$$

Backward LSTM:

$$\overleftarrow{h_t} = \text{LSTM}(x_t, \overleftarrow{h_{t+1}}) \tag{2}$$

Combined state:

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \tag{3}$$

A sequential model (Bi-LSTM) with many dense layers and a ReLU activation function is constructed. The Bi-LSTM layer analyzes EEG sequence data of brain activity in past and future signals. This helps the model focus on relevant information in the data and increases the model's accuracy. The parameters for adaptive estimates are examined by the "Adam" optimizer. Two dropout layers are added in the LSTM layer and ReLU activation function. The dropout network helps to lower the training error as the number of neural network layers rises. After receiving the output from the FC layer, probabilities are transformed into logic values using the softmax activation function. The highest values were found from the probability of each node's input in the softmax layer. Then, a fully linked layer is employed to achieve the binary classification of seizure and non-seizure classes. To track validation performance throughout training, the model uses a batch size of 128 and a validation split of 0.2 across 20 epochs. The accuracy and loss evaluated during each epoch are described in (Fig. 7) and (Fig. 8). Table 4 list the performance evaluation of BI-LSTM technique.

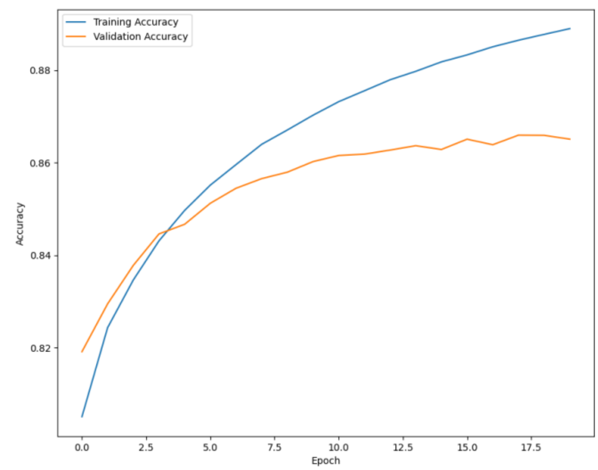

Fig. 7: Graph between epoch and model accuracy.

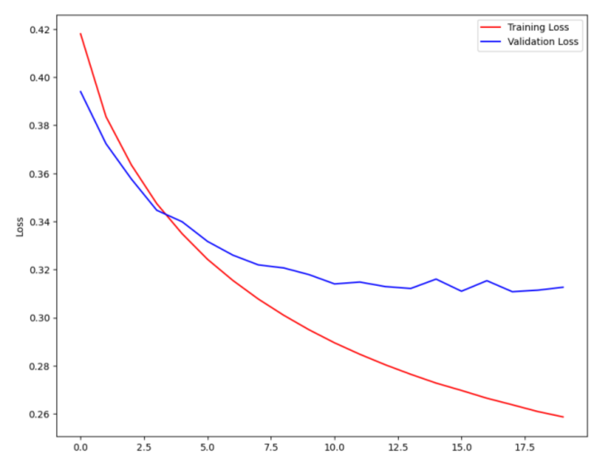

Fig. 8. Loss evaluated during each epoch.

Table 4. Performance evaluation of BI-LSTM

Performance metrics	Class 1	Class 0
Accuracy	86.395%	
Precision	89%	84%
Recall	84%	89%
F-1 Score	86%	87%

Decision tree classifier: Decision trees are constructed from the nodes that create hierarchical structures, with each node having a feature or characteristic from the dataset. Decision trees iteratively split the dataset into subsets until a stopping condition is satisfied by a sequence of binary splits based on feature values. The Bi-LSTM model gives an accuracy of 86.39%. We integrate the Decision tree into the input of the Bi-LSTM model to improve the performance. To reduce impurity and increase class homogeneity, the tree partitions the feature space during training. A dataset's entropy is a measure of its randomness or impurity. The Gini impurity (G) of a dataset for a binary classification having classes {0, 1} is computed as follows:

$$G(p) = 1 - \left(p_0^2 + p_1^2\right) \tag{4}$$

p_0 = Samples indicating absence of seizures (class 0)

p_1 = Samples indicating the presence of seizures (class 1)

The Gini impurity-based cost function in decision tree training aims to reduce the likelihood of an inaccurate categorization by lowering the Gini impurity at each split. More child nodes are result from the decision tree algorithm's selection of the characteristic that optimizes the process. To assess classifiers' overall classification accuracy, a confusion matrix, Accuracy, Sensitivity, and F1-score to evaluate each binary classification task's performance is used. EEG data is sequential (time-ordered) by nature. The time-dependent components of the EEG data can be challenging for a simple Decision Tree to extract on its own. Temporal features are extracted using a Bi-LSTM and then sent to the Decision Tree. In combination, the architecture can perform better than individual models. It is described in the following equation.

$$y = \mathrm{DecisionTree}(\mathrm{BiLSTM}(x_t)) \tag{5}$$

Bi-LSTM extracts high level complex features and decision tree interprets the result based on extracted features by providing high-level classification. The system gains precision, rule-based categorization from Decision Tree and capacity to handle sequential input from Bi-LSTM. Fig. 9 shows the confusion matrix of Bi-LSTM and decision tree.

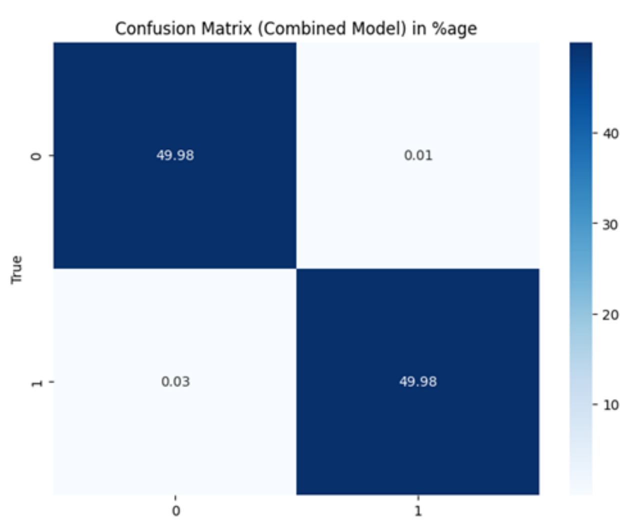

Fig. 9. Confusion matrix of Bi-LSTM and decision tree Results and discussion.

The combined Bidirectional LSTM and decision tree classifier model performs well, achieving high seizure prediction accuracy. Additionally, the effectiveness of Decision Trees and Artificial Neural Networks (ANN) in seizure prediction is evaluated as well. Further Table 5 and 6 show the comparison table with other models and performance metrics of proposed model, respectively.

Table 5. Comparison table with other models

Sr.	Methodology	Performance
[2]	MDCNN	Accuracy of 99.56%
[1]	Bi-LSTM	Accuracy of 95.6%
[14]	DCNN, LSTM, D-LSTM	Accuracy of 98.80%
	Proposed method	Accuracy of 99.99%

Training Loss: Over epochs, the training loss gradually drops from 0.42 to 0.34 and the validation loss decreases from 0.37 to 0.32.

Bi-LSTM and Decision tree: The model is assessed on the test set after training. With an accuracy of 86.39% on the Bi-LSTM model, the output is fed to the decision tree classifier to enhance the working of the model.

Table 6. Performance metrics of proposed model

Performance metrics	Our model
Accuracy	99.99%
Precision	99.98%
Recall	99.99%
F-1 Score	99.98%

Working on epilepsy detection encountered many challenges. A good quality database is hard to find. The popular available datasets [31] have the EEG recordings of a small set of patients. Even the diversity in the state of the patient is minimal. The annotations are not proper in some databases. Incorrect seizure annotations create difficulty in the epilepsy detection and the patient's treatment. EEG recording also contains noise and artifacts like eye blink, muscle twitch. Artifacts are not generated by brain but by other factors. These noise and artifacts hinder seizure activity. Predicting seizures accurately before they happen in a real-time is a challenge for researchers. For many patients, real-time, continuous monitoring is limited because the majority of existing EEG based technologies is only available in clinical settings. The majority of detection technologies rely on generalized models, which may not work well for all patients because of the variation in seizure patterns. The detection of seizures is limited when relying only on EEG data since it excludes important physiological contexts. To create real-time monitoring devices and to evaluate it experts are still needed.

4. CONCLUSION AND FUTURE WORK

The study demonstrates how effectively EEG recordings can predict epileptic seizures using both deep learning and traditional machine learning models. Understanding complicated patterns and capturing temporal correlations are advantages of deep learning models. A traditional machine learning model like ANN still perform well but does not capture complex characteristics properly. When it comes to forecasting medical outcomes, the Decision Tree Classifier shows encouraging results. The Bidirectional LSTM model achieves an accuracy of 86.39% on the test set, indicating good performance in predicting medical outcomes. Then the model is integrated with a decision tree classifier to give a higher accuracy of 99.99%. The model is useful in predicting epileptic seizures from long-term EEG because of its capacity to capture temporal connections and generalize.

Better signal processing methods, such as adaptive filtering, can help distinguish real EEG signals from artifacts, producing cleaner data and more precise detection. By leveraging patient specific data and creating personalized seizure detection model could enhance accuracy. This can be achieved by transfer learning, where model is developed using individual patient data. The creation of non-invasive, wearable EEG equipment may enable ongoing, in-person monitoring. Observing and studying the effect of brain tumors on epilepsy patients and how it affects the brain signals. Build an effective seizure detection model by utilizing spectrogram images for EEG signals.

REFERENCES

[1] L. Duan, Z. Wang, Y. Qiao, Y. Wang, Z. Huang, and B. Zhang, “An Automatic Method for Epileptic Seizure Detection Based on Deep Metric Learning,” IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 5, pp. 2147–2157, May 2022,

[2] Z. Chen, G. Lu, Z. Xie, and W. Shang, “A unified framework and method for EEG-Based early epileptic seizure detection and epilepsy diagnosis,” IEEE Access, vol. 8, pp. 20080–20092, 2020.

[3] W. Mardini, M. M. Bani Yassein, R. Al-Rawashdeh, S. Aljawarneh, Y. Khamayseh, and O. Meqdadi, “Enhanced detection of epileptic seizure using EEG signals in combination with machine learning classifiers,” IEEE Access, vol. 8, pp. 24046–24055, 2020.

[4] Y. Xiong, F. Dong, D. Wu, L. Jiang, J. Liu, and B. Li, “Seizure Detection Based on Improved Genetic Algorithm Optimized Multilayer Network,” IEEE Access, vol. 10, pp. 81343–81354, 2022.

[5] Y. Tang, Q. Wu, H. Mao, and L. Guo, “Epileptic Seizure Detection Based on Path Signature and Bi-LSTM Network with Attention Mechanism,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2024.

[6] A. Miltiadous et al., “Machine Learning Algorithms for Epilepsy Detection Based on Published EEG Databases: A Systematic Review,” IEEE Access, vol. 11, pp. 564–594, 2023.

[7] C. S. L. Prasanna, M. Z. U. Rahman, and M. D. Bayleyegn, “Brain Epileptic Seizure Detection Using Joint CNN and Exhaustive Feature Selection with RNN-BLSTM Classifier,” IEEE Access, vol. 11, pp. 97990–98004, 2023.

[8] Y. Jeon, Y. G. Chung, T. Joo, H. Kim, H. Hwang, and K. J. Kim, “Deep Learning-Based Detection of Epileptiform Discharges for Self-Limited Epilepsy with Centrotemporal Spikes,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 2939–2949, 2022.

[9] Y. Liu et al., “Deep C-LSTM Neural Network for Epileptic Seizure and Tumor Detection Using High-Dimension EEG Signals,” IEEE Access, vol. 8, pp. 37495–37504, 2020.

[10] Hassan F, Hussain SF, Qaisar SM. Epileptic Seizure Detection Using a Hybrid 1D CNN-Machine Learning Approach from EEG Data. J Healthc Eng. 2022 Nov 29;2022:9579422. doi: 10.1155/2022/9579422. PMID: 36483658; PMCID: PMC9726261

[11] Z. Song, B. Deng, J. Wang, G. Yi, and W. Yue, “Epileptic Seizure Detection Using Brain-Rhythmic Recurrence Biomarkers and ONASNet-Based Transfer Learning,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 979–989, 2022.

[12] P. Khan et al., “Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances,” IEEE Access, vol. 9, pp. 37622–37655, 2021.

[13] W. Dang, D. Lv, L. Rui, Z. Liu, G. Chen, and Z. Gao, “Studying Multi-Frequency Multilayer Brain Network via Deep Learning for EEG-Based Epilepsy Detection,” IEEE Sensors Journal, vol. 21, no. 24, pp. 27651–27658, Dec. 2021.

[14] M. Yazid et al., “Simple Detection of Epilepsy from EEG Signal Using Local Binary Pattern Transition Histogram,” IEEE Access, vol. 9, pp. 150252–150267, 2021.

[15] M. U. Abbasi, A. Rashad, A. Basalamah, and M. Tariq, “Detection of Epilepsy Seizures in Neo-Natal EEG Using LSTM Architecture,” IEEE Access, vol. 7, pp. 179074–179085, 2019.

[16] X. Tian et al., “Deep Multi-View Feature Learning for EEG-Based Epileptic Seizure Detection,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 10, pp. 1962–1972, Oct. 2019.

[17] C. L. Liu, B. Xiao, W. H. Hsaio, and V. S. Tseng, “Epileptic Seizure Prediction with Multi-View Convolutional Neural Networks,” IEEE Access, vol. 7, pp. 170352–170361, 2019.

[18] D. Wu et al., “Automatic epileptic seizures joint detection algorithm based on improved multi-domain feature of cEEG and spike feature of aEEG,” IEEE Access, vol. 7, pp. 41551–41564, 2019.

[19] M. S. J. Solaija, S. Saleem, K. Khurshid, S. A. Hassan, and A. M. Kamboh, “Dynamic mode decomposition based epileptic seizure detection from scalp EEG,” IEEE Access, vol. 6, pp. 38683–38692, Jul. 2018.

[20] Z. Brari and S. Belghith, “A novel Machine Learning approach for epilepsy diagnosis using EEG signals based on Correlation Dimension,” in IFAC-PapersOnLine, Elsevier B.V., 2021, pp. 7–11. doi: 10.1016/j.ifacol.2021.11.018.

[21] Z. Chen, G. Lu, Z. Xie and W. Shang, "A Unified Framework and Method for EEG-Based Early Epileptic Seizure Detection and Epilepsy Diagnosis," in IEEE Access, vol. 8, pp. 20080-20092, 2020.

[22] Y. Liu et al., "Deep C-LSTM Neural Network for Epileptic Seizure and Tumor Detection Using High-Dimension EEG Signals," in IEEE Access, vol. 8, pp. 37495-37504, 2020.

[23] J. Rabcan, V. Levashenko, E. Zaitseva, and M. Kvassay, "EEG Signal Classification Based on Fuzzy Classifiers," IEEE Transactions on Industrial Informatics, vol. 18, no. 2, pp. 757–766, Feb. 2022.

[24] D. Wu et al., "Automatic Epileptic Seizures Joint Detection Algorithm Based on Improved Multi-Domain Feature of cEEG and Spike Feature of aEEG," in IEEE Access, vol. 7, pp. 41551-41564, 2019.

[25] M. U. Abbasi, A. Rashad, A. Basalamah and M. Tariq, "Detection of Epilepsy Seizures in Neo-Natal EEG Using LSTM Architecture," in IEEE Access, vol. 7, pp. 179074-179085, 2019.

[26] Ibrahim, Fatma & Emara, Heba & El-Shafai, Walid & Elwekeil, Mohamed & Rihan, Mohamed & El-Dokany, I.M. & Taha, Taha & El-Fishawy, Adel & El-Rabaie, El-Sayed & Abdellatef, Essam & Abd El-Samie, Fathi. (2022). Deep-learning-based seizure detection and prediction from electroencephalography signals. International Journal for Numerical Methods in Biomedical Engineering. 10.1002/cnm.3573.

[27] Deepa B, Dr.Ramesh K, May 22, 2021, "Preprocessed CHB-MIT Scalp EEG Database", IEEE Dataport, doi: https://dx.doi.org/10.21227/awcw-mn88.

[28] Deepa, B., & Ramesh, K. (2022). Epileptic seizure detection using deep learning through min max scaler normalization. International Journal of Health Sciences, 6(S1), 10981–10996. https://doi.org/10.53730/ijhs.v6nS1.7801

[29] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.

[30] Ali Shoeb, Herman Edwards, Jack Connolly, Blaise Bourgeois, S. Ted Treves, John Guttag. Patient-Specific Seizure Onset Detection. Epilepsy and Behavior. August 2004, 5(4): 483-498. [doi:10.1016/j.yebeh.2004.05.005].

[31] S. Kumar, S. Kumar, M. K. Chaube, S. K. Gupta, R. K. Saket, "Role of Mathematical Modelling and Learning Techniques for Privacy Preservation," GMSARN International Journal, 17(1), 96-110, 2023.

[32] P. Handa, M. Mathur, and N. Goel, "Open and free EEG datasets for epilepsy diagnosis," arXiv preprint, vol. arXiv:2108.01030, 2021. Available: https://arxiv.org/abs/2108.01030.

[33] Jemal, Imene, Amar Mitiche, and Neila Mezghani. 2021. "A Study of EEG Feature Complexity in Epileptic Seizure Prediction" Applied Sciences 11, no. 4: 1579. https://doi.org/10.3390/app11041579.

[34] S. Mondal, M. Shafi, S. Gupta, S. K. Gupta, "Blockchain based Secure Architecture for Electronic Healthcare Record Management," GMSARN International Journal, 16 (4), 413-426, 2022.