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EEG-Based Epileptic Seizure Prediction Using Variants of the Long Short Term Memory Algorithm

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Abstract: One of the most widespread neurological disorders worldwide is epilepsy. Seizures that are caused by sudden aberrant electrical activity in the patient's brain, causing unpredictable episodes, are called epileptic seizures. Epileptic seizure patient's life can be significantly impacted by early detection of seizure. For the prediction of seizures based on zero-crossing intervals of examination of the scalp, an approach known as electroencephalograms (EEGs) is introduced. EEG signals are examined to anticipate seizures and prevent unwarranted life risks. Deep Learning (DL) has been used in this research as it can automatically generate hierarchical representation from unprocessed EEG data, making it possible to quickly uncover complicated patterns and information associated with brain activity. This required preprocessing EEG scalp recordings, automatic feature extraction, and classification. In this paper, we proposed the Long Short Term Memory (LSTM) variants, Bi-LTSM, vanilla LSTM, and stacked LSTM, and compared the results with GRU, MLP, and DCNN for epileptic seizure prediction. We compared these models using the CHB-MIT dataset to improve accuracy, sensitivity, and specificity for predicting epileptic seizures. The results show that the Bi-LSTM algorithm performed better than the other proposed algorithms in terms of evaluation metrics.

Keywords: epilepsy; deep learning; EEG signals; seizure prediction; long short term memory; RNN; CNN; GRU; MLP

1. Introduction

Epilepsy is known as a neurological brain illness characterized by frequent episodes of symptoms, which can be termed epileptic seizures due to aberrant brain activity. There are almost 23–100 per 10,000 people are prone to epilepsy. Loss of consciousness, movement abnormalities, or any other cognitive processes is all symptoms of seizure, which, as a result, diminish the quality of life of epilepsy patients. Neural networks in the brain are affected by abnormality, leading to these seizures [1]. Prediction of epileptic seizures is crucial so that we can avoid the potential risks to one's life, as epilepsy, known as drug-resistant epilepsy, is said to have seizures that continue despite being properly medicated [2].

Over the past few decades, an electroencephalogram (EEG) has been used to record electrical brain activity. It is a graph produced using advanced electronic technology. These recordings have been used for the diagnosis and prediction of epileptic seizures, resulting in a high level of accuracy [1]. Depending upon data acquisition, EEG is further divided into intracranial and scalp EEG [3]. If aberrant brain activity is recorded before seizure onset, it can significantly enhance the treatment of epilepsy.

EEG signals must be continuously monitored, which is time-consuming and tiring. Therefore, a clinical specialist who is trained and qualified is required [4]. Conventional clinical methods used for EEG analysis can be sensitive to intra and inter-rater variability. EEG data is intrinsically complex and has limited human perception, so more scalable and objective methods are needed. EEG signals are



subjected to many disturbances, such as noises, artifacts, etc. It makes it challenging to identify the type of seizure, and it still requires the intervention of professionals of medical for detection. Incorrect prescriptions of Anti-Seizure Drugs can have some side effects due to misdiagnosis. Also, due to the unpredictable character of EEG signals, a non-linear method is needed [5].

In recent years, machine-learning approaches have been used to forecast human seizures. Machine learning, as the name suggests, is the model where computers learn from the data independently without any direct programming. These models can quickly examine and spot patterns in data on brain activity, making them crucial for detecting seizures [5]. Epileptic seizure prediction continues to improve with increased data and processing capacity due to the flexibility and scalability of machine learning techniques. Furthermore, these algorithms are versatile and incorporate diverse data sources like EEG signals and characteristics of patients. These methodologies enhance the accuracy of the prediction of risk factors of epileptic seizures.

In machine learning, deep learning has become a potent technique for predicting epileptic seizures. It is a subset of Machine Learning (ML) that can easily extract raw data features. Manual Feature engineering is not required in DL methodologies as it can extract features from the data. This ability of these models makes them suitable for picking up on subtle patterns, which are essential for the accurate prediction of epileptic seizures [6]. Various DL algorithms are being used by the researchers nowadays for predicting the epileptic seizures like Convolutional Neural Network (CNN), Autoencoders, Long Short Term Memory (LSTM). This research paper explored variants of Long short-term memory (LSTM) algorithm like Vanilla LSTM, stacked LSTM, Bidirectional Long Short-Term Memory (Bi-LSTM) and compared the results with Gated Recurrent Unit (GRU), Multi-Layer Perception (MLP), and Deep Convolutional Neural Network (DCNN).

This paper is divided into sections, where Section 2 briefly describes past works done in predicting seizures. Section 3 discussed various techniques for classifying EEG signals, and Sections 4 and 5 describes the working of the baseline models and the proposed algorithms. Section 6 presents the experimental setup, and results and analysis are done in Section 7. Section 8 provides the conclusion.

2. Related Works

This section has been divided into two parts—work done using machine learning models and work done using deep learning models.

2.1. Machine Learning Models

Ntahobari et al. [9] implemented SHAP (Shapely Additive exPlanations), a feature selection method, and combined it with extra tree classifiers to predict seizure. This benefited in preserving the AUC (Area Under Curve) performance of the model and also made the model appropriate for use in wearable devices to extend the life of a battery as it reduced the prediction and training time. A model that learns from imbalanced data, namely Principal Component Analysis (PCA), was introduced [11], which extracted both low and high variant Principal Components (PCs) at the first stage, and ones linked with low variance could capture the minor class implicit pattern contributing to better performance of the model. They experimented with various combinations of these two variants on the dataset used to evaluate the proposed model.

Begam et al. [21] proposed XG Boost on real-time epilepsy patients. Nnakenyi et al. [15] developed an ensemble model for predicting epileptic seizures and got an accuracy of 97.4%. Tanner et al. [16] employed logistic regression on the SMILE study dataset and assessed using specificity, accuracy, and sensitivity. Usman et al. [22] employed CNN to extract features and used a Support Vector Machine (SVM) for classification. They got an average specificity and sensitivity of 90.8% and 92.7%, respectively. Seifi et al. [2] introduced three algorithms: K-Nearest Neighbors (k-NN), Support Vector Machine (SVM), and Naïve Bayes. These three models were assessed using evaluation metrics such as false positive rate, recall, and true positive rate. It was observed that Naïve Bayes outperformed the other two. Real-time EEG recordings were utilized by combining k-cross validation with SVM, which achieved an accuracy of 85.9% [17].

AbdElminaam et al. [18] classified the Bonn University dataset using one DL model and three ML models, namely CNN, Decision Tree (DT), KNN, and Random Forest (RF). On the other side, CNN, SVM, and Artificial Neural Networks (ANN) were applied to the EEG signal data of 18 channels, which were acquired at Helinski University Central Hospital, Finland (Children's Hospital). They used ROC-AUC, accuracy, and recall to evaluate the models. Ra et al. [32] took unprocessed EEG recordings and STFT (Short-time Fourier transform) and SET (Singular Spectrum Transformation) to convert them. Singular Value Decomposition (SVD) was used to reduce the dimensionality of the results acquired by the SET. It was further classified using different neural networks, namely, Multi-layer perceptron (MLP)

and 1D-CNN, and their classification results were compared.

Dutta et al. [5] employed various machine learning and deep learning models, such as SVM and KNN, and deep learning models LSTM. For each EEG, seven different epileptic seizures, which have 19 channels, were classified using these models. A train-test ratio of 75-25 was used. LSTM, SVM, and KNN produced an accuracy of 82.6%, 90.41%, and 94.46%, respectively. From the results, it was observed that KNN performed better than the other two. Anandaraj et al. [28] proposed a Tree-based Ensemble for Enhanced Prediction (TEEP) comprising 3 phases: feature selection, feature extraction, and prediction. This model was applied to two different epileptic seizure recognition datasets from Melbourne University and Bonn University. Chakrabarti et al. [31] proposed four models: random forest, ensemble learning, artificial neural networks, and decision trees. They employed the dataset of CHB-MIT. After comparing the results, it was observed that the random forest performed better than others, achieving specificity, accuracy, and sensitivity of 89.7%, 91.9%, and 94.1%, respectively.

2.2. Deep Learning Models

Kumar and Prakash [7] worked on the UCI EEG dataset and employed CNN to differentiate between seizure and non-seizure. They achieved training and validation accuracy: 99.27% and 96.37% respectively. To forecast seizures in canines with epilepsy, Nejedly et al. [14] developed a CNN-based DL model. They analyzed dog iEEG recordings from epileptic canines. The model's results showed that the forecasting performance was far better than a by-choice prediction of the dogs studied.

The system of seizure forecasting was used to identify preictal times linked with higher seizures using an EPAD tablet computer for monitoring real-time seizures.

Manju et al. [8] used two datasets, one having only a preictal class and the other being healthy. They employed CNN on these datasets for binary classification, healthy or preictal, and achieved an accuracy of 98.58%. In [12], three different benchmark datasets were taken into account on which they employed CNNs and got the results that indicated different patients could show sensitivity differently to varying sizes of models and other energy-efficient methods. That is, we can employ patient-specific models for the prediction of seizures. Li et al. [24] employed CNN on three different datasets. Where the dataset of the University of Bonn was used for the detection of seizures, for which they got an accuracy of 99.84%, and the dataset of SWEC-ETHZ and CHB-MIT were used for the prediction of seizures, for which they got an accuracy of 97.54%, 99.01% respectively. Eberlin et al. [19] used two public datasets and employed CNN on them, but it failed to work on the second dataset's patient 1, and the reason for this is still unknown.

Assali et al. [33] proposed a CNN on the CHB-MIT dataset. In this paper, to increase the performance of the high-level feature of EEG recordings, the SI (stability index) was fed to CNN. The model was stabilized by integrating SI, which improved epileptic state classification. It helped the model compete with state-of-the-art methods based on performance evaluation. A model named SPERTL was introduced by [10], in which Transfer Learning (TL) methodologies are used in the training of Residual network (ResNet), which helped predict ES earlier from EEG recordings. This model showed superiority in differentiating between interictal and preictal classes and performed better than state-of-the-art methods on accuracy, sensitivity, and specificity by 14.7%, 5.4%, and 19.9%, respectively.

Considering the real-time prediction of seizures, Daoud et al. [13] employed different deep-learning models for accurately predicting the early prediction of seizures. They got sensitivity, accuracy, and specificity of 99.72%, 99.6%, and 99.60%, respectively. Wang et al. [20] worked on the Bonn University dataset on which they employed three different models LSTM, Gated Recurrent Unit (GRU), and Random Forest. The results showed GRU worked better than LSTM and much better than RF. Sun et al. [25] employed RNN and CNN on the Kaggle dataset, which they evaluated using the AUC Curve, showing that CNN performed better. It was also observed that if it was combined with the Fourier Transform, it accurately predicted pre-seizure states.

Mengnan et al. [27] used two datasets, one from Xinjiang Medical University and one from Sun Yat-sen University. They proposed Bidirectional Neural Long Short-Term Memory with Channel Attention and Signal Adaptive (BNLSTM-CASA) without extracting features but optimizing the EEG lead's weight and further verified their results on the CHB-MIT dataset. Lu et al. [3] introduced a model named CBAM-3DCNN-BiLSTM, which they employed on a dataset of CHB-MIT where CBAM was used for filtration, 3DCNN helped in extracting features, and Bi-LSTM was used for classification. This model got sensitivity, accuracy, and FPR of 98.40%, 97.95%, and 0.017%, respectively. Xu et al. [23] classified multichannel artificial EEG preictal samples. They are the first to apply Graph Neural Network (GNN) for ES prediction. They compared various GAN architectures using the AUC Curve. Zhang et al. [26] used the AES dataset and applied 1DSCNN. When applying this model, the results showed that it performed better than any state-of-the-art model.

Dong et al. [30] proposed an Attention-based Graph ResNet (AGRN) model on the CHB-MIT dataset.

Each EEG Channel represented the graph’s node in this model, and an adjacency matrix was used to model inter-channel relationships. To cope with the problem of class imbalance, the model’s loss function was designed again with the help of focal loss. Singh et al. [29] proposed a hybrid model combining LSTM and ResNet50. Spectrogram images were used to train this model. Experiments were conducted to evaluate the performance of the model proposed on 5, 15, and 30 minutes of the preictal phase, after which they interpreted that the preictal phase of 5 minutes was ideal. Table 1 summarizes the ML/DL algorithms used to predict seizures.

Table 1. Summary of machine learning models for predicting epileptic seizures.

Authors	Datasets	Models Used	Performance Metrics
Kumar and Prakash (2023) [7]	UCI dataset (publicly available)	CNN	Accuracy
Purnima P S et al. (2023) [6]	Helinski University Central Hospital (Children’s Hospital), Finland	ANN, SVM, RCNN	ROC-AUC, Loss, Recall, Accuracy
Manju et al. (2023) [8]	CHB-MIT dataset + EEG recording over ten minutes from 11 healthy individuals	CNN	Precision, Accuracy, Support, Recall, F1-score
Ntahobari et al. (2022) [9]	Kaggle dataset + Neuro Vista iEEG trial dataset	Extra Tree Classifiers	AUC
Seifi et al. (2022) [2]	PANACEE Dataset	Naïve Bayes, SVM, KNN	Precision, F-measure, TP rate, recall, FP rate
Mohammad and Saeed (2022) [10]	CHB-MIT dataset	SPERTL: Applying TL to ResNet	Specificity, Accuracy, Sensitivity
Masum et al. (2020) [11]	UCI Repository	PCA	FPR, TPR, F-beta score
Zhao et al. (2022) [12]	AES Dataset, CHB-MIT Dataset, Melbourne University Dataset	CNN	Sensitivity, Specificity
Daoud and Bayoumi (2019)	CHB-MIT Dataset	MLP, DCNN, Bi-LSTM, DCAE	Accuracy, Specificity, FalseAlarm, Sensitivity,
Nejedly et al. (2019) [13]	iEEG data from 4 canines	CNN	Sensitivity
Nnakenyi et al. (2022) [14]	CHB-MIT, TUG EEG Corpus, Git Hub EEG Repository	LSTM, CNN, SAE	Sensitivity, Accuracy, Specificity
Tanner et al. (2023) [16]	Dataset from SMILE study	Logistic Regression	Accuracy, Sensitivity, Specificity
Bhattacharjee (2021) [17]	Real time seizure patients	K- fold cross validation + SVM	Accuracy
Abdelminaam et al. (2022) [18]	Bonn university dataset	KNN, Random Forest, Decision Tree, CNN	Accuracy, Recall, Precision, F1-Score

Eberlin et al. (2018) [19]	Dataset from 5 canines+ dataset from 3 humans	CNN	AUC Curve
Wang et al. (2021) [20]	Bonn University dataset	LSTM, GRU, Random Forest	Sensitivity, accuracy, specificity
Begam et al. (2019) [21]	Real time epilepsy patients	XGBOOST	Accuracy
Usman et al. (2020) [22]	CHB-MIT dataset	SVM, CNN	Specificity, Sensitivity
Xu et al. (2022) [23]	CHB-MIT Dataset	GAN	AUC Curve
Li et al. (2022) [24]	3 benchmark datasets	CNN	Accuracy
Lu et al. (2023) [3]	CHB-MIT	CBAM-3DCNN-BiLSTM	Accuracy, FPR, Sensitivity
Sun et al. (2018) [25]	Kaggle dataset	CNN, RNN	AUC Curve
Zhang et al. (2022) [26]	AES Dataset	1D-CNN	AUC, Sensitivity, FPR
Mengnan et al. (2021) [27]	2 Datasets	CSAP, BNLSTM	Specificity, Sensitivity, AUC, Accuracy
Singh et al. (2023) [29]	CHB-MIT	LSTM + ResNet50	Accuracy, FPR, Sensitivity, F1-Score
Dutta et al. (2023) [5]	TUHEEG Dataset	KNN, SVM, LSTM	Accuracy
Dong et al. (2022) [30]	CHB-MIT	AGRN	Accuracy, Specificity, AUC Curve, Sensitivity, Precision
Chakrabarti et al. (2022) [31]	CHB-MIT	Random Forest, Decision Tree, Ensemble Learning, Artificial Neural Network	Sensitivity, Accuracy, Specificity
Ra et al. (2021) [32]	CHB-MIT	KNN + SVM	Specificity, Sensitivity, Accuracy
Assali et al. (2023) [33]	CHB-MIT	CNN	Sensitivity, Accuracy

It is observed from Table 1 that most of the work is done on the CHB-MIT dataset, and CNN, kNN, random forest, and LSTM are the popular deep learning algorithms for predicting epileptic seizures. The performance of the algorithms is compared using accuracy, specificity, sensitivity, and AUC curves. Therefore, in this paper, we have proposed three variants of LSTM and compared their results with the baseline algorithms. Before getting into details, we have discussed the preliminaries required for processing EEG data for epileptic seizures prediction in the subsequent section.

3. Preliminaries

EEG Classification involves the following components (see Figure 1):

1. Data Acquisition: Electrodes are kept on the scalp to record EEG signals.
2. Preprocessing: It involves filtering to remove noise and artifacts like electrical interference.
3. Feature Extraction: It extracts the most relevant features from preprocessed EEG signals to depict various aspects of brain activity [18].
4. Feature Selection: To choose the most important features to remove complexity and further classification.
5. Model Construction: Choosing the most accurate model for the data depending on its nature and size.
6. Model Evaluation: The model is assessed using various evaluation metrics such as precision, accuracy, specificity, etc.

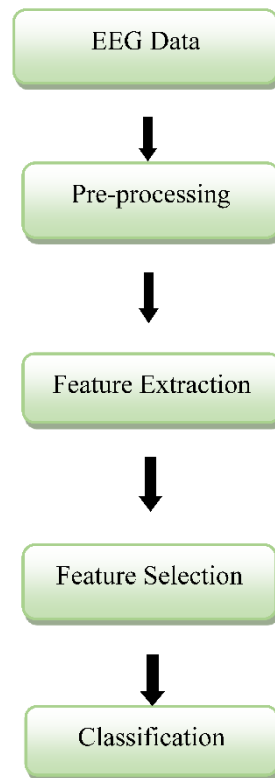


Figure 1. Flow diagram of Epileptic Seizure Prediction.

3.1. Preprocessing

EEG signals contain noise and are affected by many other artifacts. Thus, EEG signals must be preprocessed to minimize noise and improve signal quality. Types of noises in EEG Signals:

1. Eye movement: Fast eye movements can alter the frequency and amplitude of the signal.
2. Electrode Popping Artifact: Physical disruption leads to abrupt change in the impedance of electrodes, which further leads to sudden shifts in EEG data
3. Baseline Drift: Variation in electrode contact can alter the baseline voltage of EEG recordings, leading to slow shifts in the amplitude of signals.
4. Muscle Artifacts: Muscle activity creates unwanted electric signals.

3.2. Filtering

Filtering is used in EEG signals to remove noise, such as electrical interference and muscular aberrations. Filtering in EEG signals involves [18]:

1. Low-pass filters: Remove high-frequency noise while maintaining slower rhythmic components linked to brain activity
2. High-pass filters: Separates EEG components of higher frequency from lower-frequency ones.
3. Band-pass filters: Transmit signals inside a specified frequency and block other signals
4. Notch filters: Suppress undesired artifacts, say, power line interference.

3.3. Normalization

It involves scaling data values to a specified range scale. It ensures every feature contributes equally to analysis and prevents the features with large values from dominating the training model. Commonly used normalization techniques are min-max, z-score, and robust scaling.

3.4. Feature Extraction

It involves identifying and isolating essential and relevant features from the raw data. Commonly used feature extraction techniques used in EEG signals are [18]:

1. Time-domain features: These are extracted in the initial processing of EEG signals. These features include skewness, mean, and median of signal amplitude.
2. Frequency-domain features: These are created using the frequency spectrum of EEG signals. These include spectral entropy, Spectral centroid, etc.
3. Time-frequency domain features: Extracted using wavelet transform or (STFT) Short Time Fourier transform. These may include wavelet coefficients and spectrograms.
4. Nonlinear features: Extract nonlinear features of EEG signals. These features include correlation dynamics.

3.5. Feature Selection

In EEG analysis, Feature selection helps identify relevant features and reduce dimensionality. Types of feature selection methods used primarily:

- Filter method: It evaluates the feature relevance without using any learning algorithm, e.g., Chi-square test, Information-Gain, and feature analysis are some of the approaches used commonly.
- Wrapper Method: It evaluates the best feature subset by repetitively testing and training the model. It includes backward elimination and forward selection.
- Embedded Method: It combines the best qualities of filter and wrapper method. Tree-based algorithms and lasso are some of the techniques that are primarily used.

4. Baseline Algorithms

We have proposed three variants of LSTM algorithms based on the combinations of the baseline models: Deep Convolution Neural Network (DCNN), Recurrent Neural Network (RNN), and Long short-term memory (LSTM) which are summarized below:

4.1. Deep Convolution Neural Network (DCNN)

DCNN is also known as Deep Convolutional Neural Network. These networks use a convolutional layer to automatically extract hierarchical EEG signal features. They record temporal and spatial patterns efficiently, helping analyze EEG signals. It allows the network to gather contextual data due to the gaps in the convolutional elements. Its working is as follows:

1. Input Layer: It acquires the input data, which usually consists of a sequence of features.
2. Dilated Convolutional Layers: Increases the receptive field and receives more contextual data.
3. Activation Function: Helps the convolution output by imparting non-linearity.
4. Pooling Layers: usually employing max pooling, these layers reduce the spatial dimensions of mapping the features, preserving the relevant information.
5. Full Connected Layers: Handle top-level characteristics for regression or classification tasks.

Final results are generated by the Output Layer, which could be numerical values in regression or probabilities for classes in classification.

4.2. Recurrent Neural Network (RNN)

This artificial neural network can identify data patterns and sequences, including text, time series, audio, and others. Unlike the feedforward conventional neural networks, which do input-to-output data processing one directionally, it can create cycles to show temporal dynamics. Basic RNN architecture includes network nodes having recurrent connections, which helps, over time, the induration of information. There is a hidden state in the network to record data's past input. Therefore, the network can use earlier information in the current decision-making. However, it faces the problem of a vanishing gradient.

4.3. GRU

GRU is a type of RNN that efficiently extracts temporal dependencies and patterns from the data. It may discard or keep information over time by utilizing a gating mechanism. It captures long-term relationships in EEG signals, which is important for analysis.

It has set of gates for regular information flow. Layers of GRU:

1. Input Layer: Receives input data.
2. GRU layer: Every unit of GRU layer has two gates: reset gate and update gate.
3. Output layer: It depends on the task. For binary classification, it is used with sigmoid function.

4.4. MLP

These are a type of feedforwarding artificial neural networks. It is made up of various neuron layers where each and every layer is connected. Layers include: 1 input layer, 1 output layer and 1 or more hidden layers. These models can easily learn from nonlinear data. In our model, MLP comprises three completely linked dense layers. The first layer employs a Rectified Linear Unit (ReLU) with 64 neurons, adding non-linearity to the model. With the ReLU activation, the second layer comprises 32 neurons. An output layer neuron with a sigmoid activation function produces the probability score.

After this, the features were normalized by employing StandardScaler from sci-kit-learn. The model is compiled and trained. While training, the model changes its parameters iteratively, and then the performance of the model is evaluated.

5. Proposed Algorithms

LSTM is a kind of RNN that solves the RNN's vanishing gradient problem and works well in processing sequential data. This has special types of layers:

1. Forget Gate Layer: Decides the data to be removed based on states of the previous hidden and current input.
2. Input Gate Layer: Determine the new data by considering the prior concealed state.
3. Cell State Update layer: Uses the input and forget gates for data updation.
4. Output Gate Layer: Decides the output information depending upon the previous hidden and current input states.

5.1. Vanilla LSTM

This is a type of RNN (recurrent neural network). In this architecture, the previous time step input is processed by the LSTM cell, and the current time step output is produced. It has one LSTM layer with 64 units to record temporal dependencies. To create binary classification, an output layer having a sigmoid function is added.

5.2. Stacked LSTM

This model is applied to the preprocessed data. This is also a type of RNN architecture. It is commonly known as multi-layer LSTM. It considers hierarchical representation learning. Each layer produces output for the layer after and processes the input from the layer before. In this model, these layers are sequentially stacked. Each layer contains 64 units of memory. The first two layers return sequences, but the third layer doesn't; it acts as a hidden state. The output layer is dense with a sigmoid function and a single neuron.

5.3. Bi-LSTM

It is also a type of RNN. It processes the input sequence both backward and forward. It comprises two LSTM layers where the input sequence is processed by one layer in reverse and the other from start to end. It helps in gathering context from the past and future. The architecture of this model consists of the following:

1. Input Layer: It shapes the input for processing.
2. Bidirectional LSTM Layers: Record temporal dependencies using 64-unit Bi-LSTM layers in both forward and backward directions.
3. Dropout Layer: Applied after the 2 Bi-LSTM layers each to prevent overfitting.
4. Output Layer: Used for binary classification with a sigmoid function and a single neuron.

6. Experimental Setup

The entire process of epileptic seizure prediction was done on a Jupyter Notebook environment using Python 3. Several deep learning models were used for the binary classification of EEG data aiming at the detection of seizures. These models include Vanilla LSTM, Stacked LSTM, GRU, MLP, Bi-LSTM, and DCNN. Each model was trained using Adam optimizer, loss function: Binary Cross Entropy as a loss function with ten epochs in a batch size 32. The proposed deep learning networks are trained using the CHB-MIT dataset [9]. It is the most often used dataset for the prediction of epilepsy. It includes EEG recordings collected using 23 electrodes (see Figure 2) from 22 patients consisting of 17 females and five males. After stopping the anti-seizure medicine, the patients were kept under observation for a few days to evaluate whether they were suitable for surgery. The majority of the files have 23 EEG signal recordings. Each signal is sampled using a resolution of 16-bit and a sampling frequency of 256 Hz. These signals are classified into different classes, namely pre-ictal, ictal, inter-ictal, and post-ictal.

Pre-ictal: It refers to the time before the seizure happened.

Ictal: It refers to the time during the seizure.

Inter-ictal: It refers to the time between two seizures.

Post-ictal: It refers to the time exactly after the seizure.

In this paper, we used a preprocessed version of this data from <https://iee-dataport.org/>; <https://iee-dataport.org/open-access/preprocessed-chb-mit-scalp-eeeg-database#> (accessed on 19 November, 2023) [34] to binary classify data into pre-ictal and ictal.

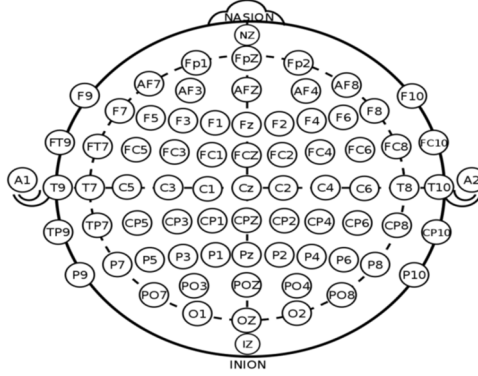


Figure 2. Electrode locations of the International 10–20 system for EEG Recording [20].

6.1. Evaluation Metrics

Confusion Matrix is used to evaluate the model. It provides different prediction outcomes to give an overview of the performance when applied to the data that needs to be tested. It is divided into four categories:

True Positive (TP): When models predict the positive class accurately.

True Negative (TN): When models predict the negative class accurately.

False Negative (FN): When models fail to predict the negative class accurately.

False Positive (FP): When the models fail to predict the positive class accurately.

Some commonly used performance metrics based on the above information are:

6.1.1. Accuracy

It is the ratio of totally corrected points to the total predicted instances. It shows the model's capacity to categorize negative and positive cases accurately.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

6.1.2. Precision

The ratio of true positive prediction to the total positive prediction. It evaluates how the model measures the positive prediction accurately.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

6.1.3. Recall

It is the ratio of the true positive predictions to true positive and false negatives. It gives the rightly identified actual positives.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

6.1.4. Specificity

The ratio of true negatives by true negatives and false positives. It shows the capability of a model to detect negative instances accurately.

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (4)$$

6.1.5. F1-Score:

Harmonic means of precision and recall.

$$\text{F1-Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

7. Data Analysis and Results

We conducted experiments using the proposed DL models. All these models were trained, validated, and tested, and their performance was evaluated using various performance metrics, including accuracy, precision, f1-score, specificity, and recall as presented in Table 2 and Figure 3.

Table 2. Performance comparison of the proposed algorithms.

Model	Accuracy	Specificity	F1-Score	Recall	Precision
MLP	86.26%	90.377%	85.68%	82.15%	89.52%
DCNN	86.76%	87.23%	86.70%	86.8%	87.12%
GRU	85.4%	88.66%	84.92%	82.16%	87.88%
Stacked LSTM	87.26%	89.22%	87.01%	85.30%	88.77%
Vanilla LSTM	85.3%	88.4%	84.8%	82.1%	87.7%
Bi-LSTM	89.78%	92.20%	89.53%	87.36%	91.81%

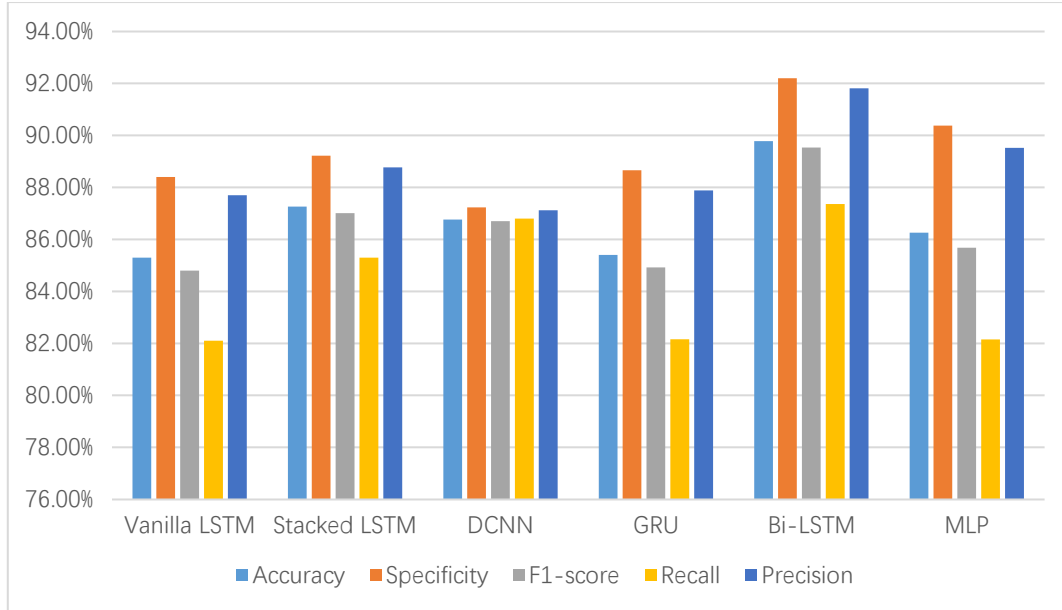


Figure 3. Performance evaluation of the proposed algorithms.

It is observed from Table 2 that the proposed Bi-LSTM outperformed the other proposed algorithms and the baseline algorithms with an accuracy of 89.78%. Stacked LSTM (87.26%) have comparable performance with DCNN (86.76%). It is followed by MLP (86.26%). Vanilla LSTM (85.3%) and GRU (85.4%) achieved lower accuracies comparatively. Epileptic seizures must be identified without error, so we need high recall. Bi-LSTM outperformed the DCNN, Stacked LSTM, GRU, MLP, and Vanilla LSTM in the same order as their occurrence in terms of recall. It is also better than the other algorithms regarding specificity (92.20%). MLP, Stacked LSTM, and GRU followed with the specificity of 90.37%, 89.22%, and 88.66%, respectively, followed by DCNN and vanilla LSTM. Moreover, Bi-LSTM provided better precision, i.e., accurately identifying the positive classes and the performance of the other algorithms, followed by MLP, Stacked LSTM, GRU, Vanilla LSTM, and DCNN. Additionally, the F1- score of the algorithms followed the decreasing order as Bi-LSTM, Stacked LSTM, DCNN, MLP, GRU, and Vanilla LSTM.

The observation reveals that Bi-LSTM demonstrated superior performance among the other models. After this, Stacked LSTM showed competitive performance, having the second highest specificity, accuracy, recall, F1 score, and precision. It performed slightly lower than Bi-LSTM but outperformed others in various metrics. DCNN was the third-highest performer with accuracy, recall, F1-score, and specificity. In conclusion, Bi-LSTM is the best algorithm, followed closely by stacked LSTM and DCNN.

8. Conclusions

In this paper, we proposed deep-learning models like Vanilla LSTM, Stacked LSTM, GRU, DCNN, and MLP for the prediction of epileptic seizures. After testing and training these models, they were validated using various performance metrics: precision, accuracy, specificity, F1-score, and recall. It is observed from the results that Bi-LSTM performed superiorly across all the metrics as compared to the other variants of LSTM, i.e., Vanilla LSTM and Stacked LSTM. In the future, we can use hybrid models to get better results for predicting epileptic seizures.

Author Contributions

Conceptualization, and methodology, Anu Bajaj (A.B.); software, and validation, Akshita (A.); formal analysis, Vikas Sharma (V.S.); investigation, A.B.; resources, data curation, and writing—original draft preparation, A; writing—review and editing, and supervision, A.B. and V.S.; supervision; project administration, A.B. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

The authors declare no conflict of interest.

Data Availability Statement

In this research, the dataset used was taken from an open source. It is publicly available at <https://ieee-dataport.org/>. <https://ieee-dataport.org/open-access/preprocessed-chb-mit-scalp-ecg-database#> (accessed on 19 November, 2023).

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