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Prediction of the epileptic seizure through deep learning techniques using electroencephalography

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ABSTRACT

Electroencephalography (EEG) is a widely used and significant technique for aiding in epilepsy diagnosis and investigating the electrical patterns of the human brain. Due to the non-stationary nature of EEG signals, seizure patterns will vary across different recording sessions for individual patients. In this study, a new deep learning long short-term memory (LSTM) model is implemented for the detection of brain tumors and seizures. The process consists of four key steps: EEG signal pre-processing, preictal feature extraction, hyper optimization using grey wolf optimization (GWO), and LSTM-based classification. The evaluation makes use of long-term EEG recordings from the EEG and ABIDE fMRI datasets. By experimenting with various modules and layers of memory units, a pre-analysis is first conducted to determine the best LSTM network architecture. The LSTM model makes use of numerous retrieved features, including temporal and frequency domain information between EEG channels that were extracted before classification. The discovery of the implemented methodology revealed significant advantages in accurately predicting seizures while minimizing false alarms. The implemented LSTM method achieves a 99% accuracy rate, 98% precision, 99% recall, and 98% f1-measure which is better when compared with cross sub-pattern correlation-based principal component analysis (SUBXPCA) and gradient-boosting decision tree (GBDT) methods.

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1. INTRODUCTION

Epilepsy is a chronic brain disease caused by the sudden abnormal discharge of neurons in the brain resulting in temporary impairment of brain function [1], [2]. One of the most prevalent neurological non-communicable illnesses is epilepsy. An abnormality in the brain's electrical activity, which can be classed as focal, generalized, or undetermined, is what causes epileptic seizures [3], [4]. Electroencephalography (EEG) signals are electrical impulses generated by biological brain activity in humans. Disabled or elderly people can utilize a particular wearable EEG device to collect EEG data and generate control signals for motor imaging, allowing for remote control [5]. With the aid of an EEG device, electrodes can be placed on the scalp in a non-invasive way to detect brain activity [6]. To analyze variations in brain activity and to distinguish between normal and abnormal processes occurring in the human brain, EEG is frequently utilized. EEG is also quite inexpensive, which makes it the best test for epilepsy sufferers [7]. When used on EEG recordings, common spatial pattern filters, and optimized spatial pattern filters also offer a higher signal-to-noise ratio [8]. Accurate prediction is made possible by spatial attention, which also realizes adaptive learning of feature characteristics [9]. The convolutional neural network (CNN) deep learning model's main input type is a single domain input, including feature signals or EEG signals, according to the most recent EEG research [10]. The creation of an automatic seizure detection system is beneficial for reducing workload and monitoring epilepsy for medical staff [11]. The simplest method for diagnosing epilepsy is to utilize non-invasive EEG to record the voltage of brain fluctuations [12]. EEG monitors continuous brain activity by inserting many electrodes at various locations across the brain and detecting voltage variations [13]. Even for highly skilled neurologists, proper diagnosis of EEG is time-consuming and challenging despite its great temporal resolution. The development of intelligent EEG diagnostic technologies enables doctors to handle more patients while providing high-quality EEG diagnoses [14]. Many wearable and implantable systems and circuits have been created recently to detect or forecast the appearance of seizures, allowing time for emergency preparation in high-risk situations without medical assistance, such as operating heavy machinery and driving [15]. Various epileptic seizure states can be classified based on when the epileptic seizure occurs. Three steps make up a common seizure prediction approach, they are pre-processing, feature extraction, and classification [16], [17]. Finally, the network's input is the raw EEG signal, which has not been subjected to any feature pre-processing. Data-driven concepts and DL approaches both benefit better from automatically extracting characteristics from data [18].

Zubair *et al*. [19] implemented cross-sub-pattern correlation-based principal component analysis (SUBXPCA) and sub-pattern-based principal component analysis (SPPCA) techniques of dimensionality reduction to improve the different machine learning models of classification accuracy. Correlating function dimensionality reduction methods include SPPCA and SUBXPCA. The various features that are obtained after executing discrete wavelet transform (DWT) and EEG signals, to choose the most notable aspects and maintain their attributes. The implemented techniques accurately identify seizures while reducing the dimensionality of the features with decreased computational complexity. However, the accuracy of seizure identification was affected by the compression or discarding of EEG signals during dimensionality reduction. Lopes *et al*. [20] implemented an EEG artifact removal model based on a deep convolutional neural network. The implemented method was tested using long-term recordings of EEG made by epileptic patients and made accessible in the database of EPILEPSIAE. Deep convolutional neural networks (DCNNs) were used to create the implemented method quickly and automatically remove errors from EEG segments. The amount of time needed for manual artifact removal was decreased by using DCCN-based artifact removal methods, which analyzed EEG data in real-time or close to real-time. However, EEG data was subject to noise and artifacts, which impaired seizure detection precision. Jana and Mukherjee [21] implemented a CNN with channel minimization which was employed to provide an effective seizure prediction technique. CNN has been used to automatically classify the states of epilepsy patients and extract feature information. This method provides a reliable seizure prediction system based on unprocessed EEG signals that notify epilepsy patients or dependents to take protective measures to reduce undesired life risks. The implemented method was utilized to decrease the rate of overfitting during training, lower the computational overhead, reduce power consumption, and increase the time efficiency. However, the implemented method was developed as a patient-specific seizure prediction, making it ineffective for predicting seizures for other epilepsy patients. Usman *et al*. [22] implemented a deep learning-based ensemble learning method to predict epileptic seizures. This method involves preprocessing EEG signals with empirical mode decomposition and bandpass filtering to remove noise. The implemented method decreases the impact of class imbalance issues and predict epileptic seizures with improved sensitivity and a low false positive rate. However, using deep learning techniques of seizure prediction and EEG signals processing of applications was restricted.

Prathaban and Balasubramanian [23] implemented an adaptive optimization approach employing the gradient technique of non-linear conjugate. In collaboration with the fletcher reeves (FR) algorithm-based three-dimensional optimized convolutional neural network (3D OCNN) classifier and the sparsity-based EEG reconstruction (SER) technique. A sparsity-based method was used to eliminate artifacts, a lightweight neural network architecture was used to extract and classify seizure data, and a predictor was used to correctly predict future seizures. However, the implemented model's success depends on the availability of substantial and varied EEG datasets, which was difficult due to privacy issues. Jemal *et al*. [24] implemented an interpretable deep learning model architecture that considered the kind of lengthy continuous EEG data. The CNN based on filter bank common spatial pattern (FBCSP) paradigm was implemented and its layers were mapped to well-known signal processing operations including spatial sub-frequency band. The Children's Hospital Boston and the Massachusetts Institute of Technology (CHBMIT) dataset was used to assess the architecture's performance for the patient-specific prediction task. The highest sensitivity was attained with the lowest false alarm rate using the implemented architecture and accuracy prediction was attained high. However, training models of interpretable deep learning frequently need a lot of annotated data.

Xu *et al*. [25] implemented a gradient-boosting decision tree (GBDT) method based on nonlinear EEG signal features for epilepsy seizures early prediction. Utilizing EEG data from the CHB-MIT Scalp EEG Database, the implemented method was determined using data from 13 individuals. The result of the implemented method shows that this method was to forecast seizures with a low fast alarm rate and effectively identify EEG signals. However, the model has several issues, it depends on annotations concerning seizures and it was still unclear the way InT affects the model. Seizure identification's accuracy was affected by compression, representing a constraint in using deep learning for predicting epileptic seizures from EEG signals. The model's effectiveness relies on having substantial data available, and training interpretable deep learning models usually demands a vast amount of annotated data. Due to EEG signals being complicated and non-linear, it is difficult to identify important features that capture the underlying patterns connected to seizure activity. The class imbalance harms the prediction model's performance. To create a deep learning algorithm that is trained on a large dataset of epilepsy patients to effectively predict epileptic seizures using EEG signals. The contributions of this work are given below,

- Here, in this research, LSTM models are employed to categorize the encoded EEG signals to achieve the principles of stability among time consumption, accuracy, trust, and categorization accuracy of encoded spectrogram EEG signals.
- According to experimental data, the implemented technique has a higher detection accuracy and a shorter execution time. The EEG and fMRI datasets are used as benchmark datasets for the prediction of epileptic seizures.

This research paper is structured as: Section 2 presents proposed methodology. Section 3 explains the process of long short-term memory based classification. Section 4 gives the result discussion and its comparison. Section 5 describes the conclusion.

2. PROPOSED METHOD

The five main steps of the implemented method are the collection of the EEG, autism brain imaging data exchange (ABIDE) fMRI datasets, pre-processing, feature extraction, hyperparameter optimization, and classification. Patients and healthy subjects provide raw EEG, and ABIDE fMRI data, which is then processed to eliminate noise and extract 20 eigenvalues as features. The optimal characteristics that efficiently offer enough data to distinguish between EEG records of normal and patient are then selected from the feature extraction. Finally, the EEG is then classified using an LSTM classifier. The overview of the implemented method is represented in Figure 1.

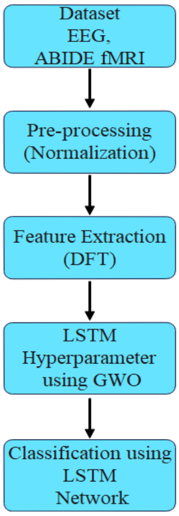

Figure 1. The implemented method's block diagram

2.1. Dataset

2.1.1. EEG dataset

Children's Hospital Boston and the Massachusetts Institute of Technology worked to gather the datasets of EEG for patients suffering from uncontrollable epileptic seizures. This dataset includes scalp EEG recordings from 22 epilepsy patients. Twenty-two patients 5 men and 17 women were observed over days without receiving any medicine. EEG signals were captured for one hour utilizing the 10-20 standard electrode placement technique. All EEG recordings were stored as files in European data format (EDF). The dataset for the onset of the seizure and the end of the seizure has been defined in each file containing data in which a seizure occurred. The majority of EEG sessions use 23 electrodes and 256 Hz to record data.

2.1.2. ABIDE fMRI dataset

Autism brain imaging data exchange is a multisite platform that collects functional and structural brain imaging information from 17 laboratories all over the world. ABIDE includes 1,112 datasets and there are 539 people with autism spectrum disorder (ASD) and 573 typically developing (TD) controls. These datasets of 1,112 contain structural and resting state functional magnetic resonance imaging (FMRI) data together with the associated phenotypic data. From these subjects, 1,112, and 1,035 are chosen for further screening as qualified candidates since these subjects have full data of phenotypic. The 505 ASD and 530 TD patients, including 157 females and 878 men, make up these 1,035 subjects. The purpose of integrating EEG and ABIDE fMRI data is that the signals measured in each modality have complementary features, and the combined evaluation of those signals tells about the functions of the brain.

2.2. Pre-processing

For deep learning (DL) network applications, the preprocessing includes two steps: removal of noise, and normalization. Empirical mode decomposition (EMD) is used for noise removal from signals of EEG and to enhance the signal to noise ratio (SNR) of EEG signals. Then normalization is carried out through different techniques, such as the Z-score technique. Normalization of the Z-score is a technique of processing signals that is commonly utilized to ensure accurate analysis of the data. Large trends typically dominate small trends in signals and expand the signal of dynamic amplitude range. All features are made to follow a normal Gaussian distribution based on (1),

$$x = \frac{x- \mu}{\sigma} \tag{1}$$

where μ – mean of zero
σ – standard deviation of 1

2.3. Feature extraction using discrete fourier transform

Dominant frequency (DF), and spectral entropy (SE) are two frequency variables of the domain. First, the signal in the time domain must be converted into the domain frequency utilizing discrete fourier transform (DFT) as expressed in (2) to obtain the features of the frequency domain. According to (2) is described in,

$$S(k) = \sum_{n=0}^{N-1} s[n]e^{-j\frac{2\pi}{N}kn} \tag{2}$$

- Dominant drequency: A sub-domain maximum peak frequency is referred to as the dominant frequency. Due to its improved results, this feature is particularly helpful in the epilepsy identification process.
- Spectral entropy: For every sub-pattern, the SE is determined among two frequencies, f_1 and f_2. It can be expressed as shown in (3). The SE is divided by $log(N)$, yielding the normalized spectral entropy (NSE) which is defined in (4). In feature extraction, the EEG dataset contains 4,509 features that are extracted. As well as ABIDE fMRI dataset contains 5,983 features that are extracted in the dataset of ABIDE fMRI by using the DFT.

$$SE = \sum_{f_i=f_1}^{f_2} P_n(f_i)x\, log(\frac{1}{P_n(f_i)}) \tag{3}$$

$$NSE = \frac{SE}{log(N)} \tag{4}$$

where f_i – range of frequency between f_1 and f_2
$P_n(f_i)$ – normalized power spectrum component at frequency f_i

2.4. Hyperparameter using grey wolf optimization

Grey wolf optimization (GWO) is a metaheuristic search technique that draws its inspiration from nature and ensembles the identification of the ideal response to the problem. This method is employed to determine the ideal hyperparameter namely: the hidden layers number, window size, and the number of cells per layer to be considered for the network of LSTM. To determine the exact position, the method resembles the social behavior and mechanism of hunting of grey wolves. Grey wolves are classified into four different subspecies: alpha, delta, beta, and omega. The most dominant wolves in the team are the few often one or two alpha wolves. They are in charge of making decisions and leading the hunt. The beta wolves support the alpha wolf's judgment and other tasks. These are less numerous than delta and omega wolves but more numerous than alpha wolves. The two wolves with the most experience in the teams are alpha and beta. While dominating the omega wolves, delta wolves support the alpha and beta wolves. Omega wolves, the least dominant category are mostly baby-sitters. To represent the social behaviour of grey wolves statistically, the candidate is fittest in the population of size N consider alpha ($\propto$), followed by the 2nd and 3rd fittest candidates as delta (δ) and beta (β). The alternative potential results are classified as omega (ω). The process of hunting is directed and the prey is mathematically encircled using (5) and (6),

$$\vec{L} = \left|\vec{K}.\overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{5}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{H}.\vec{L} \tag{6}$$

where t = iteration number of current.
$\vec{H}, \vec{K}$ = coefficient vectors.
$\overrightarrow{X_p}$ = prey position.
$\vec{X}$ = position of the grey wolf .
The $\vec{H}$ and $\vec{K}$ vectors are expressed in (7) and (8).

$$\vec{H} = 2.\vec{h}.\vec{r_1} - \vec{h} \tag{7}$$

$$\vec{K} = 2.\vec{r_2}I \tag{8}$$

During hunting, it is considered that the candidates of gamma, alpha, and beta, have a superior understanding of the prey area and direct the entire search process to the ideal solution. The candidates' position is updated during each iteration based on the candidate's top three positions. The Evolution technique is used to update the values if they are outside the solution space, or if the window size is altered to a negative integer. The formula for updating the wolves' positions is provided in (9)-(15).

$$\overrightarrow{L_\alpha} = \left|\overrightarrow{K_1}.\overrightarrow{X_\alpha} - \vec{X}\right| \tag{9}$$

$$\overrightarrow{L_\beta} = \left|\overrightarrow{K_2}.\overrightarrow{X_\beta} - \vec{X}\right| \tag{10}$$

$$\overrightarrow{L_\delta} = \left|\overrightarrow{K_3}.\overrightarrow{X_\delta} - \vec{X}\right| \tag{11}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{H_1}.(\overrightarrow{L_\alpha}) \tag{12}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{H_2}.(\overrightarrow{L_\beta}) \tag{13}$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{H_3}.(\overrightarrow{L_\delta}) \tag{14}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \tag{15}$$

The range (0.1) contains random selections for the values of r_1 and r_2. This enables the wolves to reach the prey from any position. H takes values from the interval $[-h, h]$, and h is selected from the range [0, 2]. The wolves can utilize the space solution, when $|H| < 1$, which means they can get closer to the prey. The wolves can explore the space of solution, when $|H| > 1$ which means they can move the prey away and investigate the space of search. K and H also allow leaving wolves their local maxima or minima. Finally, the optimal solution for the fittest candidate is returned at the end of the last iteration. Pseudocode 1 for GWO hyperparameter optimization for LSTM is given:

Pseudocode 1. GWO hyperparameter optimization for LSTM

```
Begin
Initialize hyperparameters of LSTM like number of neurons, number of layers and learning rate
Initialize the parameters popsize, maxiter, ub and lb
popsize: size of population,
maxiter: maximum number of iterations,
ub: upper bound(s) of the variables,
lb: lower bound(s) of the variables;
Generate the initial positions of grey wolves with ub and lb;
```

```
Initialize a, A and C
Calculate the fitness of each grey wolf;
alpha = the grey wolf with the first maximum fitness;
beta = the grey wolf with the second maximum fitness;
delta = the grey wolf with the third maximum fitness;
While k < maxiter
     for i = 1: popsize
        Update the position of the current grey wolf by Eq. (14);
     end for
     Update a, A and C
     Calculate the fitness of all grey wolves;
     Update alpha, beta, and delta;
     k = k + 1
end while
Return the optimal set of hyperparameters;
End
```

3. LONG SHORT-TERM MEMORY BASED CLASSIFICATION

The term “long short-term memory” (LSTM) refers to a specific type of recurrent neural network (RNN), that is capable of learning effectively in long-term dependencies in given sequences of data by learning the details for a longer time, hence avoiding the problems associated with RNN vanishing gradient. LSTM has the advantage of not having an overfitting problem when compared to another classifier because the top layer is fed with characteristics that can improve the features. The LSTM has multiplicative units, which are made up of different characteristics, that manage the data stream in the memory block, and multiplicative cells that are gathered from the temporal data. LSTM networks are frequently employed to classify issues involving time series data, text, audio, biomedical signals, and speech. A simple LSTM cell is shown in Figure 2, which has 3 gates for regulating the information flow from the state of one cell to another and serves as the basis for the architecture of LSTM.

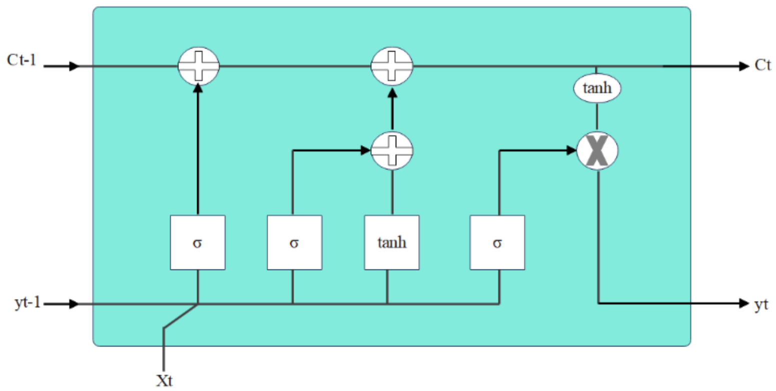

Figure 2. LSTM Cell

The input gate, forget gate, and output gate are some of these gates. All 3 gates use activation of sigmoid σ to provide a determination and regulate the flow of information. In a given data sample, determines the forget gate whether a particular information piece must be forgotten or maintained. It interprets the present input signal X_t and the sequences of prior output y_{t-1} In the cell state C_{t-1} as providing outcome f_t in the range of 1 and 0, where 1 denotes completely remembering the information, and 0 denotes fully forgetting the information. The output multiplying with the output C_t of the activation layer tanh, the input gate determines the information that is contained in the current cell state C_t. Similar to this, combining the output of the LSTM cell with another activation layer tanh output, determines the output gate flow of the proportion of details y_t in C_t at the cell’s outcome. According to (16)-(21) mathematically denote the LSTM cell of three gates operations to produce the outcome y_t in state of the cell C_t.

$$f1 = \sigma\,(W_f.[y_{t-1}, x_t] + b_f) \tag{16}$$

$$i_t = \sigma\,(W_i.[y_{t-1}, x_t] + b_i) \tag{17}$$

$$\widetilde{C_t} = tanh(W_c.[y_{t-1}, x_t] + b_c) \quad (18)$$

$$C_t = f_t * C_{t-1} + i_i * \widetilde{C_t} \quad (19)$$

$$O_t = \sigma (W_o.[y_{t-1}, x_t] + b_o) \quad (20)$$

$$y_t = O_t * tanh\, C_t \quad (21)$$

where w – weight matrices

b – bias factor for various LSTM cell gates

It additionally considers decision tree (DT), random forest (RF), Naïve Bayes (NB), support vector machine (SVM), and k- nearest neighbor (KNN) classifiers for seizure activity prediction in addition to the LSTM models. For the hyper-tuning for various parameters, these classifiers have features with grid search-based parameter estimation. The spectral properties of various EEG channels have been concatenated to alter the input map of features for these classifiers.

4. RESULT

In this experiment, Anaconda Navigator 3.5.2.0 and Python 3.7 are used to simulate the epileptic seizure prediction utilizing EEG signals. The following are the system requirements for the implemented research project: Windows 10 (64-bit) operating system, intel core i7 processor, and 16 GB of RAM. The effectiveness of the implemented model is examined here in precision, f-measure, and categorization accuracy.

4.1. Evaluation parameters

Accuracy: The correctness of an image is a percentage based on the image classification that displays the total amount of accurately classified pixels relative to the total number of pixels in the image. It analyses all of the correctly arranged pixels in an image. It is expressed in (22).

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (22)$$

Precision: Positive prediction's accuracy is gauged by a static called precision. It is equated to the overall accurate forecasts divided by the sum of accurate predictions and false positive predictions. It expressed in (23).

$$Precision = \frac{TP}{(TP+FP)} \quad (23)$$

Recall: The wide range of positive predictions is measured by the recall. It is equated to the number of true positive predictions divided by the number of false negative predictions plus true positive predictions. It expressed in (24).

$$recall = \frac{TP}{(TP+FN)} \quad (24)$$

F1-measure: F1- measure is also known as F1-score. It is a single metric that captures both features by combining precision and recall. It expressed in (25).

$$F1 - measure = \frac{(2*Precision*Recall)}{(Precision+Recall)} \quad (25)$$

The proposed model's performance has been tested by using the accuracy, precision, recall, and f1-measure of parameters. The implemented model is to compare the current approaches that are in this comparison study. Table 1 shows it in terms of precision, accuracy, f1-measure, and recall. The implemented model outperformed all other models, including RNN, logistic regression, KNN, and SVM. When the LSTM implemented model is measured with the prior model, the presentation of the implemented model's performance is high, and it gives a better result of the effective prediction of epileptic seizure using EEG signal.

Accuracy, precision, recall, and f1-measure are evaluated based on the epileptic features. For LSTM methods by utilizing different methods such as RNN, logistic regression, SVM, and KNN obtaining outcomes which are shown in Table 1. LSTM classification method achieved the best performance, showing a precision of 98%, accuracy of 99%, f1-measure of 98%, and recall of 99%.

Table 1 compares the precision, accuracy, f1-measure, and recall of the implemented method with RNN, logistic regression, KNN, and SVM of existing methods. It demonstrates the comparison of the implemented approach outperforms by producing improved prediction accuracy and a lower false alarm rate. A model must be trained using many parameters, and deep learning algorithms are often used in feature extraction and/or classification to increase processing. State-of-the-art seizure prediction techniques are contrasted with the outcomes of the implemented strategy in Figure 3. It has been found that the implemented LSTM method for predicting epileptic seizures performs better than the existing methods such as RNN, logistic regression, KNN, and SVM concerning precision, accuracy, f1-measure, and recall. According to observations, the implemented LSTM offers epileptic patients effective seizure prediction because it achieves high true positive rates with little false alarms.

Table 1. Classification model metrics

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-Measure (%)
RNN Model	95	92	94	93
Logistic Regression	66	55	57	55
KNN	92	95	81	86
SVM	97	97	94	95
LSTM	99	98	99	98

A confusion matrix also known as an error matrix, is a specific table structure that allows performance visualization of an algorithm. Frequently supervised learning (in the learning of unsupervised, it is typically referred to as a matching matrix) in the field of deep learning and more specifically the issue of statistical classification shown in Figure 4. Each row represents a case in the real class, and each column denotes occurrences in the predicted class in both matrix versions. In the confusion matrix, 0 indicates normal patients and 1 indicates the seizure patients. This section displays the model's findings and details which the LSTM model performed in terms of seizure detection. This is the problem of binary classification, either seizure or non-seizure events were classified in input samples. The confusion matrix from the best model (LSTM) is shown in Figure 4.

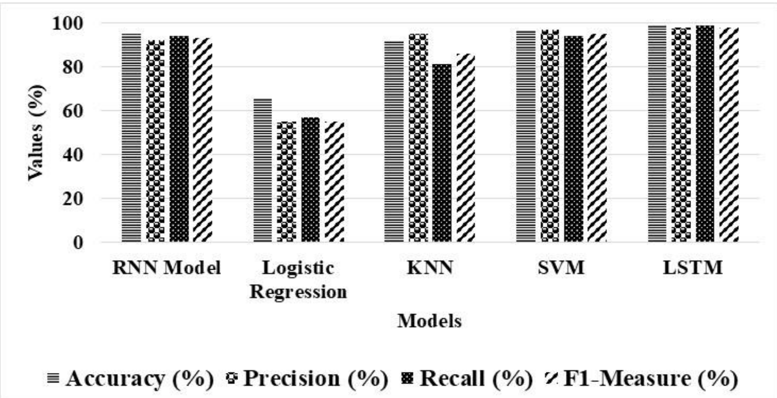

Figure 3. Graphical representation of classification model metrics

The classification of training accuracy and training loss is shown in Figure 5, in that 50 epochs were used and the accuracy varies from 0.2 to 0.8. The training loss is indicated in green color and the training accuracy is indicated in blue color. The validation loss and validation accuracy of the LSTM model are shown in Figure 6. In validation loss and validation accuracy, 50 epochs are used and the accuracy varies from 0.2 to 0.7. The validation loss is indicated in blue and validation accuracy is indicated in black color. A training accuracy of 99.04% is achieved.

Both, the ABIDE fMRI dataset, which has 5,983 features that are extracted. The EEG dataset comprises 4,509 features that are extracted and specified 3,742 amounts of features were selected. The number of features extracted and selected from EEG and ABIDE fMRI datasets are shown in Table 2.

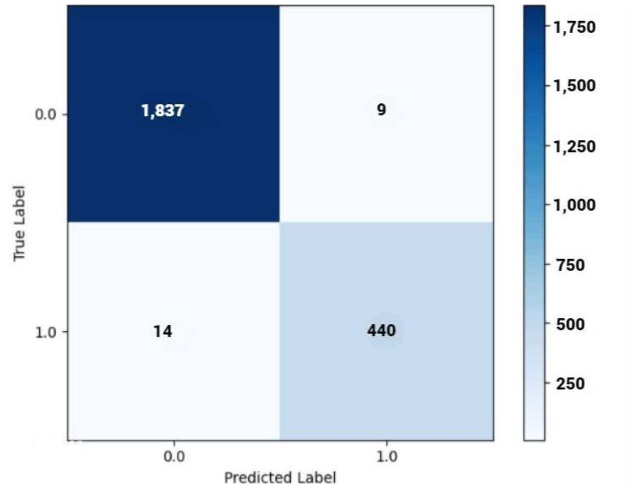

Figure 4. Confusion matrix from LSTM classification

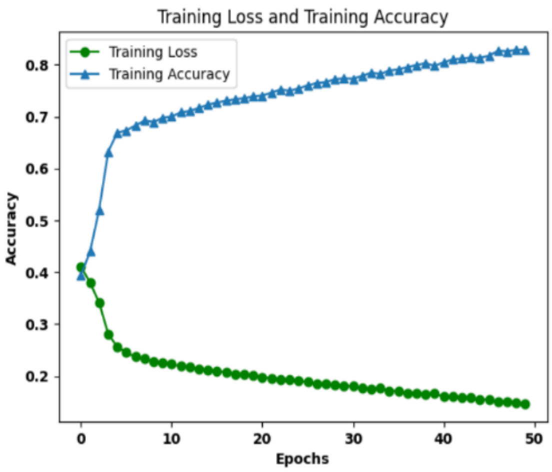

Figure 5. Graphical representation of training loss and accuracy

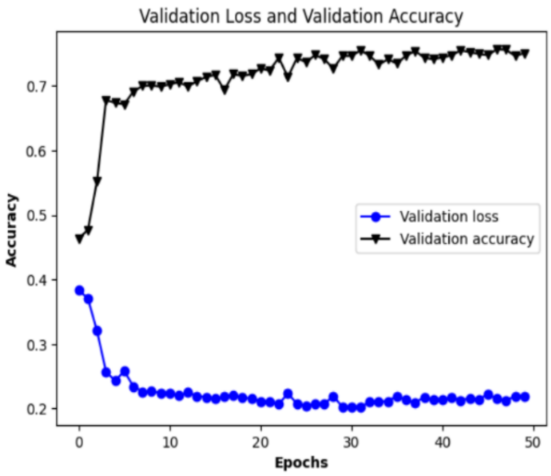

Figure 6. Graphical representation of validation loss and accuracy

Table 2. Number of features extracted and selected from datasets

Datasets	Extracted features	Feature selection
EEG	4,509	3,742
ABIDE fMRI	5,983	4,620

4.2. Comparative analysis

The implemented method compares with the existing method concerning the precision, accuracy, f1-measure, and recall. Compared to other existing methods, the implemented LSTM method achieve high values. The comparative analysis of existing methods with implemented method is shown in Table 3.

Table 3. Comparative analysis of existing and implemented methods

Authors	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-measure (%)
Zubair *et al.* [19]	SUBXPCA and SPPCA	90.9	88.5	96.1	91.9
Jana and Mukherjee [21]	CNN	98.47	-	97.83	-
Prathaban and Balasubramanian [23]	3D OCNN	98.86	-	98.52	-
Jemal *et al.* [24]	CNN based FBCSP	90.9	84.7	96.1	-
Xu *et al.* [25]	GBDT	92.50	-	91.90	92.37
Proposed model	LSTM	99	98	99	98

4.3. Discussion

This section provides a discussion about the proposed LSTM method and compares those results with existing methods such as SUBXPCA and SPPCA [19], CNN [21], 3D OCNN [23], CNN based ilter bank common spatial pattern (FBCSP) [24], and GBDT [25]. The major aim of this study is to predict the epileptic seizure using EEG signals. Better classification results have been achieved using LSTM, and the implemented method reduces the false alarm rate and improves prediction accuracy. LSTM models are employed to classify the encrypted signals of EEG to achieve the principles of stability between time consumption and accuracy, trust, and classification accuracy of encrypted spectrogram EEG data. Experimental data show that the implemented method has better detection accuracy and a faster execution time. The dataset of EEG is employed as a benchmark dataset for epileptic seizure detection. Assuming that the deep LSTM model employed is intended to handle the complexity of the EEG input. The experiment was successful since it was able to accurately anticipate the patients' preictal states with a 99% accuracy rate. This model is more appropriate for real-time applications than others because it is based on feature extraction techniques that demand a high level of expertise and evaluation of epileptic seizures.

5. CONCLUSION

Deep learning has been used to develop a system for anticipating epileptic seizures. If seizure frequency and duration are correctly predicted, epilepsy patients can live a healthy and risk-free life. This experiment implemented a method for the prediction and detection of seizures with long short-term memory utilizing an EEG signal. The implemented method combines feature extraction and classification using LSTM to obtain more precision, accuracy, f1-measure, and recall compared to other methods. The LSTM model is employed to categorize the encoded EEG signals to achieve the principles of stability among time consumption, accuracy, trust, and categorization accuracy of encoded spectrogram EEG signals. This experiment detects seizures with a 99% accuracy rate. If epilepsy is identified, it is essential to help persons who are having seizures identify them, so they can take the appropriate precautions in advance. LSTM has the benefit of not having an overfitting issue because the top layer is fed with characteristics that can improve the features. The LSTM has multiplicative units, which are made up of different characteristics, that manage the data stream in the memory block, and multiplicative cells that are gathered from the temporal data. The experiment was successful since it was able to accurately anticipate the patients' preictal states with a 99% accuracy rate. When using deep learning algorithms for the extraction feature and/or classification, a large number of parameters must be learned. In the future, an advanced optimization technique will be used to improve seizure prediction performance.

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