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Epileptic Seizure Detection Using Deep Learning Based Long Short-Term Memory Networks and Time-Frequency Analysis: a Comparative Investigation in Machine Learning Paradigm

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HIGHLIGHTS

- A hybrid approach using time frequency analysis and deep learning for risk stratification of epileptic seizure is proposed.
- An extensive comparative study of various machine learning and feature selection techniques is conducted.
- Implemented andevaluatedthedeep learning based long short-term memory networks.

Abstract: Epilepsy is a noncontagious brain abnormality, which causes electrical distraction and strains the neural system. Generally, epilepsy is treated and diagnosed through continuous examination and interpretation of the electroencephalography (EEG) signals. This is a very time-consuming and tedious job. Further, it is subjected to observational errors and observer variability. Hence, the development of an efficient automatic alarm system to recognize epileptic seizure signals is of important concern. The objectives of the present study are to investigate deep learning based long short term memory (LSTM) networks for the classification of epileptic EEG signals using time-frequency analysis. Additionally, a comparative investigation is carried out to evaluate the various state-of-the-art feature selection and classification models for automatic classification of EEG signals for Epilepsy detection. Features based on statistics, entropy, and fractal were extracted from both the time domain and frequency domain. The extracted features were supplied to LSTM networks and traditional machine learning models for epileptic EEG classification. High classification accuracy of 100% (under hold out and 10-fold protocol) and 99.80% (under 10-fold protocol) is achieved by the proposed LSTM strategy followed by the Back Propagation Artificial Neural network (BPANN) which achieves 99.6% classification accuracy when all the 150 EEG biomarkers were used as input to the classifier under 10-fold cross-validation technique. Further, when the top 30 most relevant features selected by different feature selection techniques are used for classification, the proposed approach achieves similar performance followed by BPANN which reports 99.4% classification accuracy when combined with the Relief F feature selection technique.

Keywords: EEG; epileptic seizure; risk stratification; deep learning; long term short memory networks; machine learning.

INTRODUCTION

Epilepsy is the fourth most common neurological disruption which initiates abnormal excessive electrical discharge inside the brain of a patient causing a malfunction in the nervous system [1]. World Health Organization reported that approximately 50 million people of the world population suffer from this agonizing disease. The prime cause of Epilepsy may be brain impairment from prenatal or perinatal injuries, head infection due to severe injury, and strokes that restrict the oxygen supplies to the brain [2]. There are several imaging techniques like computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET) and single photon emission computed tomography (SPECT) that can be used to detect epilepsy and other brain-related functional anomaly. Though, these are costly procedures which require additional complex settings and medicine intervention. Some of them also suffers from lack of temporal resolution. Tracking of epileptic events efficiently with respect to the time is a prime diagnostic trait for its clinical evaluation.Therefore, the most typical and cost-effective modality to capture and characterize the complex brain signal is electroencephalography (EEG). The EEG possesses excellent temporal resolution hence become the most suitable modality for epilepsy detection. Continuous examination and interpretation of the EEG signals can be a time-consuming and tedious job for clinicians. Hence a precise automatic alarm system is required for the long-term investigation and treatment of an epileptic patient. Recent studies based on modern computational approaches have proved their significance in detecting diseases and disorders related to human body organs. The various machine learning and deep learning techniques were involved not only for screening complex structural and functional deficiencies e.g., breast cancer, brain anomalies, but also track and assist human being to perform daily-life movement-related activities in case they are bed-ridden [3, 4, 5, 6]. This article investigates long short-term memory (LSTM) deep learning networks for the classification of epileptic EEG signals using time-frequency features. Different feature selection techniques are implemented and evaluated to determine relevant EEG biomarkers which can be used for the identification of Epilepsy. Further, we implement and evaluate the various state-of-the-art classification models for automatic classification of EEG signals for Epilepsy detection.

Related Work

In this subsection, research work concern to epileptic EEG database from the University of Bonn is discussed. The database used in this work consists of five sets (Set A-E) of EEG signals. Set A and B were related to the normal subject's EEG signals. On the other handset C, D and E were related to epileptic patient's EEG signals [7]. More information about this database is available in a later subsection.

Bhardwaj and coauthors, (2016) [8] reported a unique technique for epileptic detection using genetic programming. In this study, EEG data were decomposed with empirical mode decomposition, and constructive genetic programming (CGP), standard genetic programming (ST-GP), and semantic search based genetic programming (SEM-GP) was used as a classifier. CGP showed better performance than other classifiers. Feature selection technique based on epileptic seizure detection is reported in [9]. Firstly, Haar, Daubechies, Bi-orthogonal, and Coiflet discrete wavelet coefficients were extracted from EEG signals. Wavelet-based statistical, fractal, and entropy features were then calculated. Fisher score, Relief F, and information gain were used for feature selection followed by classification using least squares-Support vector machine (SVM). A simple random sampling with a sequential feature selection approach for epileptic EEG signal classification is proposed in [10]. Max, Min, Mean, Median, Mode, first quartile, second quartile, range, and standard deviation were statistical features extracted in this study. Classification accuracy of 99.90% was achieved to distinguish set A vs set E. Kabir and coauthors (2016) [11] reported epileptic seizure identification using the Optimum Allocation Technique (OAT). Statistical features were extracted after reducing the segment size using OAT. Logistic Model Trees (LMT), Multinomial Logistic Regression (MLR) with ridge estimator, and SVM were used as a classifier. The performance of the LMT classifier is found to be higher than the other two classifiers achieving 95.33 % accuracy. Zamir, (2016) [12] has reported Linear

Least Squares Processing (LLSP) based feature extraction technique for classification of seizure from EEG signals. Author found logistic regression, IB1, IB5, and decision tree with J48 algorithm as efficient classifiers according to the assessment of performance. A weighted complex networks based community structure identification of epileptic and nonepileptic signals was reported in [13]. Eight different combinations were made to classify in this study. Weighted complex network and statistical methods based attributes were calculated. Least Square SVM (LS-SVM), k-means, Naïve Bayes, and k -nearest neighbor classifier were utilized for classification. In their work, the LS-SVM classifier achieved the highest average accuracy of 98%. Sharma and coauthors [14] reported epileptic seizure detection using Analytic Time-Frequency Flexible Wavelet Transform (ATFFWT) with Higuchi algorithm based fractal dimension estimation. Here also, eight different group-wise classification problems were formed. Fractal dimension based 17 features were extracted and three features were selected using the student t-test. The LS-SVM with RBF kernel was used as a classifier. They reported classification accuracy of 100% for three classification problem groups.

Mutlu, (2018) [15] has proposed simple Hilbert vibration decomposition based detection of an epileptic seizure. LS-SVM with linear, polynomial, and RBF kernel were used as a classifier. The best classification accuracy of 97.66% was achieved by SVM with the RBF kernel. Lahmiri, (2018) [16] has reported an estimation technique for the classification of healthy and epileptic patients using Generalized Hurst Exponent (GHE). They tested the significance of Hurst Exponent using the Kruskal-Wallis test, Wilcoxon test, and student t-test. Statistical features, Hurst exponent demonstrated good ability to distinguish between control subjects and epileptic patient's EEG signal. Automatic epileptic seizure detection and prediction system are reported in [17]. In this work, EEG signals were preprocessed and decomposed with Multiscale Principal Component Analysis (MSPCA), Empirical Mode Decomposition (EMD), Discrete Wavelet Transform (DWT), and Wavelet Packet Decomposition (WPD). Features such as the mean, average power, and standard deviation of the coefficients, the ratio of absolute mean values, skewness, and kurtosis were extracted for classification. Epileptic seizure classification using 4096 sample points of EEG and LSTM networks is proposed in [18]. An average test accuracy of 91.25% was achieved by them with an area under receiver operating characteristics (AUC) of 0.9582. Subasi and coauthors [19] reported a comparative investigation of hybrid SVM based epileptic seizure classification techniques. In their work, DWT based features like mean, average power, standard deviation, and the ratio of absolute mean values were extracted from detail and approximation coefficients. Particle swarm optimization (PSO) and genetic algorithm (GA) based features selection techniques were combined with the SVM classifier. Classification accuracy of 99.38% was achieved with PSO based hybrid SVM. Akyol, (2020) [20] has proposed a stacking ensemble based deep neural network (DNN) based epileptic seizure identification technique. In this, input features set were normalized and 10-fold cross-validation was used for training and test data set reservation. They achieved an average classification accuracy of 97.17%. EEG classification for detection of Epileptic Seizures using locality preserving projections based feature selection was proposed by [21]. Classification precision of 98.5% is reported in differentiating interictal and ictal EEG signals. In another work, hybrid multi-class SVM is proposed for recognizing epilepsy and an accuracy of 96.5% was reported [22]. Fuzzy classifiers based epileptic seizure detection approaches were proposed in [23]. In this work, DWT based temporal and spatial features were extracted from EEG signals. For inter-ictal and ictal EEG signals classification, the highest accuracy of 99.38% was reported using the fuzzy rough nearest neighbor (FRNN). A new feature generation method based on 1D octal pattern for the classification of epileptic seizure is proposed by Tuncer and coauthors in [24]. For selecting EEG features, neighborhood component analysis was used and KNN did the classification. This study reported an accuracy of 96%.

In summary, techniques such as SVM, KNN, CGP, decision tree, ensemble classifier, naïve Bayes, and ANN have been used for classification. However, a systematic study for the evaluation of various machine learning components is missing. In particular, feature extraction, feature selection, and classifications which are important components of risk stratification in machine learning paradigm need further investigation. Choice of appropriate machine learning models plays a critical role in Epileptic seizure classification. Further, a more extensive study is required to determine relevant biomarkers for the identification and quantification of epilepsy from EEG signals. Current developments on deep learning based approaches have gained wide attention in data classification problems including their incorporation in computer-aided disease diagnosis/classification. However, popular deep learning models such as convolutional neural network (CNN) use very intricate networks and need a large number of samples for training to achieve superior performance which may not be clinically feasible. This article proposes a deep learning based long short-term memory network and time-frequency analysis for the classification of epileptic EEG signals. On contrary to other approaches, LSTM networks are capable of learning long-term dependencies making them widely accepted in a wide variety of problems. The contributions of this article are summarized in the following sub-section.

Contributions of the paper

The contributions of this study are briefed out as follows:

1. An extensive comparative study of various feature selection techniques and 23 machine learning paradigms for risk stratification of epileptic seizure using EEG is carried out and discussed.
2. We implement and evaluate deep learning based long short-term memory networks and time-frequency analysis for classification of epileptic EEG signals using EEG features. The results obtained are compared with those obtained in 1.
3. Combination of statistical and DWT based composite features is utilized. Different feature combinations are evaluated for determining the most relevant biomarkers which can be used to identify Epilepsy from EEG signals.
4. The proposed models are evaluated under different data division protocols so that the best machine learning model can be selected.

The rest of the article is organized in the following sections. The material and methods section presents the data description, feature extraction, feature selection, and proposed methodology used in the present work. Further, the next section presents the results and discussions and at the end conclusions and future scopes are presented.

MATERIAL AND METHODS

Data Description and Preprocessing

An open-source EEG database is used in this study, which has been collected from the University of Bonn, Germany. This database has five sets (sets A-E) with each data set containing 23.6 seconds long 100 single-channel EEG segments. The artifacts due to muscular activities and eye movements were removed during the selection of segments from recorded EEG signals. Five healthy control subjects and five patients were volunteers for this database. The set A and B were taken from healthy control subjects with eyes open and eyes closed situation respectively. The rest set of the database was taken from the epileptic patients. EEG data segments of set C were collected from the hippocampal formation of the opposite hemisphere of the brain. The set D contains the segmented EEG signals within the epileptogenic zone. The EEG segments of sets C and D were taken during no ictal activities. The segments of set E were taken from all recording sites during ictal activities which exhibit epileptic seizure. This database was recorded using a 128 channel amplifier system with a 12-bit analog to digital converter. The sampling rate of the data acquisition system was set to 173.61 Hz. A band-pass filter of 0.53-40Hz was used for preprocessing of this open-source database. A detailed discussion of this database is available in Andrzejak and coauthors [7].

Feature Extraction

Feature extraction provides a better solution to distinguish classes. In the present work, both time domain and frequency domain features are extracted. Eleven statistical features are calculated such as mean, kurtosis, skewness, entropy, variance, standard deviation, min, max, range, crest factor, and form factor. Two fractal features are also acquired using the Katz algorithm and the Higuchi algorithm. Complexity measuring features such as Approximate Entropy (ApEn) and Permutation Entropy are also determined. These fifteen features are extracted from all 500 segments (100 segments from each set). Each segment has 4097 discrete values in the time domain. Many researchers in this field also reported that DWT based features, which have shown significant improvement in classification [9, 14, 25]. Hence nine different DWT are studied in this work. The third level wavelet decomposition is performed using nine wavelet functions such as Daubechies (db4), Biorthogonal (bior3.1 and bior3.2), Coiflets (Coif1, Coif2, Coilf3, Coif4, and Coif5), and Haar. The third level decomposition of EEG signal generates approximation and detailed coefficients. Further, from the generated approximation coefficients, the same fifteen features mentioned above are calculated. Table 1 shows the feature category and name of all features with their corresponding notation for the present work. Thus in the present work, a total of 150 features have been extracted using without DWT and with DWT.

Table 1. Concise table of features extracted from preprocessed EEG signals

Feature title	Feature Category									
	Without wavelet	With wavelet (3rd level approximate coefficient)								
		db4	bior 3.1	bior 3.2	Coif 1	Coif 2	Coif 3	Coif 4	Coif 5	Haar
Mean	F1	F16	F31	F46	F61	F76	F91	F106	F121	F136
Kurtosis	F2	F17	F32	F47	F62	F77	F92	F107	F122	F137
Skewness	F3	F18	F33	F48	F63	F78	F93	F108	F123	F138
Entropy	F4	F19	F34	F49	F64	F79	F94	F109	F124	F139
Variance	F5	F20	F35	F50	F65	F80	F95	F110	F125	F140
StD[1]	F6	F21	F36	F51	F66	F81	F96	F111	F126	F141
Min	F7	F22	F37	F52	F67	F82	F97	F112	F127	F142
Max	F8	F23	F38	F53	F68	F83	F98	F113	F128	F143
Range	F9	F24	F39	F54	F69	F84	F99	F114	F129	F144
Crest factor	F10	F25	F40	F55	F70	F85	F100	F115	F130	F145
Form factor	F11	F26	F41	F56	F71	F86	F101	F116	F131	F146
Katz FD[2]	F12	F27	F42	F57	F72	F87	F102	F117	F132	F147
ApEn[3]	F13	F28	F43	F58	F73	F88	F103	F118	F133	F148
Higuchi FD[2]	F14	F29	F44	F59	F74	F89	F104	F119	F134	F149
PermutationEn[3]	F15	F30	F45	F60	F75	F90	F105	F120	F135	F150

[1]StD=Standard Deviation;[2]FD=Fractal Dimension; [3]En=Entropy

Feature Selection

The next task after feature extraction is feature selection. The feature selection process helps to identify the most relevant features from a large number of attributes. It reduces the computation complexity as well as improves or maintains the performance of the classification technique. Feature ranking and feature subset evaluation are the two most popular techniques of feature selection. They are also known as filter method and wrapper method respectively. In the filter method, each feature is evaluated according to its prediction performance on the target class. On the other hand, the wrapper evaluates the subset of features and selects the best subset from all generated subsets. Feature selection using filter-based approaches is faster than wrapper approaches, which suffer from high computational costs. In the present work, six different feature ranking selection techniques, namely Gain Ratio (GR), Information Gain (IG), one R (1R), Correlation (P), Relief F (RLF), Symmetrical Uncertainty (SU) were employed to select 30 most relevant features. The performances of these feature ranking techniques have been elaborated in the results and discussions section. Further, we also evaluate a hybrid feature selection technique by combining the mentioned six filter based techniques using the concept of Robust Rank Aggregation [26]. In this method, six different feature selection techniques are integrated in an unbiased manner to determine the final rank of individual features. This is illustrated in figure 1. In this method, the extracted 150 features from EEG signals are supplied to 6 different feature selection modules. Each module generates a list of 150 ranked features. The ranked features by six different feature selection techniques are then combined to determine the final rank.

Classification

This subsection presents brief information about classifiers used in the present work. The proposed methodology and performance evaluation is also discussed.

Back-Propagation Artificial Neural Network (BPANN)

BPANN is the simplest type of multilayer Artificial Neural Network, which has one input layer, several hidden layers, and one output layer [27]. The learning rule for back-propagation is based on gradient descent. In this network, the weights are initialized with a random value which is changed during the training process. In the present work, Mean Squared Error (MSE) is used as a performance function, and Scaled Conjugate Gradient (SCG) Back Propagation (BP) is used as a training function. A total of thirty neurons are placed in the hidden layer. The initial learning rate is set to 0.01.

Decision Trees

Decision trees are one of the fastest and simple classifiers. It contains branches and two types of nodes namely root node and leaf node. The prediction of response is done using split criterion in the root node and finally, the branches reach the leaf node by following the decision in the root node [28]. In the present work, three different types of decision trees are utilized for classification namely simple, medium, and complex tree with maximum numbers of splits 4, 20, and 100 respectively.

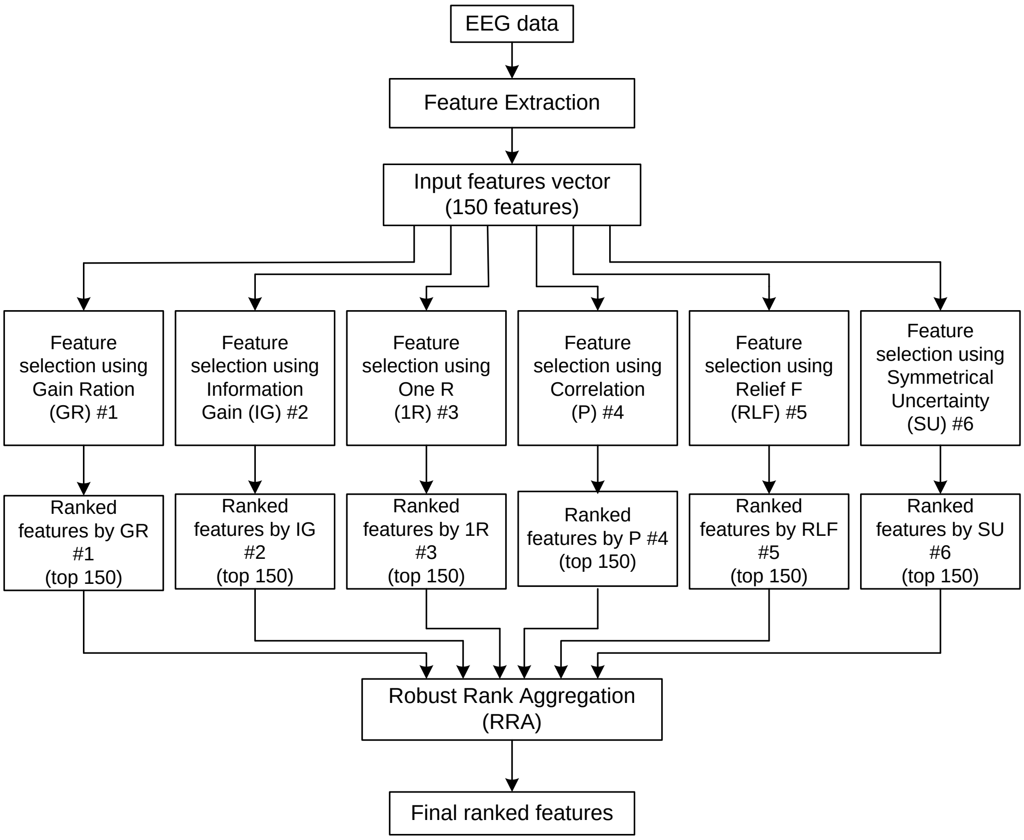

Figure 1. Hybrid feature ranking scheme using Robust Rank Aggregation (RRA)

Discriminant Analysis

In this classification technique, the Gaussian distribution related parameters of each class are estimated using some fitting function and a priori probabilities of the belonging of class [29]. In the present work, both linear and quadratic discriminant classifiers are analyzed which create linear and nonlinear boundaries between classes respectively.

Logistic regression

It is a binary classification technique based on the sigmoid function [30]. A threshold level is defined and based on this threshold level, the class of predictors is decided. This multivariate analysis model estimates the presence and absence of characteristics of different classes based on predictor variables [31].

Support Vector Machine (SVM)

The SVM is the most popular supervised machine learning technique in the field of classification, regression, and estimation. In this technique, the machine learns several hyperplanes using training data set that separates one class from another. The highest margin maintaining hyperplane from members of one class to that of another is selected as the best hyperplane for classification [32]. In SVM classifier, the kernel function maps the input to the desired dimensional space [33]. In this work, several SVM with different kernel functions are used for classification namely linear SVM, quadratic SVM, cubic SVM, fine Gaussian SVM, medium Gaussian SVM, and coarse Gaussian SVM. Table 2 shows the parameters used for different SVM classifiers.

k-nearest neighbor (kNN)

K-nearest neighbor is another machine learning technique that performs classification tasks using some distance measure from the nearest sample (K denotes the number of neighbors). Euclidean distance, Chebyshev distance, Manhattan distance are some common distance measures used in the k-nearest neighbor classification technique [34]. In this work, the value of k is set to k=1, 10, and 100 with different distance measures such as Euclidean, cosine, cubic, and weighted for binary classification. This results in different K-NN types based on the number of neighbors and distance measures used namely, fine K-NN (K=1, distance metric: Euclidean), medium K-NN (K=10, distance metric: Euclidean), coarse K-NN (K=100,distance metric: Euclidean), cosine K-NN (K=10, distance metric: cosine), cubic K-NN (K=10, distance metric: Minkowski (cubic)) and weighted K-NN (K=10, distance metric: Euclidean with squared inverse distance weight).

Table 2.Different types of SVM and the parameters used in this study

Type of classification method	Kernel type	Description
Linear SVM	Linear kernel	$k(x_i, x_j) = (x_i \,.\, x_j)$
Quadratic SVM	Polynomial kernel	$k(x_i, x_j) = (1 + x_i \,.\, x_j)^2$
Cubic SVM	Polynomial kernel	$k(x_i, x_j) = (1 + x_i \,.\, x_j)^3$
Fine Gaussian SVM	Gaussian Radial Basis Function	$k(x_i, x_j) = \exp\left(-\frac{\|\|x_i - x_j\|\|^2}{2\sigma^2}\right), \sigma = 0.75$
Medium Gaussian SVM	Gaussian Radial Basis Function	$k(x_i, x_j) = \exp\left(-\frac{\|\|x_i - x_j\|\|^2}{2\sigma^2}\right), \sigma = 3$
Course Gaussian SVM	Gaussian Radial Basis Function	$k(x_i, x_j) = \exp\left(-\frac{\|\|x_i - x_j\|\|^2}{2\sigma^2}\right), \sigma = 12$

Ensemble Classifiers

Ensemble classifiers are the combination of more than one classifier. Random forest, AdaBoost, bagging, and Rotation Forest are some techniques for generating the Ensemble classifiers [35]. In this study, ensemble classifiers based on bagging, discriminant learner, nearest neighbor, and RUSBoost are used in this classifier group to evaluate the classification model.

Proposed methodology

An LSTM network is a kind of recurrent neural network (RNN) that can gain knowledge of long-term dependencies among time steps of sequence data. It includes self-loops to create paths where the gradient can flow for a prolonged period [36]. The proposed model using the LSTM network and time-frequency analysis of EEG signals for epilepsy detection is shown in figure 2. In LSTM network, the input is in form of several data points, time steps, or variables. Thus feature extraction step is first carried out as shown in figure 2. Both time and frequency domain features are extracted in this step. Firstly, fifteen time-domain statistical, fractal, and entropy based features namely mean kurtosis, skewness, entropy, variance, standard deviation, min, max, range, crest factor, form factor, Katz algorithm based fractal feature, Higuchi algorithm based fractal feature, approximate entropy, and permutation entropy are extracted from each segment. Further, each EEG segment is subjected to third-level wavelet decomposition resulting in approximate and detailed coefficients A3 and D3 for each EEG segment. The same fifteen features (statistical, fractal, and entropy based features) are extracted from approximate coefficients A3 of each EEG segment. The wavelet based feature extraction process is performed using nine wavelet functions namely Daubechies (db4), Biorthogonal (bior3.1 and bior3.2), Coiflets (Coif1, Coif2, Coilf3, Coif4, and Coif5), and Haar one after another. Hence, fifteen frequency domain features (statistical, fractal, and entropy based features) from nine different wavelet functions are extracted.

The time-domain and frequency-domain are fused. Thus, in the present work, a total of 150 features have been extracted resulting in a feature vector of size 500 x 150 followed by feature selection as discussed in feature extraction and feature selection subsection respectively. The feature selection stage generates top 30 most relevant features resulting in a feature vector of size 500 x 30. The extracted/selected features are supplied to LSTM networks which are utilized for learning the high-level representations of the epileptic and non-epileptic EEG signals. In this study, a bidirectional LSTM layer is employed because it looks at the sequence in both forward and backward directions. The total number of hidden units used are set to 250.

The details of conventional LSTM can be found in [37]. The output of LSTM layer is supplied to a fully connected layer which multiplies the extracted variables by a weight matrix followed by bias addition. A softmax function is then applied to the input and a classification layer returns an output category of supplied EEG signal i. e. epileptic or non-epileptic. The maximum numbers of epochs were set to 50 and initial learning rate of 0.01 is used in experiments.

The proposed prototype model for risk stratification of epileptic seizure using EEG signals and comparative investigation strategy is shown in figure 3. The proposed model is divided into two main parts as shown by a vertical discontinuous line. The left side of the model is depicted as an offline system and the right side of the model represents the online system. Both systems in the proposed model have two similar processes i.e. preprocessing and feature extraction. In offline systems, a total of 150 statistical and wavelet-based features are extracted. The next consecutive process after feature extraction in the offline system is feature selection which is used here to rank the relevant attributes in ascending order.

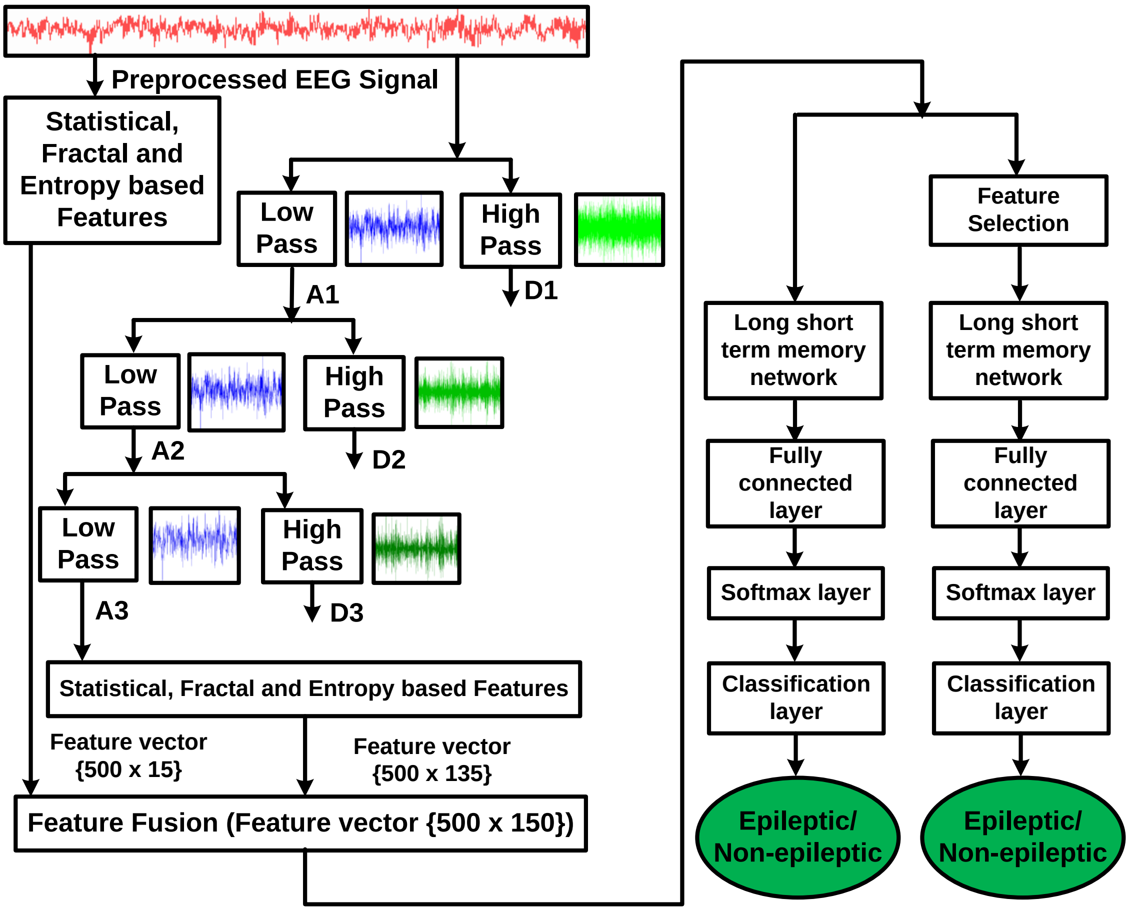

Figure 2. Proposed classification scheme using time-frequency analysis and classification using LSTM network.

The top 30 features are selected for the training of the classifier by using the known class to supervise the model and training parameters were generated. In an online system, the unknown EEG signals without class labels are preprocessed to remove the artifacts and noises which is a similar process as in an offline system. The next step is to extract the top 30 features selected in the offline process as relevant attributes. The trained classifier then takes the live decision as a normal control or epileptic seizure for the supplied unknown EEG test sample. An extensive comparative study of various feature selection techniques, 23 machine learning paradigms, and LSTM network for risk stratification of epileptic seizure using EEG is carried out and discussed.

Performance evaluation

In the present work, two Cross-Validation techniques namely Holdout and k-fold are utilized for performance evaluation. For performance evaluation of different classifiers, the whole sample of data is partitioned using K-fold data division protocol into two parts namely training and testing set. In this protocol whole set is divided into K subsets. (K-1) subsets are used as training sets and the remaining one set is used

for testing of the trained model. This testing process is repeated K times. Each subset is used as a testing set once in a K-fold Cross-Validation (CV) process. To compare the performance of different classifiers, five statistical parameters are evaluated namely classification accuracy, sensitivity, specificity, Area Under the receiver operating characteristic curve (AUC), and Matthew's Correlation Coefficient (MCC). These performance measures can be explained and mathematically expressed as below:
Classification Accuracy (CA): It is a statistical measure that shows the percentage of test cases correctly classified out of the total number of cases.

$$CA(\%) = \frac{\delta_{tp}+\delta_{tn}}{\delta_{tp}+\delta_{fn}+\delta_{tn}+\delta_{fp}} \times 100 \quad (1)$$

Sensitivity: It is a statistical measure that shows that the total percentage of positive cases (detection of epileptic seizure signal) is correctly classified.

$$Sensitivity(\%) = \frac{\delta_{tp}}{\delta_{tp}+\delta_{fn}} \times 100 \quad (2)$$

Specificity: It is a statistical measure that shows that the total percentage of negative cases (detection of non-epileptic signal) is correctly classified.

$$Specificity(\%) = \frac{\delta_{tn}}{\delta_{tn}+\delta_{fp}} \times 100 \quad (3)$$

Area Under the receiver operating characteristic curve (AUC): It is a statistical measure that shows average measure using a combination of sensitivity and specificity.

$$AUC(\%) = \frac{1}{2}\left(\frac{\delta_{tp}}{\delta_{tp}+\delta_{fn}} + \frac{\delta_{tn}}{\delta_{tn}+\delta_{fp}}\right) \times 100 \quad (4)$$

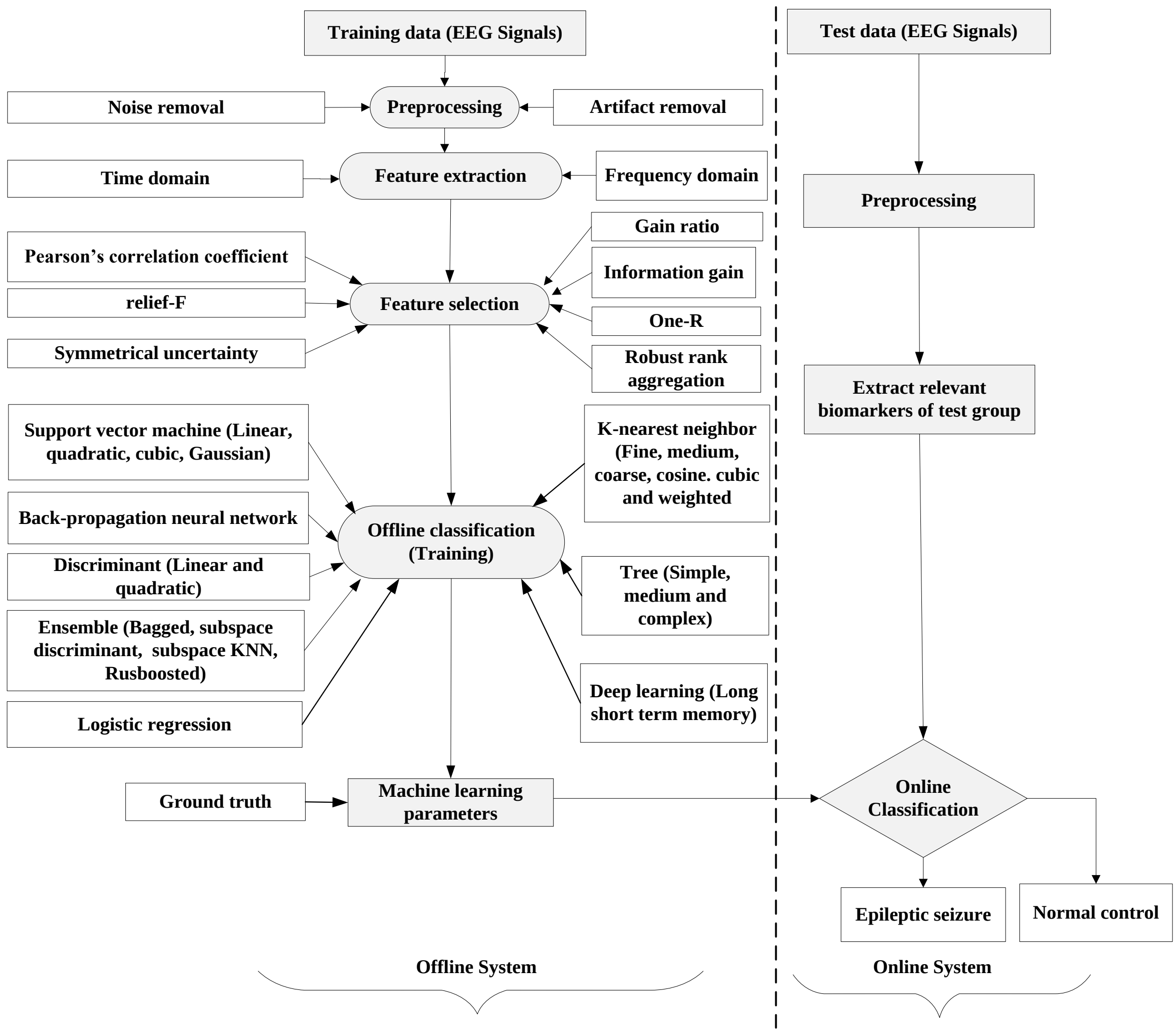

Figure 3. Proposed methodology for comparative investigation of different machine learning models and LSTM.

Matthew's Correlation Coefficient (MCC): This statistical measure was introduced by biochemist Brian W. Matthews in 1975. It is very useful when the two classes i.e. positive and negative are different in size.

$$MCC(\%) = \frac{\delta_{tp}\times\delta_{tn}-\delta_{fp}\times\delta_{fn}}{\sqrt{(\delta_{tp}+\delta_{fp})(\delta_{tp}+\delta_{fn})(\delta_{tn}+\delta_{fp})(\delta_{tn}+\delta_{fn})}}\times 100 \quad (5)$$

The symbol δ with subscript TP, TN, FP, and FN denotes true positive, true negative, false positive, and false negative respectively. MATLAB® software platform has been used to evaluate the performance of all classifiers.

Statistical significance analysis

Statistical significance analysis provides evidence of sufficient difference among the extracted features corresponding to different groups [38]. There are two types of statistical significance analysis tests namely parametric test and Non-parametric test. In this study, we have used the Independent sample t-test at a 95% confidence interval. The significance value (p-value) of less than 0.05 is considered to be significant.

RESULTS AND DISCUSSIONS

This section presents the results of various experiments discussed in the material and methods section. Initially, a comparative investigation of various feature selection and traditional machine learning techniques for epileptic seizure detection under different data division protocols is presented and discussed. Then we present and discuss the results of the proposed LSTM strategy. The results are also discussed in light of other related studies. Table 3 illustrates the results of attribute selection techniques. In the present work, six filter based attributes ranking techniques are chosen for the study along with one hybrid method called robust rank aggregation (RRA). Out of 150 attributes, the top 30 prime attributes with their ranking order are tabulated in Table 3. It is clearly shown that the ranking order of attributes is not similar for all feature selection techniques. For example, feature F5 is ranked in the first position by SU feature selection, second position by GR and 1R feature selection, third position by IG feature selection, and eighth position by RRA. F5 is not ranked in the top 30 positions by Relief F and correlation feature selection. Thus, the study and evaluation of different feature selection techniques are extremely important to determine the most important biomarkers. It is found that the features F6 and F5 both are the most important features, selected very often in the top 5 features by the majority of feature selection techniques like Gain Ratio (GR), Information Gain (IG), One R (1R), and Symmetrical Uncertainty (SU). The selected top 30 features from each attribute selection technique are utilized for epileptic seizure detection from EEG signals using machine learning approaches. It is also perceived from Table 3 that all the feature selection techniques select the F6, F21, F66, F81, F96, F111, F126, and F141 features in the top 30 features accordingly, these 8 features can be considered as most relevant biomarkers.

Table 3.Prime features selected by different attribute selection techniques

Method	Prime attributes
Gain Ratio (GR)	F6, F5, F65, F21, F20, F80, F111, F110, F125, F81, F66, F126, F95, F96, F141, F24, F140, F114, F99, F144, F84, F129, F143, F98, F128, F68, F36, F35, F23, F69
Information Gain (IG)	F6, F125, F5, F21, F36, F95, F35, F81, F20, F80, F126, F110, F96, F111, F51, F66, F65, F140, F141, F50, F39, F127, F22, F54, F9, F112, F67, F12, F97, F82
One R (1R)	F6, F5, F20, F65, F66, F21, F81, F80, F96, F95, F125, F126, F110, F111, F140, F141, F127, F22, F112, F39, F7, F50, F97, F144, F82, F51, F37, F69, F67, F84
Correlation (P)	F96, F81, F111, F51, F21, F126, F66, F6, F141, F36, F12, F9, F39, F54, F22, F112, F69, F99, F82, F97, F114, F24, F84, F52, F129, F67, F7, F144, F37, F38
Relief F (RLF)	F6, F81, F21, F96, F111, F51, F141, F66, F126, F36, F9, F7, F69, F144, F99, F54, F12, F84, F24, F39, F114, F129, F22, F52, F8, F112, F82, F38, F67, F119
Symmetrical Uncertainty (SU)	F5, F6, F65, F126, F21, F20, F111, F81, F125, F80, F110, F96, F66, F95, F141, F140, F24, F114, F36, F84, F99, F35, F144, F129, F51, F50, F143, F98, F128, F68
Robust Rank Aggregation (RRA)	F6, F21, F81, F126, F96, F111, F66, F5, F141, F36, F51, F69, F7, F20, F99, F9, F144, F84, F80, F65, F112, F114, F125, F129, F24, F97, F39, F12, F22, F8

Table 4 shows the performance of twenty-three different classifier models employing all the 150 features extracted along with a 10-fold cross-validation data division technique. It is found that the classification accuracy of 99.60% (see Table 4) is achieved by BPANN without using any feature selection technique. Table 5 shows the performance of twenty-three different classifier models with top thirty features obtaining from six different feature ranking techniques namely Gain Ratio (GR), Information Gain (IG), One R (1 R), Correlation (P), Relief F (RLF), Symmetrical Uncertainty (SU) respectively and RRA using 10-fold cross-validation protocol.

Table 4. Performance parameters of classifier models using 10-fold cross-validation for 150 features

Classifier Model	**Statistical parameter (%)**				
	Accuracy	**Sensitivity**	**Specificity**	**AUC**	**MCC**
BPANN	**99.60**	98.00	100.00	99.00	98.75
Complex TREE	97.20	90.00	99.00	94.50	91.12
Medium TREE	97.20	90.00	99.00	94.50	91.12
Simple TREE	97.20	90.00	99.00	94.50	91.12
Linear Discriminant	94.80	78.00	99.00	88.50	83.18
Quadratic Discriminant	96.60	92.00	97.75	94.88	89.42
Logistic Regression	94.20	76.00	98.75	87.38	81.15
Linear SVM	96.20	85.00	99.00	92.00	87.84
Quadratic SVM	97.20	90.00	99.00	94.50	91.12
Cubic SVM	97.80	94.00	98.75	96.38	93.10
Fine Gaussian SVM	82.60	13.00	100.00	56.50	32.68
Medium Gaussian SVM	97.60	95.00	98.25	96.63	92.56
Coarse Gaussian SVM	95.00	78.00	99.25	88.63	83.86
Fine KNN	97.20	90.00	99.00	94.50	91.12
Medium KNN	95.80	82.00	99.25	90.63	86.52
Coarse KNN	90.80	56.00	99.50	77.75	69.33
Cosine KNN	97.60	90.00	99.50	94.75	92.39
Cubic KNN	95.40	80.00	99.25	89.63	85.20
Weighted KNN	96.20	85.00	99.00	92.00	87.84
Ensemble Bagged	98.00	93.00	99.25	96.13	93.69
Ensemble Subspace Discriminant	97.80	91.00	99.50	95.25	93.03
Ensemble Subspace KNN	97.00	94.00	97.75	95.88	90.74
Ensemble RUSBoosted	98.40	97.00	98.75	97.88	95.04

Table 5. Performance of classifier models using Gain Ratio (GR), Information Gain (IG), 1R, Correlation (P), Relief F (RLF) and Symmetrical Uncertainty (SU) feature selection with 10-fold cross validation for top 30 attributes

Classifier Model	**Classification Accuracy (%)**						
	GR	**IG**	**1R**	**P**	**RLF**	**SU**	**RRA**
BPANN	**98.80**	98.40	**98.00**	**98.80**	**99.40**	**99.00**	**98.60**
Complex TREE	95.80	98.40	97.20	98.00	98.80	97.00	97.60
Medium TREE	95.80	98.40	97.20	98.00	98.80	97.00	97.60
Simple TREE	96.60	**98.60**	97.40	98.00	98.80	97.80	98.40
Linear Discriminant	93.80	93.60	93.60	94.40	94.60	93.80	94.40
Quadratic Discriminant	95.00	96.00	96.20	96.20	96.00	95.00	95.80
Logistic Regression	95.80	96.40	95.40	96.80	96.20	96.00	96.40
Linear SVM	95.60	96.60	96.20	96.20	97.20	95.60	96.00
Quadratic SVM	97.20	96.80	96.80	96.40	97.60	97.00	96.00
Cubic SVM	97.60	96.80	97.40	97.00	98.00	97.60	97.00
Fine Gaussian SVM	96.40	97.20	96.60	97.20	96.60	97.80	97.40
Medium Gaussian SVM	95.80	97.00	96.40	97.00	97.80	96.60	97.00
Coarse Gaussian SVM	94.40	94.80	95.00	95.00	95.40	94.20	94.60
Fine KNN	95.80	97.60	96.40	96.80	97.20	96.60	96.80
Medium KNN	97.00	97.40	97.20	97.40	97.60	97.40	97.20
Coarse KNN	92.60	93.00	92.60	92.80	93.20	92.40	92.60
Cosine KNN	97.60	97.20	97.00	97.20	97.80	97.60	97.20
Cubic KNN	96.40	97.40	96.80	97.20	97.60	97.20	97.20
Weighted KNN	96.40	97.20	97.20	97.40	97.80	97.40	97.20
Ensemble Bagged	96.60	97.20	96.80	97.20	98.60	97.40	97.60
Ensemble Subspace Discriminant	96.20	96.80	96.00	94.00	94.40	96.40	96.40
Ensemble Subspace KNN	96.60	97.20	96.60	96.20	96.20	97.60	95.40
Ensemble RUSBoosted	96.00	97.20	97.20	97.60	98.40	97.60	98.00

It was found that the RLF feature selection technique outperforms others by achieving the highest classification accuracy of 99.40% using BPANN classifier. Due to superior performance of RLF feature selection, the features selected by RLF i.e., F6, F81, F21, F96, F111, F51, F141, F66, F126, F36, F9, F7, F69, F144, F99, F54, F12, F84, F24, F39, F114, F129, F22, F52, F8, F112, F82, F38, F67, and F119 are further used in remaining of the study. We further validated the discriminating efficacy of the above features with the statistical significance analysis using independent sample t-test. Table 6 shows statistical significance analysis results for the top 30 features selected by the RLF feature selection technique. We found that all the 30 features are statistically significant with a p-value less than 0.05 (95% confidence interval).

Table 6. Mean ± standard deviation values and p-value for top 30 features selected by Relief F method using t-test

Feature	Title of Feature	Feature category	Non epileptic	Epileptic	p-value (t-test)
F6	StD[1]	Without Wavelet	54.574 ± 33.375	306.610 ± 147.977	<0.05
F81	StD[1]	Coif 2 Wavelet	136.203 ± 90.633	729.184 ± 329.986	<0.05
F21	StD[1]	db4 Wavelet	136.157 ± 90.826	729.208 ± 330.474	<0.05
F96	StD[1]	Coif 3 Wavelet	136.375 ± 90.471	730.092 ± 330.129	<0.05
F111	StD[1]	Coif 4 Wavelet	136.649 ± 90.382	730.621 ± 331.155	<0.05
F51	StD[1]	bior 3.2 Wavelet	196.498 ± 118.013	1143.077 ± 555.808	<0.05
F141	StD[1]	Haar Wavelet	131.110 ± 88.718	683.711 ± 308.305	<0.05
F66	StD[1]	Coif 1 Wavelet	134.819 ± 90.332	716.884 ± 323.974	<0.05
F126	StD[1]	Coif 5 Wavelet	136.468 ± 90.150	731.408 ± 332.858	<0.05
F36	StD[1]	bior 3.1 Wavelet	201.257 ± 117.405	1202.329 ± 610.692	<0.05
F9	Range	Without Wavelet	400.418 ± 233.248	1858.960 ± 868.355	<0.05
F7	Min	Without Wavelet	-205.945 ± 101.040	-948.910 ± 503.488	<0.05
F69	Range	Coif 1 Wavelet	882.290 ± 552.511	3647.675 ± 1632.654	<0.05
F144	Range	Haar Wavelet	857.653 ± 539.826	3581.980 ± 1676.918	<0.05
F99	Range	Coif 3 Wavelet	897.410 ± 562.214	3728.136 ± 1688.663	<0.05
F54	Range	bior 3.2 Wavelet	1305.559 ± 812.797	6271.412 ± 3051.622	<0.05
F12	Katz FD[2]	Without Wavelet	1.418 ± 0.126	2.001 ± 0.300	<0.05
F84	Range	Coif 2 Wavelet	897.649 ± 558.697	3733.122 ± 1707.020	<0.05
F24	Range	db4 Wavelet	893.136 ± 554.148	3742.190 ± 1725.102	<0.05
F39	Range	bior 3.1 Wavelet	1342.128 ± 817.821	6832.527 ± 3446.937	<0.05
F114	Range	Coif 4 Wavelet	902.941 ± 560.472	3745.340 ± 1710.224	<0.05
F129	Range	Coif 5 Wavelet	899.495 ± 562.766	3748.610 ± 1725.480	<0.05
F22	Min	db4 Wavelet	-464.240 ± 234.065	-1918.140 ± 914.141	<0.05
F52	Min	bior 3.2 Wavelet	-668.595 ± 357.692	-3172.909 ± 1668.122	<0.05
F8	Max	Without Wavelet	194.472 ± 159.614	910.050 ± 440.926	<0.05
F112	Min	Coif 4 Wavelet	-468.460 ± 232.153	-1913.124 ± 912.996	<0.05
F82	Min	Coif 2 Wavelet	-465.474 ± 230.820	-1906.426 ± 927.025	<0.05
F38	Max	bior 3.1 Wavelet	653.116 ± 559.209	3406.175 ± 1727.706	<0.05
F67	Min	Coif 1 Wavelet	-456.662 ± 221.994	-1825.306 ± 888.709	<0.05
F119	Higuchi FD[2]	Coif 4 Wavelet	1.98 ± 0.015	1.997 ± 0.010	<0.05

1StD=Standard Deviation; 2FD=Fractal Dimension

Furthermore, we have evaluated the proposed technique (LSTM) for all the extracted 150 features and top 30 most relevant RLF features. Training and test dataset is obtained by splitting the whole dataset using three data division techniques i. e. holdout (33%), 5-fold cross-validation & 10-fold cross-validation. The training performance of the proposed approach is shown in Figure 4. It is found that the training accuracy reaches 100% before the 10th iteration itself. Tables 7 and 8 show the results of the proposed LSTM approach for training and testing respectively. The results on test data from Table 8 indicate that the LSTM network combined with time-frequency features attains 100% classification accuracy under hold out and 5-fold, and 99.8% for 10-fold data decision protocols. Thus, the proposed LSTM performed superior to the traditional machine learning techniques to detect epileptic events using the whole 150 as well as top 30-RLF features for holdout, 5-fold, and 10-fold protocols.Though the BPANN performs close to the proposed technique achieving 99.6% and 99.4% classification accuracies for all and the RLF selected features respectively, these were attained only for 10-fold cross validation scheme. The Receiver Operating Curve (ROC) for the proposed approach on test data under holdout and 5-fold data division protocol is shown in Figure 5. The area under ROC curve is 1 for a significance value of $p<0.001$ which supports our findings.

Finally, we compare the performance of the proposed approach in light of some related studies. Table 9 shows the performance summary of some recent and previously reported epileptic seizure detection from the EEG signal. The results are arranged in ascending order of publication year. It is observed from Table 9 that neural networks, linear SVM, least square SVM, and Logistic Model Trees (LMT) have been utilized by different research groups. It is concluded that our proposed work outperforms others in terms of classification performance in differentiating epilepsy and non-epileptic EEG signals. Compared to some of the recent studies by Subasi and coauthors [19], Akyol [20], Ayesha and coauthors [23], Sujatha [22], and Tuncer and coauthors [24], it is observed that the proposed study achieves better performance than the existing ones. Our outcomes reflect that the proposed approach has potentials to act as a significant tool to assist clinicians for detecting epilepsy. However, the present study was based on a single repository of epileptic EEG signals. Therefore, for building up the trust of medical professionals in such systems, larger and distinguished databases of epileptic patients with improved ground truth validations are needed in future. Also, this study may be expanded from unimodal to multimodal analysis in the future where patient's physiological data can be acquired from more than one sources and analyzed together.

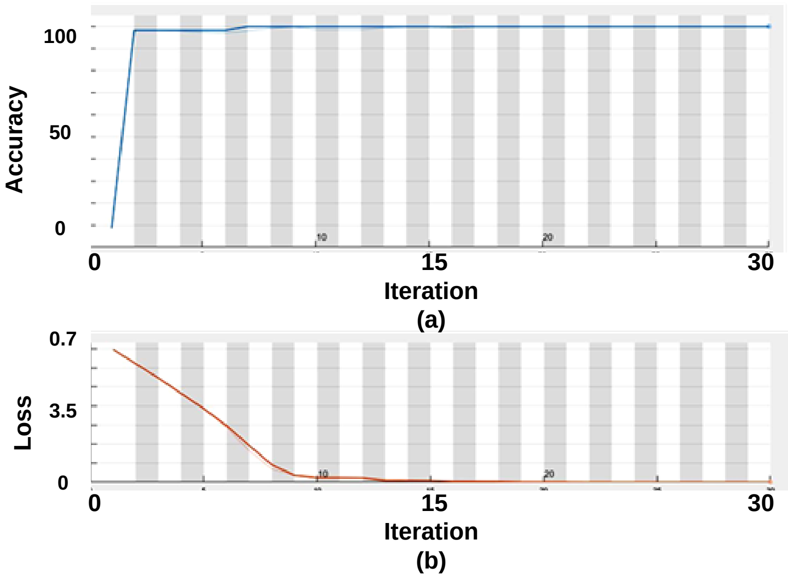

Figure 4. Training performance of the proposed approach: (a) Accuracy (%) (b) Loss.

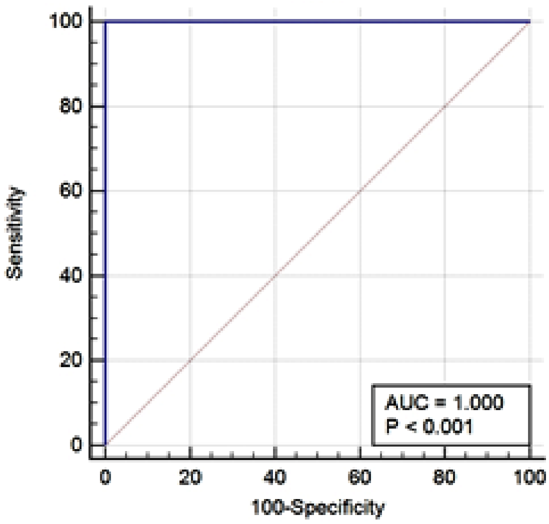

Figure 5. Receiver operating characteristics of the proposed approach for holdout and 5-fold data division protocol on test data.

Table 7. Performance of proposed approach using LSTM (training)

Number of features	Data division protocol	Statistical parameter (%)				
		Accuracy	Sensitivity	Specificity	AUC	MCC
150	Holdout	100.00	100.00	100.00	100.00	100.00
	5-fold	100.00	100.00	100.00	100.00	100.00
	10-fold	100.00	100.00	100.00	100.00	100.00
Top 30 most relevant features as shown in Table 6	Holdout	100.00	100.00	100.00	100.00	100.00
	5-fold	100.00	100.00	100.00	100.00	100.00
	10-fold	100.00	100.00	100.00	100.00	100.00

Table 8. Performance of proposed approach using LSTM (testing)

Number of features	Data division protocol	Statistical parameter (%)				
		Accuracy	Sensitivity	Specificity	AUC	MCC
150	Holdout	100.00	100.00	100.00	100.00	100.00
	5-fold	100.00	100.00	100.00	100.00	100.00
	10-fold	99.80	100.00	99.75	99.88	99.38
Top 30 most relevant features as shown in Table 6	Holdout	100.00	100.00	100.00	100.00	100.00
	5-fold	100.00	100.00	100.00	100.00	100.00
	10-fold	99.80	100.00	99.75	99.88	99.38

Table 9. Comparison of the present work with the existing studies for classification of epileptic seizure

Author and Year	Preprocessing and Feature Extraction technique	Classifier	Classification Accuracy (%)
Kabir et al., (2016) [11]	Optimum Allocation Technique (OAT) based Statistical features	Logistic model trees (LMT)	95.33 %
Swami et al., (2016) [39]	DTCWT, Energy, STD, Shannon Entropy	General Regression Neural Network	>96.86%
Peker et al., (2016) [40]	DTCWT	Complex valued NN	99.33%
Diykh et al., (2017) [13]	Weighted complex network combine with time-domain statistical feature	Least Square SVM	97.90%
Mutlu, (2018) [15]	Hilbert Vibration Decomposition (HVD) based feature	SVM with RBF kernel	97.66%
Acharya et al., (2018) [41]	Z-Score normalization, zero mean, STD	Deep CNN	88.67%
Subasi et al., (2019) [19]	DWT based features and Particle Swarm Optimization (PSO)	PSO based Hybrid SVM	99.38%
Akyol, (2020) [20]	Min-max normalization	Stacking ensemble based DNN	97.17%
Sujatha , (2020) [22]	Approximate entropy and statistical method	SVM	96.5%
Ayesha et al., (2021) [23]	DWT based temporal and spatial features	Fuzzy rough nearest neighbor (FRNN)	99.38%
Tuncer et al., (2021) [24]	1-D octal pattern and DWT	KNN	96%
Present Work	Statistical and DWT based composite feature	LSTM with 30 most significant features	**100%**

CONCLUSION

In this work, the combined time domain and frequency domain features were evaluated for risk stratification of epileptic seizure EEG signals from normal EEG signals using deep learning based LSTM network and 23 different traditional machine learning classification strategies. Total of 150 features were extracted from EEG signals. Different feature ranking techniques were also utilized to determine reliable EEG features. The results of this study show that only 30 features are sufficient to achieve classification accuracy equal to that of using all 150 features. The most relevant EEG biomarkers for epilepsy detection were found to be F6, F81, F21, F96, F111, F51, F141, F66, F126, F36, F9, F7, F69, F144, F99, F54, F12, F84, F24, F39, F114, F129, F22, F52, F8, F112, F82, F38, F67 and F119 using Relief F approach. It is found that standard deviation, range, min, max, Katz fractal dimension, and Higuchi fractal dimension are the selected biomarkers from the different feature categories. The proposed work can be used for an epileptic seizure alarm system which will assist medical professionals for detecting epilepsy and reduce their burden and observational errors. Though this work was done by considering a single dataset with less number of subjects, we will validate our work using some distinguished larger databases. We also expanded our work on multimodal cognitive state classification.

Conflicts of Interest: The authors declare that they have no conflict of interest.

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