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A deep learning based model using RNN-LSTM for the Detection of Schizophrenia from EEG data

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ABSTRACT

Normal life can be ensured for schizophrenic patients if diagnosed early. Electroencephalogram (EEG) carries information about the brain network connectivity which can be used to detect brain anomalies that are indicative of schizophrenia. Since deep learning is capable of automatically extracting the significant features and make classifications, the authors proposed a deep learning based model using RNN-LSTM to analyze the EEG signal data to diagnose schizophrenia. The proposed model used three dense layers on top of a 100 dimensional LSTM. EEG signal data of 45 schizophrenic patients and 39 healthy subjects were used in the study. Dimensionality reduction algorithm was used to obtain an optimal feature set and the classifier was run with both sets of data. An accuracy of 98% and 93.67% were obtained with the complete feature set and the reduced feature set respectively. The robustness of the model was evaluated using model performance measure and combined performance measure. Outcomes were compared with the outcome obtained with traditional machine learning classifiers such as Random Forest, SVM, FURIA, and AdaBoost, and the proposed model was found to perform better with the complete dataset. When compared with the result of the researchers who worked with the same set of data using either CNN or RNN, the proposed model's accuracy was either better or comparable to theirs.

1. Introduction

Schizophrenia (SZ) is a mental disorder that badly hampers the quality of life of the patients. According to an estimate by WHO more than 20 million people worldwide are currently suffering from this disease [1]. There are wide-ranging clinical symptoms of SZ of unknown aetiology. The common symptoms are visual and auditory hallucinations along with disorganized speech and thoughts. The manifestation of the disease usually starts in late adolescence period. It had been observed that if detected early a sustained recovery within five years of the first psychotic episode [2]. Though SZ patients have structural and functional anomalies of the brain, the external manifestation of the disease overlaps with the symptoms associated with other mental disorders such as obsessive compulsive disorder, bipolar syndrome etc. [3]. Predicament of the patients sometimes continue even after prolonged treatment due to misdiagnosis. There are four different stages of evolving of SZ:

i. Stage I: At risk stage, usually children less than 12 years.
ii. Stage II: Prodome, when early symptoms start appearing. This is at an age of 12–18 years.
iii. Stage III: Psychosis, which is at age 18–24 years.
iv. Stage IV: Chronic disability, usually at age above 24 years, when recovery is no longer possible.

It is thus necessary to detect the disease at Stage I or Stage II to prevent the first episodes of psychosis and ensure some normalcy in the life of the patients.

Magnetic Resonance Imaging (MRI) of the brain has already established that white matter of the brain of schizophrenic patients keep on decreasing consistently. Functional MRI (fMRI) confirmed that SZ is associated with the weakening of the frontal portion of the brain [4]. Anomalies in the theta and gamma oscillations of electroencephalogram (EEG) also reveal memory impairments in SZ patients [5]. Interruptions in the function of a single portion of the brain cannot sufficiently explain

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Table 1
List of major research works for the identification of schizophrenia using traditional machine learning algorithms.

Author	Classifier	Dataset	Accuracy
Doan et al. [16]	Linked Independent Component Analysis (LICI)	fMRI of 295 SZ patients and 45 healthy subjects	82%
Chin et al. [17]	SVM	MRI data of 212 SZ and healthy subjects	86%
Chen et al. [18]	SVM	EEG signal with theta 1, theta 2, alpha, beta, and gamma frequency bands of 40 SZ and 12 healthy subjects	84%
Santos-Mayo et al. [19].	SVM and MLP	EEG data with 20 features of 16 SZ and 31 healthy subjects	93.42%
Boostani et al. [20]	Direct linear discriminant analysis (DLDA)	286 features of EEG from 13 SZ and 18 healthy subjects	87.51%
Sabeti et al. [12]	AdaBoost	80 features of EEG signal from	91.94%
Thilakvathi et al. [21]	SVM	10 features of EEG signal from 55 SZ and 23 healthy subjects	80%
Liu et al. [22]	SVM	EEG signal with 1500 features from 40 SZ and 40 healthy subjects	91.16%

Table 2
Some current research works on the application of RNN in the diagnosis of schizophrenia from MRI.

Author	Year	Data	Model	Accuracy
Yan et al. [30]	2017	Resting state fMRI	DNN + LRP	82%
Yan et al. [31]	2019	fMRI	Multi-scale RNN (MS-RNN)	83.2%
Sundari et al. [32]	2021	fMRI	RNN-LSTM	81.3%
Dakka et al. [33]	2017	4D-fMRI	RNN	57.89%

the numerous impairments in SZ patients. It is necessary to study the connectivity of the entire brain network. It has been confirmed by MRI and diffusion tensor imaging (DTI) that there is white matter disconnection in SZ patients [6]. Schizophrenic brain structure is associated with higher clustering, reduced general strength of connectivity and efficiency compared to the brain of a healthy person. Analysis of functional connectivity using fMRI, however, showed inconsistencies when distinguishing between healthy and schizophrenic subjects. Nonetheless, MRI technique is rather costly. On the other hand, brain network topology of SZ using EEG has not yet been fully explored [7]. Also, besides being more cost-effective than MRI, EEG requires less computational time. EEG signals are largely divided into 5 different frequency bands δ (1–4 Hz), θ (4–7 Hz), α (7–12 Hz), β (12–30 Hz) and γ (>30 Hz) [8]. Different alterations of neuronal activities detected by EEG have been related to the severity of the symptoms. Anomalous frequency bands activity had been linked to cognitive impairments. Alterations in global electrical activity of the brain is related to hallucinations, and duration of illness, discrepancies in mismatched negativity to positive symptoms and functioning impairment.

In recent times machine learning (ML) models have been proposed for the improved diagnosis of SZ from EEG data. Automated classification were carried out using support vector machine (SVM) [9,10], kernel discriminant analysis (KDA) [11], AdaBoost [12], logistic regression [13], fuzzy clustering method etc. [14]. Some other major researches using MRI or EEG data and classified using traditional machine learning classifiers are outlined in Table 1. The limitations of these works were that they failed to take into account the interaction between the channels and hence the classifications were less than accurate [15].

Deep learning (DL) enables automated detection and extraction of inherent complex information from the neuro-signal data. DL algorithms such as convolution neural network (CNN) and recurrent neural network (RNN) are able to extract features automatically.

1.1. Related work

Phang et al. [15] proposed a diagnostic model based on domain connectome CNN (MDC-CNN) to distinguish between 45 SZ and 39 healthy subjects from EEG. The proposed model is a combination of two 2D-CNNs and one 1D-CNN that are joined in parallel. The functional connectivity features that were extracted using vector auto-regression (VAR) model, partial directed coherence (PDC) model, and the complex network (CN) measures, are taken as inputs. The model achieved an accuracy of 93.06%. Oh et al. [23] used the raw signal data from 19-channel EEG signal collected from 14 SZ and 14 normal subjects for the classification using CNN. The model had 11 layers consisting of convolution, pooling, and dense layers. The accuracy of their model was 81.26%.

Aslan et al. [24] proposed a model that transformed raw EEG data into 2D image using short-term Fourier transform (STFT) for the automated diagnosis of SZ patients. From this image most relevant features were extracted using CNN. They used two data sets in this study – the first one consisted of 45 SZ and 39 normal subjects while the second one had 14 SZ and 14 normal subjects. The accuracy obtained were 95% and 97% respectively. Chu et al. [25] built a model for individual recognition of SZ from multi-channel EEG data. They used 40 high-risk, 40 SZ, and 40 healthy subjects in their study. They designed a deep learning framework for the classification by replacing the Softmax classifier with Random Forest. They received 81.6%, 96.7%, and 99.2% accuracy with high-risk, SZ, and healthy subjects respectively.

RNN models such as long short-term memory (LSTM), is a ‘state-of-the-art’ sequence classifier which can be used to analyze EEG and diagnose schizophrenia. There are some applications of RNN using MRI/fMRI for the diagnosis of SZ as shown in Table 2. However, the literature study conducted by the authors found no referred work related to the application of RNN in diagnosis of SZ using EEG data, though there had been applications for the identification of other brain disorders from EEG [26–29].

In this work the authors explored the feasibility of RNN-LSTM in the diagnosis of schizophrenia from the EEG dataset. LSTM was used to extract the features and the dense layers were used for classification. Besides the classification, the following issues were analysed in this work:

i. How accurately RNN-LSTM can identify SZ?
ii. How much better is the performance of LSTM compared to the other ML classifiers in the diagnosis of SZ?
iii. Whether there is any performance degradation of the model with feature reduction.

The rest of the paper is organized as follows: Dataset Description is given in Section 2; Section 3 contains the Methodology; Results and Discussion is given in Section 4; and Conclusion of the work is given in Section 5.

2. Dataset Description

The dataset was obtained from the EEG records database of the Laboratory for Neurophysiology and Neuro-Computer Interfaces of M.V Lomonosov Moscow State University. The database consists of EEG data collected from 84 adolescents at the resting stage. The age of the subjects were between 11 –14 years. The subjects were divided into two groups – a group of 45 people exhibiting symptoms of schizophrenia and a group

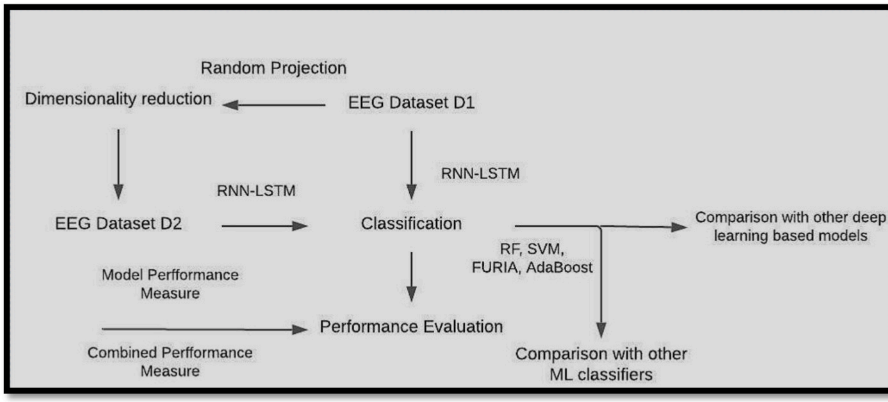


Fig. 1. Overview of the work.

of 39 normal people. All the schizophrenic subjects were diagnosed by the doctors of Mental Health Research Center (MHRC) using F20, F21, F25 of ICD-10 Classification of Mental and Behavioural Disorders, set by International Statistical Classification of Diseases and Related Health Problems [15]. No treatments were administered prior to taking the EEG.

Each EEG sample consists of EEG amplitude (mkV) reading from 16 EEG channels. Each channel produced 7680 samples taken with a sampling rate of 128 Hz over a period of 1 min [34]. 16 channels are placed on the five lobes – frontal (F), central (C), parietal (F), temporal (T), and occipital (O). Data were taken from [F7, F3, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2] set of electrodes. Noise had been removed from the EEG signal prior to the creation of the dataset. Each subject's data is this thus a 16 × 7680 matrix. As there were 84 subjects in the study, the total number of instances in the dataset is 1344. The sequence of data matrix representation is

$$\boldsymbol{x}_{1,1}^{(1)}, \boldsymbol{x}_{1,2}^{(1)}, \ldots\ldots\ldots, \quad \boldsymbol{x}_{1,n}^{(1)}$$

$$\vdots$$

$$\boldsymbol{x}_{m,1}^{(1)}, \boldsymbol{x}_{m,1}^{(1)} \ldots\ldots\ldots, \quad \boldsymbol{x}_{m,n}^{(1)}$$

$$\vdots$$

$$\boldsymbol{x}_{m,1}^{(k)}, \boldsymbol{x}_{m,1}^{(k)}, \ldots\ldots\ldots, \quad \boldsymbol{x}_{m,n}^{(k)}$$

$\boldsymbol{x}_{m,n}^{(k)}$ represents nth data point of the mth subject obtained from the kth channel, where, $m = 84$, $n = 7680$, $k = 16$.

3. Methodology

Overview of the methodology is given in Fig. 1. Original dataset D1 was reduced to obtain dataset D2. RNN-LSTM was applied on both sets of data and the model performance was measures using several statistical metrics. Comparison was made with the outcome of other machine learning classifiers. At the end, accuracy of the result of the RNN-LSTM model was compared with the works of other authors who worked with same or different dataset.

3.1. *Dimensionality reduction using random projection (RP)*

A data is said to be high dimensional if the number of parameters is greater than or equal to the number of samples in the dataset [35]. Since, the number of parameters in the dataset is ultra-high, dimensionality reduction is required to create a subset of parameters that still replicates the characteristics of the original set. Though Principal Component Analysis (PCA) is a common technique for the reduction of dimension, however, it has a time complexity which makes it unsuitable for an application where the feature set has a size of 7680 [36]. The time complexity of PCA with sample size $m = 1344$ and parameter size $p = 7680$ is $O(p^2 m + p^3)$. On the other hand, the time complexity of RP is $O(mpq)$, where, q is the reduced dimension. It is also robust to outliers.

RP works on the basis of Johnson-Lindenstrauss Lemma which states that if there are p points in a in a high-dimensional Euclidean space then it can be mapped from $\mathbb{R}^p \rightarrow \mathbb{R}^q$ while preserving the Euclidean distance between the points [37].

Algorithm.

Input: Original dataset $D_{m\times p}$

1: Normalize the columns of $C_{p\times q}$, using the equation

$$N(\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} exp(-\frac{(x-\mu)^2}{2\sigma^2})$$

2: $R_{m\times q} = D_{m\times p} \times C_{p\times q}$

Output: Reduced matrix $R_{m\times q}$ with q number of parameters

Matrix $C_{p\times q}$ *is a random 2 − dimensional where, q is the reduced dimension. RP reduced the number of parameters from* 7680 *to* 36, *giving matrix* $R_{1344\times 36}$

3.2. *Long short time memory (LSTM) network*

Recurrent Neural Network (RNN) suffers from vanishing gradient problem, thus, making it difficult to apply it for any practical purpose. LSTM, which help reduce the multiplication of gradients that are less than zero. If the current input to the network is x_t, the output from the previous cell is y_{t-1} then a LSTM consists of:

i. An input gate that uses tanh activation function given by

$$k = \tanh\left(b^{(k)} + x_t W_1^{(k)} + y_{t-1} W_2^{(k)}\right) \tag{1}$$

The input gate, which is basically a sigmoid-activated node of the hidden layer, is expressed as

$$I = \sigma\left(b^{(I)} + x_t W_1^{(I)} + y_{t-1} W_2^{(I)}\right) \tag{2}$$

The output of the input gate is

$$k \circ I \tag{3}$$

ii. The inner state of the LSTM, o_t is delayed by one time step and is added to equation (3). This provides an internal recurrence loop that

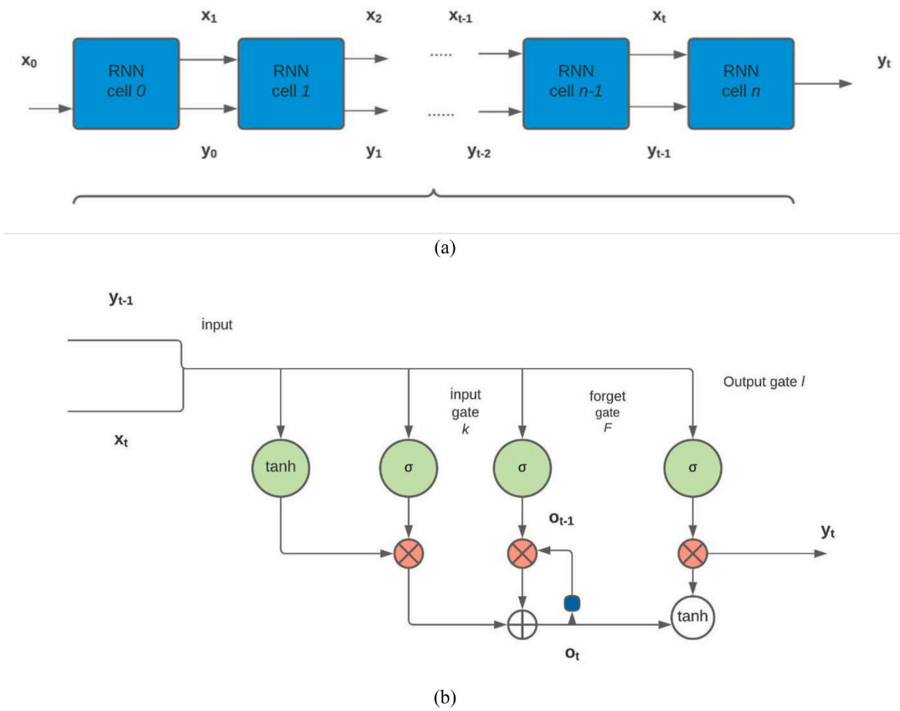


Fig. 2. (a) Unfolding of the RNN loop, (b) Cell diagram of LSTM network.

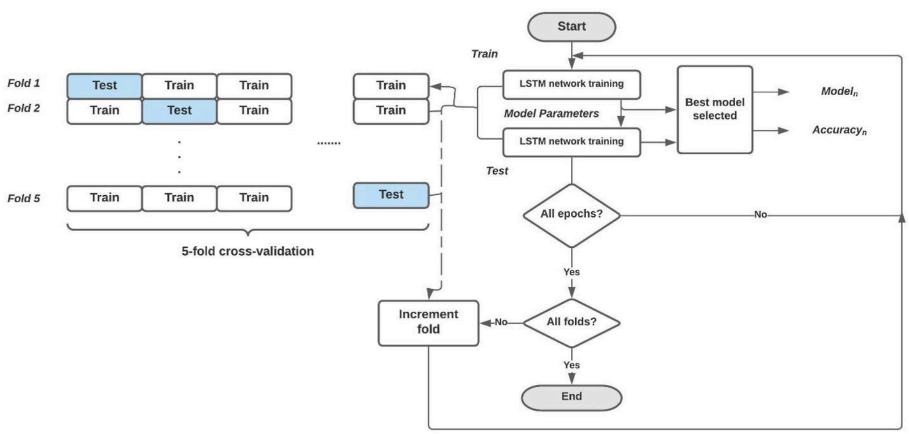


Fig. 3. 5-fold cross-validation flow diagram.

learns the relation between the inputs provided at different times. This step consists of a forget gate which are sigmoid-activated nodes that determine which previous state should be remembered. The forget gate is given by the expression

$$F = \sigma\left(b^{(F)} + x_t W_1^{(F)} + y_{t-1} W_2^{(F)}\right) \tag{4}$$

The output of this stage is

$$o_t = o_{t-1} \circ F + k \circ I \tag{5}$$

o_{t-1} is the inner state of the previous cell.

iii. The ultimate stage of the LSTM is the output gate which consists of a tanh squashing function and an output sigmoid function which is expressed as

$$L = \sigma\left(b^{(L)} + x_t W_1^{(L)} + y_{t-1} W_2^{(L)}\right) \tag{6}$$

The output of the cell is, therefore, given by

$$y_t = \tanh\,(o_t) \circ L \tag{7}$$

$b^{(i)}$, $W_1^{(i)}$, and $W_2^{(i)}$ are the input bias, weight of the input, and the weight of the previous cell's output respectively for each stage. The weights and biases are determined during the training phase.

Fig. 2 (a) shows the unfolding of the RNN loop that results in the building block of the LSTM cell is given in 2(b). During testing the model classifies the input sequence x_t and determines if the subject is schizophrenic or not.

3.3. 5-Fold cross validation

To reduce bias 5-fold cross validation was used. Data was split into 5 parts. In each of 5 iterations, one part is used for testing and the rest are used to train the model [38]. The flow diagram of the cross validation is shown in Fig. 3. The proposed model uses 100 epochs with batch-size of 50, i.e. each epoch consists of one forward pass and one backward pass and 27 iterations are required to complete one epoch. LSTM network is

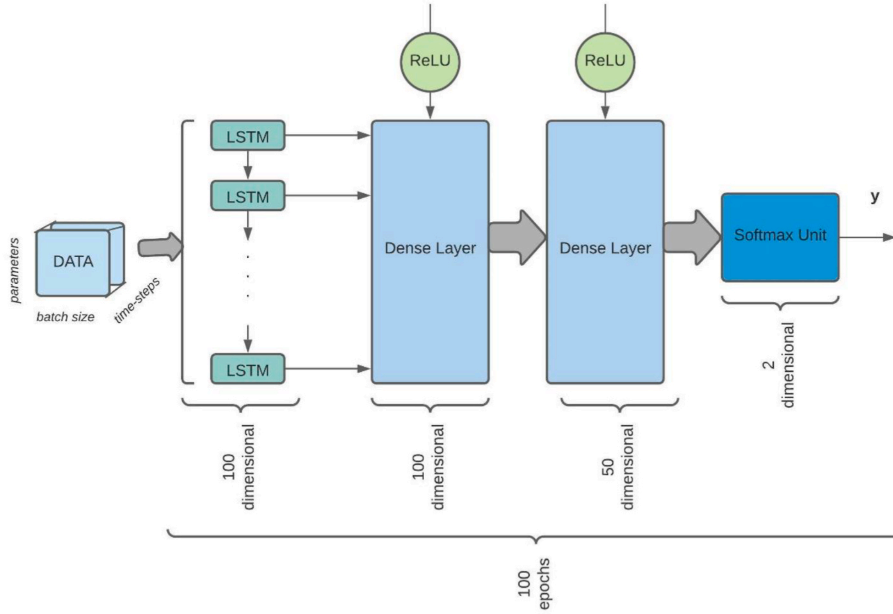


Fig. 4. Architecture of the proposed system.

trained and tested in each epoch. Weights are generated during the training phase, while during the testing phase prediction quality of the model is determined. There is a module for selecting the best model for a particular fold based on the quality of the model. When all the epochs of a specific fold are complete, the data from the subsequent fold is considered.

3.4. Proposed architecture

In the proposed architecture the authors used three dense layers on top of the 100 dimensional LSTM. The improved learning of LSTM allows us to train the models better than RNN using sequence with several hundreds of times steps. LSTMs enable RNN to remember the input values over a longer period of time. The dimensions of the dense layers are 100, 50, and 2 respectively. The dimension of the outermost layer is 2 since the proposed model does a binary classification. Rectified linear unit (ReLU) activation function was used for the first two dense layers and in the last layer Softmax activation function was used for classification. ReLU is an approximately linear function and hence is easier to optimize. It rectifies an input values less than zero and assigns the value zero to them, thus, eliminating the vanishing gradient problem [39].

$$f_{ReLU}(x_i) = \max(0, x_i) = \begin{cases} x_i; \, if \ x_i \geq 0 \\ 0; \, if \ x_i < 0 \end{cases} \tag{8}$$

Softmax predicts the probability of an instance belonging to a particular class. The value returned by the function is between 0 and 1 and the sum of the probabilities is 1 [40]. Softmax is estimated using the formula

$$f(x_i) = \frac{\exp\,(x_i)}{\sum_j \exp\,(x_j)} \tag{9}$$

The system architecture is shown in Fig. 4. Network weights were updated using Adam optimization algorithm because it has low space complexity and is best suited for datasets with large number of parameters or instances [41]. The input to the LSTM is a 3-dimensional array $batch\_size \times time\_steps \times parameters$. Categorical cross-entropy was used to estimate the loss at each stage. For 2 classes C_1 and C_2, the ground-truth and score respectively for classes C_1 and C_2 are $p_1[0,1]$ and k_1, and $p_2 = 1 - p_1$ and $k_2 = 1 - k_1$. It is given by the equation

Table 3
Metrics of the model performance measure.

Metric of Measurement	Equation	Function
Accuracy	$\frac{TP + TN}{TP + FP + TN + FN}$	Evaluates the overall efficiency of the model.
Sensitivity (Recall)	$\frac{TP}{TP + FN}$	Measures the accuracy of the positive class.
Specificity	$\frac{TN}{TN + FP}$	Measures the accuracy of the negative class.
Precision (Positive Predictive Value)	$\frac{TP}{TP + FP}$	Measures the quality of the accuracy of the model.

$$CE_{loss} = -p_1 \log(k_1) - (1 - p_1)\log\,(1 - k_1) \tag{10}$$

3.5. Experiment

Two sets of data D1 and D2 were used in our experiment; D1 is the original dataset of dimension 1344 × 7680 and D2 is the dataset of dimension 1344 × 36, after dimensionality reduction with RP. RNN-LSTM was used on both sets of data. The same set of data were also used for classification using MLP, SVM, and Random Forest classifiers using 5-fold cross validation. The performance measure of the proposed model was evaluated against the performance of the classifiers in terms of accuracy, precision, sensitivity (recall), and specificity. The robustness of the model was established using model performance measure as well as combined performance measure. SZ is considered the positive class and normal subjects were the negative class. Confusion matrix represents the True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN).

3.5.1. Model performance measure

Metrics of the model performance measures are depicted in Table 3. Though accuracy is normally considered measure for evaluating the performance of a classifier, it can be ambiguous if the dataset is not balanced. In such cases more emphasis is on the majority class which makes it difficult for the classifier to perform well on the minority class.

3.5.2. Combined performance measure

Authors also establish that the proposed model balances between

Table 4
Metrics of the combined performance measure.

Metric of Measurement	Equation	Function
Geometric Mean (G-Mean)	$\sqrt{Sensitivity \times Specificity}$	Measures the balance between the classification of the positive class and the negative class.
Discriminant Power (DP)	$\frac{\sqrt{3}}{\pi}\left[log\left(\frac{Sensitivity}{1-Sensitivity}\right) + log\left(\frac{Specificity}{1-Specificity}\right)\right]$	Summarizes the performance of sensitivity and specificity
Balanced Accuracy	$\frac{Sensitivity \times Specificity}{2}$	Average accuracy of both the positive and negative classes are measured.
Matthew's Correlation Coefficient	$\frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$	Measures the correlation coefficient between the observed and the predicted value.
Cohen's kappa	$\frac{total\ accuracy - random\ accuracy}{1 - random\ accuracy}$	Measures whether the classification accuracy is by chance.
Youden's Index	$Sensitivity - (1 - Specificity)$	Measures the ability of the classifier to circumvent misclassification.

False Positive Rate (FPR) and False Negative Rate (FNR). Such measures cannot be provided by model performance metrics. Hence, combined performance measures listed in Table 4 were also used for the analysis.

4. Result and discussion

4.1. Result with RNN-LSTM model

The loss at each fold for the complete set and the reduced set are given in Figs. 5 and 6 respectively. The confusion matrix for the complete feature set, D1, and the reduced feature set, D2, are given in Table 5. The model performance metrics and combined performance metrics for both the data sets are given in Table 6 and Table 7 respectively. Comparison of the metrics for the two datasets are shown graphically in Fig. 7.

An ideal model should be able to detect the positive subject with very high accuracy while ruling out the negative subjects, i.e. precision and recall (sensitivity) should be high. This, in turn, gives a high value of F-measure. High sensitivity implies high negative predictive value (NPV), making it the most suitable metric for rule-out test. High specificity, on the other hand, indicates high positive predictive value (PPV) and is suitable for rule-in test [42]. Schizophrenia is prevalent in about 1% of the population [43]. Hence, specificity (PPV) is a better indicator of the performance of the model than the sensitivity (NPV). The metric values are higher with D1 than with D2. Since, the specificity is high for D1 a RNN-LSTM model would work better in identifying a schizophrenic subject when used with the complete feature set.

The combined performance measure of the model is given in Table 4. A low G-mean is indicative of poor classification for positive class, even though the negative class is accurately identified. With G-mean of 0.979 for D1 and 0.940 for D2, there is no overfitting for the negative class (normal) or underfitting for the positive class (SZ). The DP are 1.84 and 1.32 respectively or datasets D1 and D2 indicating that there are certain limitations in the model when it comes to distinguishing between two classes. Balanced accuracy for both sets is approximately equal to the accuracy. Thus, the model performs equally well for both the classes, without being biased for any one of them. MCC for D1 and D2 are 0.96

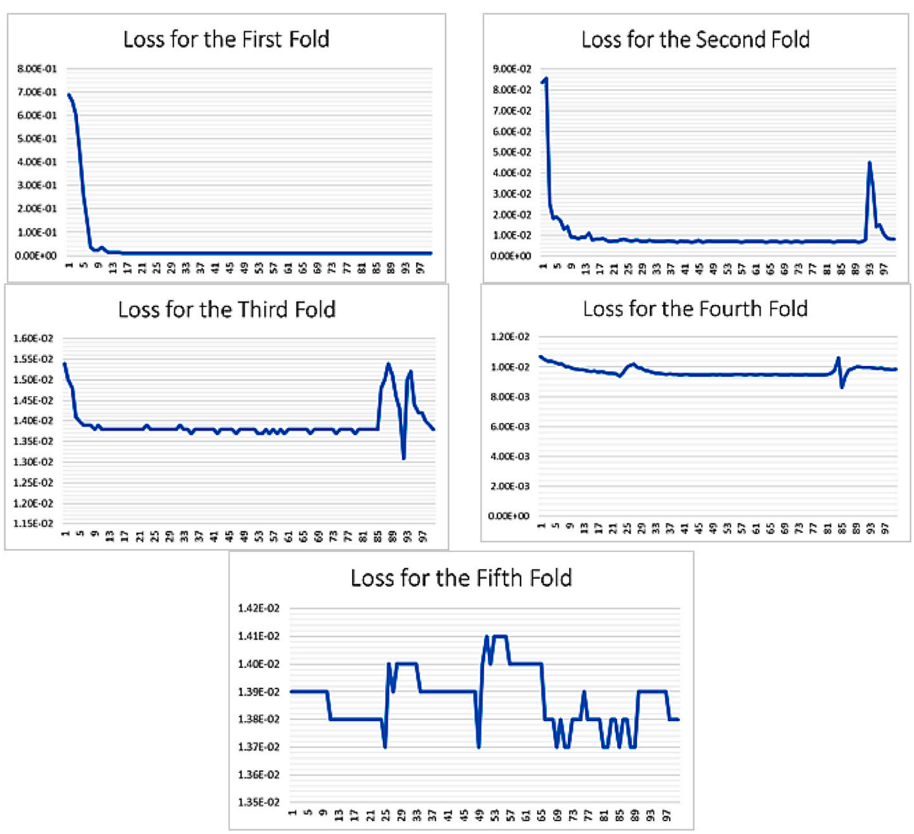


Fig. 5. Plot of loss function for the training phase with complete feature set. Mean squared error loss for the folds is not uniform.

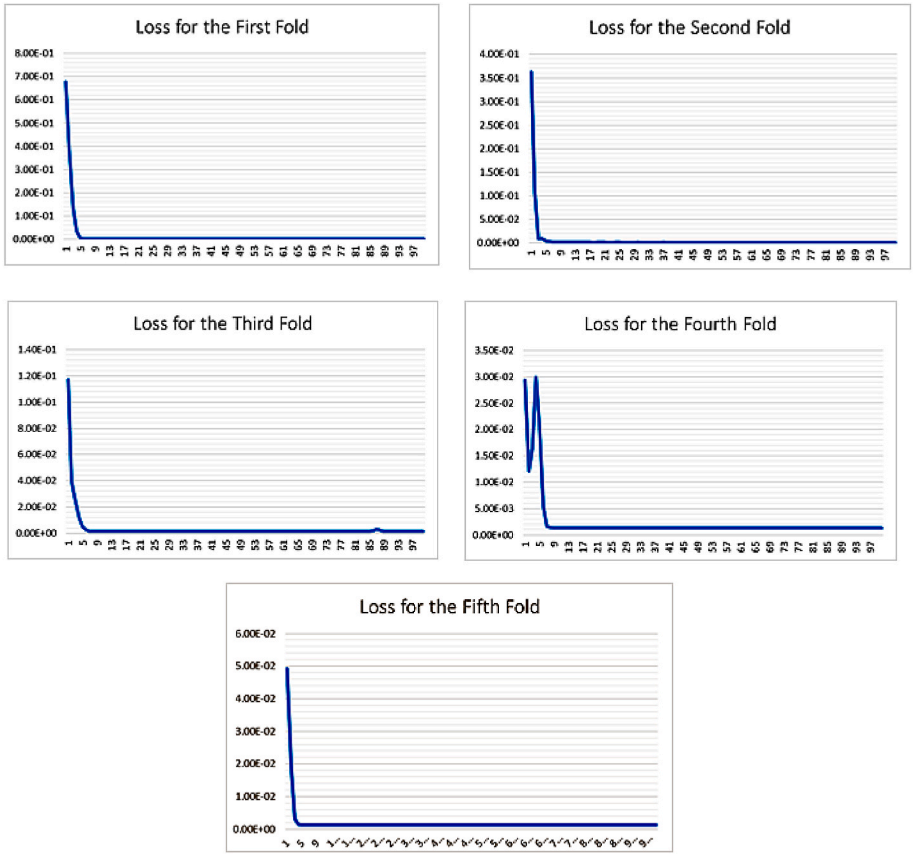


Fig. 6. Plot of loss function for the training phase with reduced feature set. Mean squared error loss is more or less uniform at each fold.

Table 5
Confusion matrix for both feature sets.

D1		Schizophrenia	Normal
	Schizophrenia	706	14
	Normal	13	611
D2		**Schizophrenia**	**Normal**
	Schizophrenia	609	49
	Normal	36	650

and 0.874 indicating highly accurate prediction. Cohen's kappa is greater than 0.8, indicating high concordance between the predicted and the actual class. Youden's index, that evaluates whether the model can avoid misclassification, are 0.958 and 0.881 respectively for classes D1 and D2. Thus, the probability of misclassification is minimal.

4.2. Comparison of RNN-LSTM with other classifiers

There is no golden standard or benchmark against which to compare results. The authors have, thus, compared the outcome of the proposed model with the outcome provided by four other machine learning classifiers – SVM, Random Forest, FURIA, and AdaBoost. Comparison in terms of accuracy, sensitivity, specificity, and precision for both schizophrenic and normal classification, as well as for the overall performance are given in Table 8 and shown graphically in Fig. 8 (a) and (b). The percentage improvement or deterioration in classification using RNN-LSTM and the other ML classifiers are given in Fig. 9.

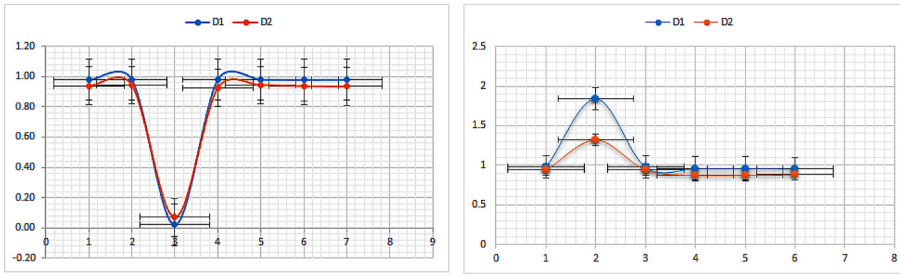
When compared with the performance of the complete dataset (D1) RNN-LSTM overall accuracy, sensitivity, specificity, and precision are better than the other classifiers, though FURIA and AdaBoost did better in identifying the positive class (schizophrenic). However, the dataset with reduced features (D2) did not perform so well compared to Random Forest, FURIA, and AdaBoost. SVM classifier failed to identify the

Table 6
Model performance metric for both feature sets.

	Accuracy	TPR	FPR	Precision	Recall	Specificity	F-Measure
D1	98%	0.980	0.02	0.981	0.980	0.978	0.980
D2	93.67%	0.944	0.07	0.926	0.944	0.937	0.935

Table 7
Combined performance metric for both feature sets.

Dataset	G-Mean	Discriminant Power (DP)	Balanced Accuracy	Matthew's Correlation Coefficient (MCC)	Cohen's kappa	Youden's Index
D1	0.979	1.84	0.979	0.960	0.96	0.958
D2	0.940	1.32	0.941	0.874	0.874	0.881



(a) (b)

Fig. 7. Comparison of the performance of the proposed model using (a) Model performance metrics, (b) Combined performance metric.

Table 8
Comparison of the performance of the proposed model with other machine learning classifiers.

	Evaluation Metrics	Class	RNN-LSTM	Random Forest	SVM	FURIA	AdaBoost
Dataset D1	Accuracy	Schizophrenic	98.06%	95.69%	99.86%	98.33%	98.75%
		Normal	97.92%	95.51%	0	97.44%	96.96%
		Overall	98%	95.61%	53.50%	97.92%	97.92%
	Sensitivity	Schizophrenic	0.980	0.957	0.999	0.983	0.988
		Normal	0.979	0.955	0	0.974	0.970
		Overall	0.980	0.956	0.535	0.979	0.979
	Specificity	Schizophrenic	0.979	0.955	0	0.974	0.970
		Normal	0.981	0.957	0	0.974	0.988
		Overall	0.980	0.956	0	0.974	0.980
	Precision	Schizophrenic	0.974	0.961	0.535	0.978	0.974
		Normal	0.985	0.951	0	0.981	0.985
		Overall	0.981	0.956	0.287	0.979	0.979
Dataset D2	Accuracy	Schizophrenic	92.55%	96.67%	99.86%	99.17%	95.83%
		Normal	94.75%	96.96%	0	95.98%	95.51%
		Overall	93.67%	96.80%	53.50%	98.41%	95.68%
	Sensitivity	Schizophrenic	0.940	0.967	0.999	0.992	0.958
		Normal	0.948	0.970	0	0.986	0.955
		Overall	0.944	0.968	0.535	0.989	0.957
	Specificity	Schizophrenic	0.948	0.970	0	0.960	0.955
		Normal	0.926	0.963	0	0.992	0.958
		Overall	0.937	0.967	0	0.976	0.957
	Precision	Schizophrenic	0.944	0.973	0.535	0.988	0.961
		Normal	0.908	0.962	0	0.990	0.952
		Overall	0.926	0.968	0.287	0.989	0.957

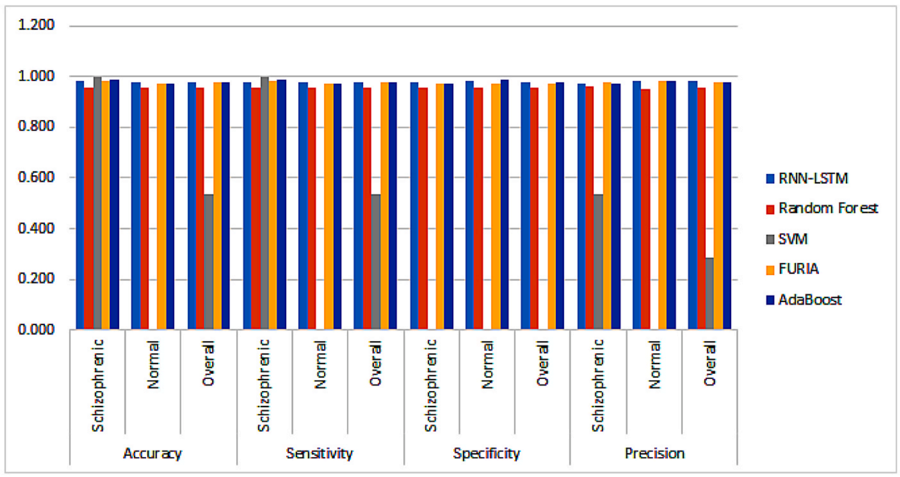
healthy subjects for both sets of data, giving rise to low metric values.

4.3. Comparison with the works of the others

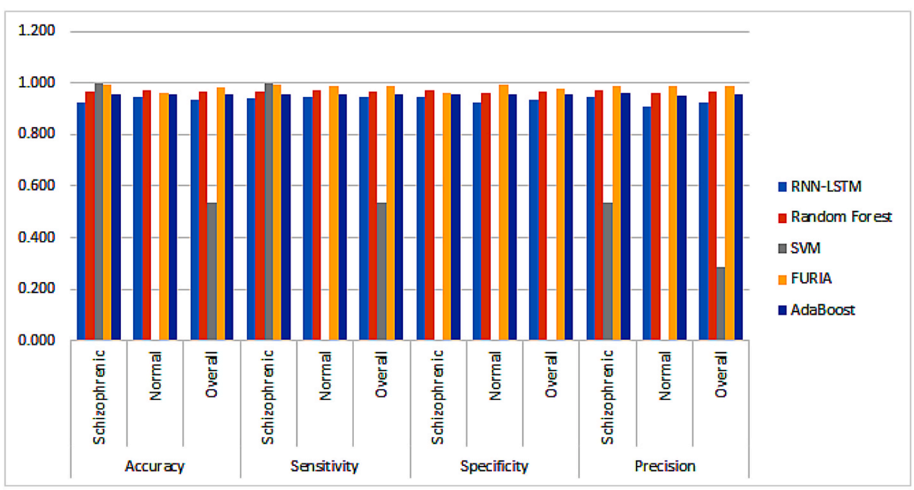
The authors have compared the result of the proposed method with that of other researchers who used deep learning to build the classification model. The comparison is divided into two groups – the ones who worked with the same dataset as the authors' and those who worked with different sets of EEG data. The comparison is shown in Table 9. The proposed method performed better than the models by the other researchers who used the same dataset. Reliance of Phang et al. [15] on additional data such as connectivity features of the brain and CNN model with 11 features by Oh et al. [23] failed to make any impact in the accuracy or in the identification of positive class. Proposed model by Chu et al. [25] performed slightly better for identifying normal subjects.

5. Conclusion

We developed a deep learning based model using RNN-LSTM for automatic classification of schizophrenic patients from the EEG data. Model architecture consists of three dense layers on top of a 100 dimensional LSTM. In terms of model performance and combined performance metrics, the performance of the proposed model is high though certain limitations exist in the model as indicated by the Discriminant Power value. The performance of the model was compared with the performance of some well-known machine learning algorithms and the performance of the proposed model was found to be better with the complete dataset. However, the loss function or the mean squared error loss for the complete dataset is non-uniform at each fold of the cross-validation and did not converge, leading the authors to conclude that mean squared error is not the appropriate loss function while using the complete dataset. Compared to the other works that used deep learning models for the diagnosis of schizophrenia our proposed model either performed better or the performances were comparable. It can thus be concluded that the RNN-LSTM architecture proposed in this work is able to successfully identify schizophrenia from the EEG data with large number of features without requiring dimensionality reduction. One drawback of RNN-LSTM model is that it works well only with vectorised input which makes it unable to preserve the spatial correlation in the brain network. Convolution-LSTM (ConvLSTM) is able to overcome this limitation [44]. In our next work we intend to implement ConvLSTM to capture the enhanced spatio-temporal correlation of EEG signal.



(a)



(b)

Fig. 8. Comparison of the parameters of RNN-LSTM with other classifiers for both the classes with (a) dataset D1, (b) dataset D2.

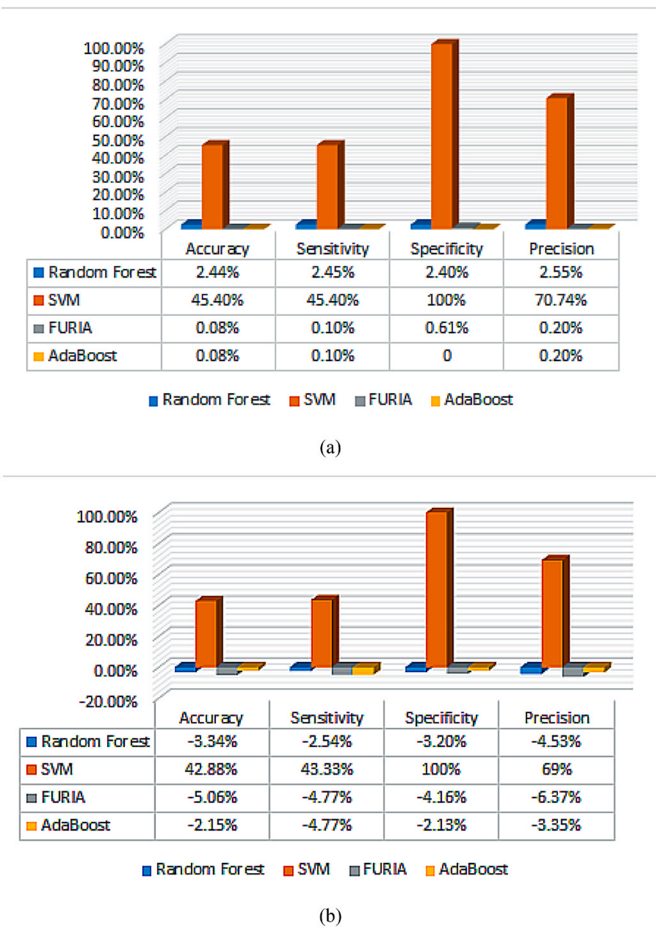


Fig. 9. Percentage improvement/deterioration in result when evaluation metrics of other classifiers is compared against LSTM-RNN for (a) Dataset D1, (b) Dataset D2.

Table 9
Comparison of the proposed method with the works of other researchers who used deep learning based method (a) When the same dataset as the author's was used, (b) When different datasets were used.

(a)		
Same Dataset as the Authors'		
Author	Model Used	Accuracy
Aslan et al. [24]	CNN	95%
Phang et al. [15]	MDC-CNN	93.06%
Proposed method	**RNN-LSTM**	**98%**
Complete dataset D1		**93.67%**
Dataset with reduced features D2		

(b)			
Different Dataset			
Author	Model Used	Accuracy	Dataset
Oh et al. [23]	CNN	81.26%	14 SZ 14 Normal
Aslan et al. [24]	CNN	97%	14 SZ 14 Normal
Chu et al. [25]	RNN	96.7% 81.6% 99.2%	40 SZ 40 High-risk 40 Normal

The core findings of the paper are

i. How accurately RNN-LSTM can identify SZ.

ii. How much better is the performance of LSTM compared to the other ML classifiers in the diagnosis of SZ.

iii. Whether there is any performance degradation of the model with feature reduction.

Declaration of competing interest

The authors hereby declare that for the paper entitled **A Deep Learning Based Model using RNN-LSTM for the Detection of Schizophrenia from EEG Data** they have no conflict of interest.

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