Automated Depression Detection Using Deep Representation and Sequence Learning with EEG Signals

Betul Ay[1] · Ozal Yildirim[2] · Muhammed Talo[2] · Ulas Baran Baloglu[2] · Galip Aydin[1] · Subha D. Puthankattil[3] · U. Rajendra Acharya[4,5,6]

Abstract

Depression affects large number of people across the world today and it is considered as the global problem. It is a mood disorder which can be detected using electroencephalogram (EEG) signals. The manual detection of depression by analyzing the EEG signals requires lot of experience, tedious and time consuming. Hence, a fully automated depression diagnosis system developed using EEG signals will help the clinicians. Therefore, we propose a deep hybrid model developed using convolutional neural network (CNN) and long-short term memory (LSTM) architectures to detect depression using EEG signals. In the deep model, temporal properties of the signals are learned with CNN layers and the sequence learning process is provided through the LSTM layers. In this work, we have used EEG signals obtained from left and right hemispheres of the brain. Our work has provided 99.12% and 97.66% classification accuracies for the right and left hemisphere EEG signals respectively. Hence, we can conclude that the developed CNN-LSTM model is accurate and fast in detecting the depression using EEG signals. It can be employed in psychiatry wards of the hospitals to detect the depression using EEG signals accurately and thus aid the psychiatrists.

Keywords Depression detection · Deep learning · CNN-LSTM · Hybrid deep models · EEG signals

Introduction

In recent years, deep learning architectures have achieved significant success in the areas of computer vision and natural

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✉ Ozal Yildirim
oyildirim@munzur.edu.tr

1 Department of Computer Engineering, Fırat University, Elazığ, Turkey

2 Department of Computer Engineering, Munzur University, Tunceli, Turkey

3 Department of Electrical Engineering, National Institute of Technology Calicut, Calicut, India

4 Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore, Singapore

5 Department of Biomedical Engineering, School of Science and Technology, Singapore School of Social Sciences, Singapore, Singapore

6 School of Medicine, Faculty of Health and Medical Sciences, Taylor's University, 47500 Subang Jaya, Malaysia

language processing [1–4]. However, very little progress has been made in neuroscience and biomedical domains due to the availability of few data [5]. With rapid enhancement of available neurological data, there has been a significant improvement in the learning and diagnosis of neural disorders including seizure, Alzheimer, Parkinson, epilepsy, Creutzfeld-Jakob, depression, emotional states and other abnormality diseases [6–10].

Electroencephalography (EEG), electrocardiography (ECG) and magnetic resonance imaging (MRI) have been used for the diagnosis of various diseases. The EEG is the electrical activity of the human brain [9] and can be used to detect the seizure [10].

Recently, deep learning based approaches [12–22, 29, 32–36, 49] are employed instead of classical machine learning methods [23–28, 37–43] in processing biomedical signals. When microphones assumed as EEG electrodes and speakers assumed as activity in cortical regions, Petrosian et al. [11] applied recurrent neural network (RNN) to extract features from EEG time series data for seizure prediction. To address the problem, Mirowski [12] used convolutional neural network (CNN) to extract features from EEG data. Acharya et al. [13] developed CNN model to detect the seizure from EEG signals with an average accuracy of 88.7%.

Wulsin [14] used deep belief net (DBN) for the detection of anomaly using EEG records. For deep feature learning from EEG recordings, [15] proposed several novel techniques including cross-trial encoders and hydra-nets. Yildirim et al. [16] proposed a 1D-CNN solution to detect the abnormal EEG signals with detection error rate of 20.66%. The other work by [17], explored the effectiveness of deep extreme machine learning (DEML) on two brain-computer interface (BCI) data sets. They have highlighted the advantages of DEML in classifying the BCI data sets. The paper [18] proposed a deep learning network with 100 hidden nodes in each layer to detect emotions from EEG signals. They achieved a low classification performance with an accuracy of 53.42%. Supratak et al. [19] used DeepSleepNet comprising of CNN and bidirectional-LSTM model learn sleep stage scoring features of single-channel EEG data for automated sleep stage classification.

Oh et al. [20] presented an automated classification of five classes of arrhythmia using unprocessed (with noisy) ECG signals using a combination of CNN and LSTM architectures. In another study wavelet transform based bidirectional LSTM network was used [21]. In [22], deep 1D-CNN attained an overall recognition accuracy of 91.33% for the detection of 17 classes of cardiac arrhythmia. The depression is a serious medical illness and negatively affects the daily activities of a patient. Since it is a treatable disease, early detection of the disease is important. To address this issue, several study has been conducted [23–29, 44–46].

Table 1 provides the overview of the automated depression detection system using EEG signals. In order to detect single channel depression EEG signals, Bachmann at al. [27] used combination of linear and nonlinear methods. Puthankattil and Joseph [28] used relative wavelet energy and entropy features extracted from the EEG signals to detect the depression. Ahmadlou et al. [44] used combination of wavelet filter bank and fractal dimension features to detect the depression automatically. Faust et al. [45] used nonlinear features extracted from the wavelet packet decomposition sub-bands of the EEG signals. Acharya et al., [46] have developed an index to detect the normal and depression subjects using a single integer developed using nonlinear features. Bairy et al. [24] used features extracted from the linear predictive coding (LPC) residuals to discriminate depression signals from normal EEG signals. Recently, Acharya et al. [29] developed a 13-layer CNN model to detect depression accurately.

The previous studies on depression detection have generally been performed using hand-crafted feature extraction techniques and shallow structured classifiers trained on these features. The main motivation for this paper is to enable a completely automated detection of depression using raw EEG signals. The feature extraction/selection and classification operations were executed automatically using a single structure with EEG signals as input. Furthermore, the developed structure can learn both local features and long-term dependencies for input signals. Hence, in this study a CNN-LSTM based hybrid deep learning model is proposed to detect the depression automatically. This model provides the sequence learning with LSTM block and enables the representation of input signals through CNN layers. Thus, an end-to-end structure for EEG signals has been presented which provides learning on both local features and long-term dependencies. One of the main contributions of the study is that the proposed CNN-LSTM model provides high performance on the signal data which is obtained from right and left hemispheres of the brain to detect depression using EEG signals. The CNN-LSTM model provides an automatic detection with

Table 1   Overview of previous studies on automated depression detection using EEG signals

| Authors	Year	Dataset	Feature Extraction Methods	Classifier	Accuracy (%)
[44]	2012	15 normal 15 depressed	Wavelet filter bank and fractal dimensions	EPNN	91.30
[28]	2012	15 normal 15 depressed	Relative wavelet energy	ANN	98.11
[45]	2014	15 normal 15 depressed	Wavelet packet and non-linear features	PNN	98.20 (Left) 99.50 (Right)
[46]	2015	15 normal 15 depressed	Non-linear features	SVM	98.00
[25]	2017	30 normal 33 depressed	Alpha interhemispheric asymmetry and power of frequency bands	SVM	98.40
[24]	2017	15 normal 15 depressed	Higher order spectra features	Bagged Tree	94.30
[26]	2017	20 normal 20 depressed	Kernel Eigen-filter-bank common spatial pattern	SVM	81.23
[29]	2018	15 normal 15 depressed	End-to-end	CNN	93.54 (Left) 95.96 (Right)
Present Study	2019	15 normal 15 depressed	End-to-end	CNN-LSTM	97.66 (Left) 99.12 (Right)
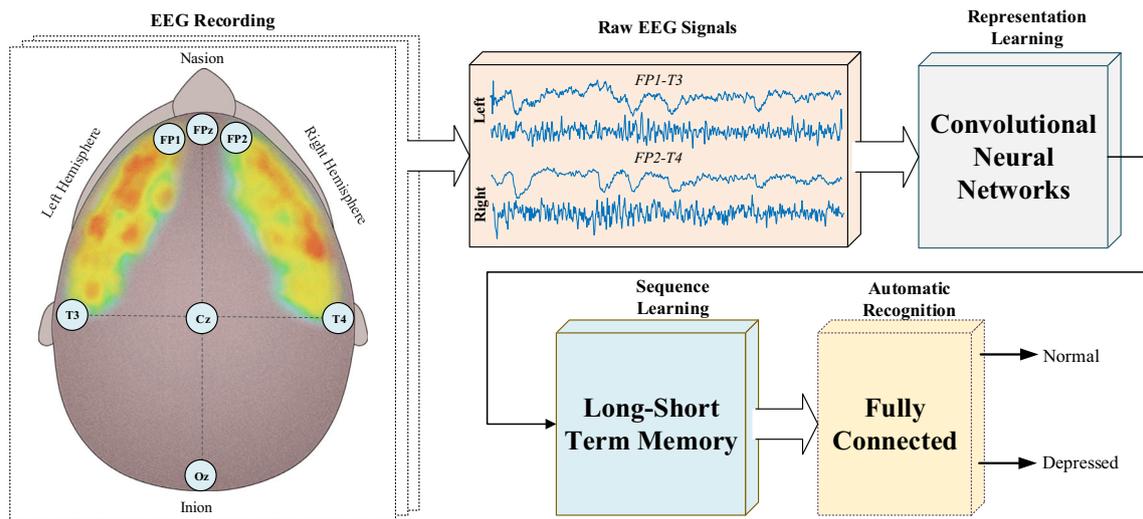
Fig. 1 An illustration of the EEG-based automatic depression detection system

EEG data without requiring any feature extraction or selection. Thus, an effective and state-of-art deep learning approach can be used in the field of healthcare to detect the depression.

The structure of the remainder of the paper can be summarized as follows: In section "Materials and method", the dataset used in the study and proposed CNN-LSTM model are presented. In section "Experimental results", experimental results are evaluated. In section "Discussion", the results and comparison with other studies on the same dataset are presented. The clinical implication of the work is presented in the conclusion section.

Materials and method

In this study, the EEG signals obtained from the right and left hemispheres of the brain are used for EEG-based automatic depression recognition process. The raw EEG signals are applied to the CNN model. The feature maps obtained from the output of the CNN model are fed to LSTM as inputs and sequence learning is performed on these signals. The LSTM outputs are passed through fully connected layers to ensure the automatic detection of depression EEG signals. Thus, a CNN-LSTM based method is developed to detect depression in a hybrid manner involving both the representation and sequence learning stages. A block diagram representation of the method used in the study is given in Fig.1.

Depression dataset

In this study, we have used the same normal and depression EEG signals used by Acharya et al. [29] (taken from Calicut, Kerala, India). The EEG signals were acquired from 15 normal and 15 depressed subjects from left half (FP1-T3 channel) and right half (FP2-T4 channel) of the brain. The EEG signals were sampled at a sampling rate of 256 Hz and the power line noise was eliminated with a 50 Hz notch filter. Artifacts resulting from muscles and eye movements within the EEG signals were manually removed by experts. The EEG data of 30 subjects were evaluated in two separate categories as left and right hemisphere EEG data belonging to normal and depressed classes. It consists of 4798 depression and 4318 normal EEG records (files) with each file having 2000 samples. The detailed information about the data is presented in Table 2. The illustrations of some signal samples in the data are shown in Fig. 2.

The proposed deep model architecture

It can be seen from the previous work [29], CNN model is good in extracting temporal features and poor in learning sequential information. To overcome this problem, we built a new hybrid architecture consisting of CNN and LSTM models. The architecture of the proposed system is illustrated in Fig. 3. The CNN learns the local features of input EEG

Table 2 The details of EEG signals used in the study

Class	Number of subjects	Right hemisphere EEG signals (FP2-T4)	Left hemisphere EEG signals (FP1-T3)	Total number of data
Depressed	15	2398	2400	4798
Normal	15	2159	2159	4318
Total	30	4557	4559	9116

Fig. 2 Sample EEG signals: **a** right hemisphere normal, **b** right hemisphere depression, **c** left hemisphere normal and **d** left hemisphere depression
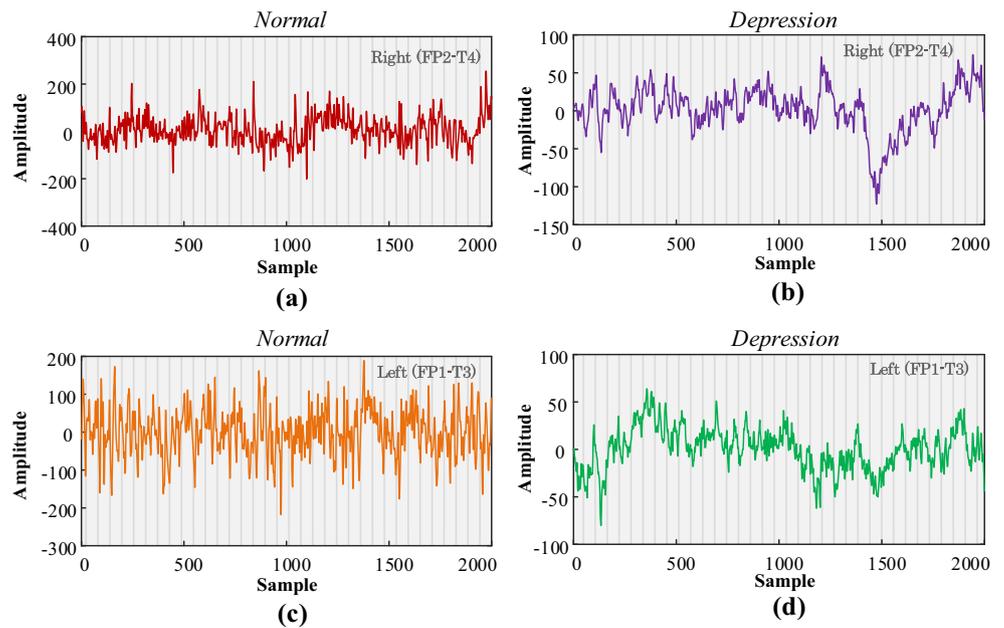
signals (representation learning), LSTM learns long-term dependencies and processes these features in a sequential manner (sequence learning). In Table 3, each layer of the proposed CNN-LSTM network and the parameters of these layers are given in detail. The filter number of the model and the parameter selection, such as kernel size, are performed using the values obtained from the previous CNN models [16, 21, 22, 48] and using the brute-force technique. Training and validation curves are examined and the most appropriate parameters are determined.

Representation learning

The CNNs are combination of the popular convolution process and neural networks. In our CNN architecture, presented in Fig. 1, there are four convolution layers and two max-pooling layers. The main purpose of the convolution process is to extract features or information from a given signal. The mathematical convolution process is defined in eq. (1).

$$a(t) = (x*w)(t) = \int_{-\infty}^{\infty} x(b)w(t-b)db \tag{1}$$

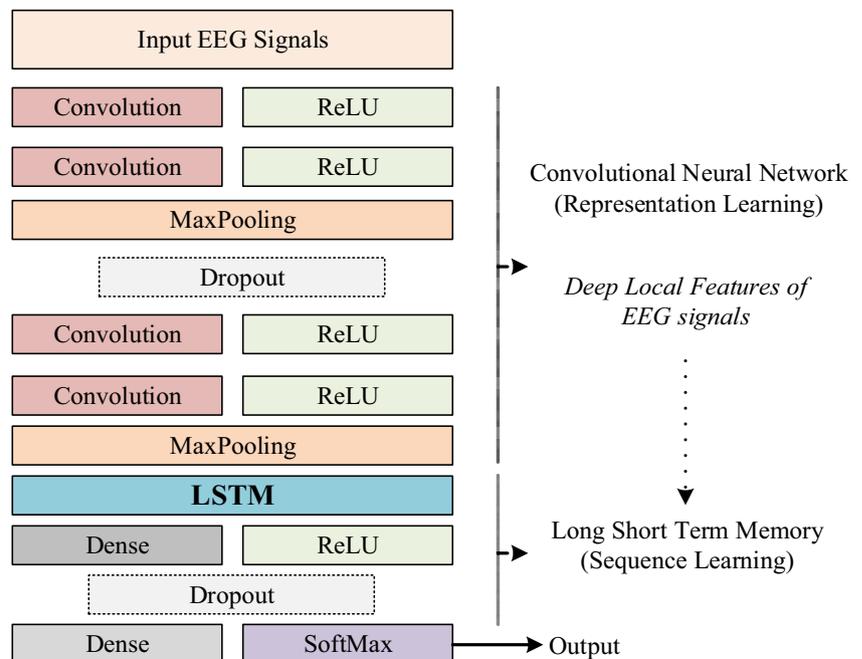**Fig. 3** An overview of the proposed architecture

Table 3 Detailed information about the proposed CNN-LSTM deep model

No	Names of layers	Kernel size	Parameters of layers	Number of parameters
1	Conv1D	64 × 5	Strides = 1, Activation = ReLU	384
2	Conv1D	128 × 3	Strides = 1, Activation = ReLU	24,704
3	MaxPooling1D	2	Strides = 2	0
4	Dropout	–	Rate = 0.2	0
5	Conv1D	128 × 13	Strides = 1, Activation = ReLU	213,120
6	Conv1D	32 × 7	Strides = 1, Activation = ReLU	28,704
7	LSTM	–	Unit Size = 32, Return Sequences = True	8320
8	Flatten	–	–	0
9	Dense	–	Unit Size = 64, Activation = ReLU	1,001,536
10	Dropout	–	Rate = 0.2	0
11	Dense	–	Unit size = 2, Activation = SoftMax	130

Here, x represents input EEG data, w is filter and a is feature map. For each convolution layer, we have chosen 64, 128, 128 and 32 specific filters (also called kernels) with different filter sizes of 5×1, 3×1, 13×1 and 7×1 respectively. These filters are convolved with the input matrix of signal data to produce feature maps after the convolution layer. We used rectified linear unit (ReLU) function after each convolution layer. As given in the eq. (2), the ReLU function takes the value 0 for the negative inputs and the x value for the positive inputs x.

$$f(x) = \max(0, x) \tag{2}$$

The extracted feature maps will be the new inputs to the next layer. The maximum pooling technique is used in the MaxPooling1D layer to reduce the input size, memory usage and number of parameters. Finally, for the binary-classification, the predictive class probabilities of the inputs given by using the Softmax function are presented as output. We also used dropout technique to prevent the proposed network from the overfitting problem.

Sequence learning

The EEG signal can be seen as time series signals of brain activities. The EEG signals over a specific period are used to diagnose various disorders. For this purpose, sequential signals can be learned by deep learning techniques. The aim of sequential learning is to model short-term and long-term memory. Although, the short-term memory is very well modeled by standard recurrent neural networks (RNN), it cannot be effective in long-term dependencies due to vanishing gradient problems. The biggest problem encountered when training artificial neural networks with back propagation is the vanishing gradient problem [30], which makes it difficult to train the previous layers and learn the network. To overcome this long-term dependency problem, there is a need for neural networks that can remember the input information given over a long time and decide which data to remember. In 1997, Hochreiter and Schmidhuber [31] proposed LSTM to meet this requirement.

In the LSTM architecture illustrated in Fig. 4, unlike the RNN architecture, there are special hidden units called memory cells that are used to remember the previous input for a long time. An LSTM architecture contains forget, learn, remember and use gates that determine whether an input is so important that it can be saved. In the LSTM unit, *four* different functions such as sigmoid (σ), hyperbolic tangent (*tanh*), multiplication ($\times$), and sum ($+$) are used, which make it easier to update the weights during the back propagation process.

More formally, sequential learning approach over EEG time series is defined as follows:

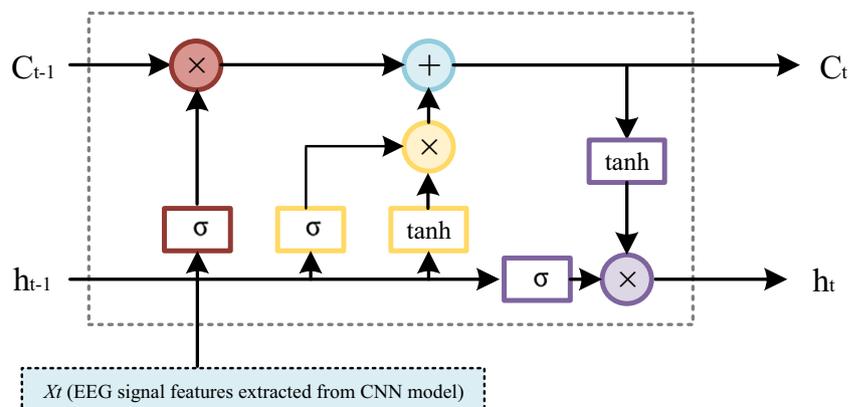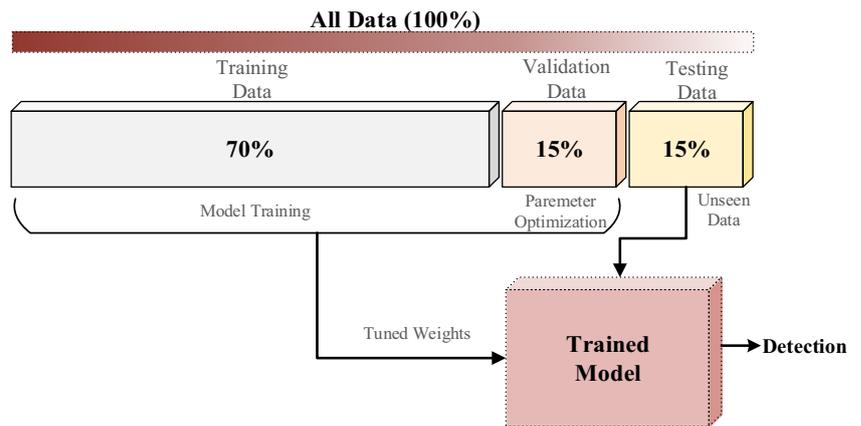**Fig. 4** An illustration of LSTM architecture

Fig. 5 Sketch of data partitioning employed to create the model

$$n_t = tanh(W_n[h_{t-1}, x_t] + b_n) \qquad (3)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad (4)$$

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \qquad (5)$$

$$C_t = C_{t-1}f_t + n_t i_t \qquad (6)$$

$$U_t = tanh(W_u C_{t-1}f_t + b_u) \qquad (7)$$

$$V_t = \sigma(W_V[h_{t-1}, x_t] + b_V) \qquad (8)$$

We suppose that there are N local features, $\{x_1, x_2 \dots x_N\}$, extracted from our CNN model. The x_t is input signal feature for time t, short term memory value h_{t-1}, long term memory value C_{t-1}, weight matrix W_n, bias b_n, ignore factor i_t, forget factor f_t; $n_t i_t$ is the output of learn gate, $C_{t-1}f_t$ is the output of forget gate, C_t is the output of remember gate and $U_t V_t$ is the output of use gate.

Experimental results

In this study, EEG signals containing 2000 samples obtained from right and left hemispheres of brain are used for automated depression detection. Raw signals belonging to 30 subjects are scaled to a range of [0, 1]. The random splitting and 10-fold cross validation techniques are employed to evaluate the deep leaning model.

Random splitting tests

In random splitting technique, the data are divided randomly in to training, validation and testing. It is a widely used technique especially in deep learning studies where data is large. In this study, the dataset for each group is divided into 70% training, 15% validation and 15% test sets and this procedure is shown in Fig. 5.

The training and validation datasets are used to train the deep learning model. The test set is the data which was never used by the model during training. Therefore, the test performance of the trained model can be observed more effectively through test data. The number of data files obtained from the right hemisphere is 4557. Among this, we have used 3189 files for training, 684 for validation and 684 for testing. Similarly, the total number of data from the left hemisphere is 4559 files. We have used 3191 files for training, 684 for validation and 684 for testing. Experiment is performed on a Linux Server (Ubuntu 16.04.4) with a NVIDIA GTX 1080 GPU. The model is implemented with Python using Keras deep learning libraries. General hyper-parameter settings of the model are given in Table 4.

Experimental studies are performed separately for right and left hemisphere EEG signals. The CNN-LSTM model is primarily trained on training set that includes normal and depression classes. By observing the performance of the model during training and validation sets, we make sure that overfitting does not occur during training. Table 5 shows the performance of the CNN-LSTM model for right hemisphere EEG signals for 15 epochs.

Accuracy and loss values indicates that, there is no overfitting during training. At the end of the training, the model for the right hemisphere EEG signals reached an accuracy of 99.34% during training and an accuracy of 98.98% using validation set. Training loss value decreased from 0.41 to 0.02 and validation loss decreased from 0.09 to 0.05. In addition, the training took an average of 52 s for each epoch. At the end of the 15th epoch, the training performances of the model for the left hemisphere EEG signals

Table 4 Various parameter settings used to create the model

Parameters	Values
Optimizer	Adam
Learning Rate and Decay	1e-4
Loss Function	Categorical cross entropy
Metrics	Accuracy
Batch Size	64
Epochs	15

Table 5 Training performances for CNN-LSTM model using right hemisphere (Fp2-T4) EEG signals for various epochs

Epochs	Time (Second)	Training accuracy (%)	Validation accuracy (%)	Training loss	Validation loss
1	59	82.85	96.78	0.4123	0.0997
2	51	96.99	97.95	0.0932	0.0820
3	51	97.59	98.39	0.0800	0.0637
4	51	98.28	98.68	0.0604	0.0653
5	51	98.31	98.83	0.0599	0.0614
6	52	98.37	98.39	0.0522	0.0682
7	52	98.62	98.54	0.0503	0.0640
8	52	98.65	98.25	0.0492	0.0742
9	51	98.34	98.83	0.0537	0.0537
10	52	99.00	98.68	0.0405	0.0625
11	52	99.18	98.39	0.0363	0.0639
12	52	99.15	98.83	0.0351	0.0541
13	52	99.25	98.83	0.0294	0.0569
14	52	99.34	98.68	0.0279	0.0614
15	52	99.34	98.98	0.0275	0.0520
Average	*52.13*	*97.55*	*98.46*	*0.0738*	*0.0655*

have reached an accuracy of 98.37% during training, 98.68% during validation, 0.04 training loss and 0.06 validation losses. The graphical representations of these performance values are presented in Fig. 6.

After the training of the CNN-LSTM model, it is tested using unused test data set. True positive (TP), false positive (FP), and false negative (FN) statistical measurements have been used to evaluate performance of the model. The calculations used in the study as follows; sensitivity (TP / (TP + FN)), specificity (TN / (FP + TN)), precision (TP / (TP + FP)), and accuracy ((TP + TN) / (FP + FN)). Tables 6 and 7 shows the performance values for right and left hemisphere EEG signals during testing of the model.

Fig. 6 Performance graphs for the right hemisphere (Fp2-T4) and left hemisphere (Fp1-T3) EEG signals of the CNN-LSTM model: a) Accuracy values of right hemisphere EEG signals, b) Loss values for right hemisphere EEG signals, c) Accuracy values for left hemisphere EEG signals, and d) Loss values for left hemisphere EEG signals
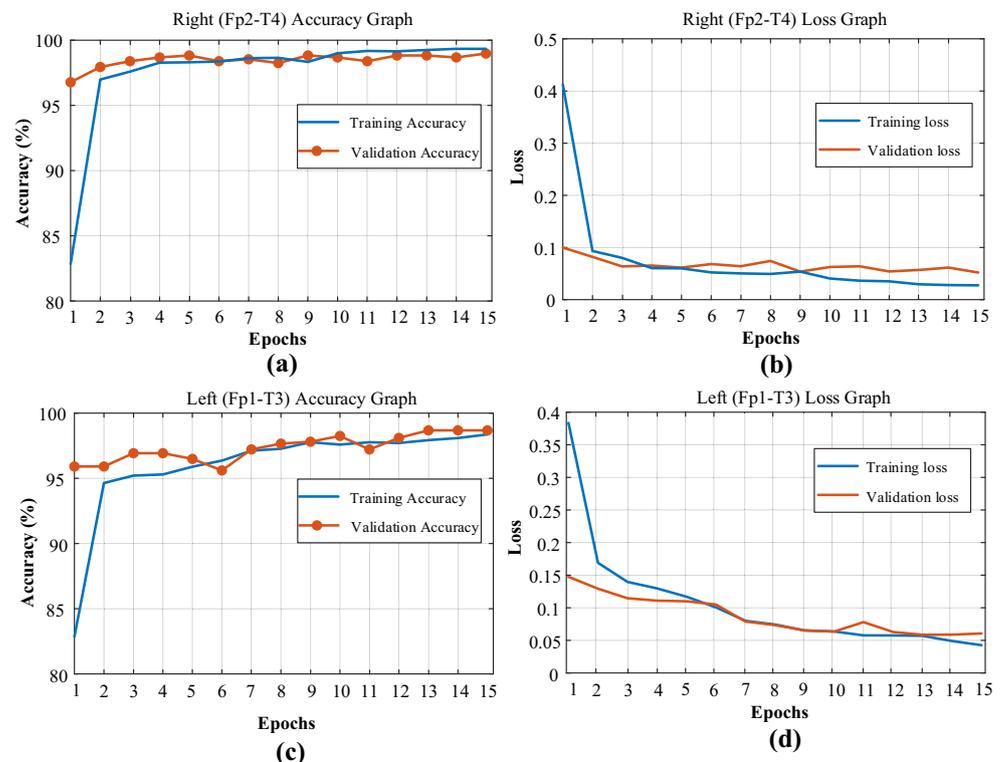
Table 6 Performance values obtained during testing the model with right hemisphere (Fp2-T4) EEG data

	Classes	Predicted		Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
		Depression	Normal				
Actual	Depression	342	5	99.12	99.70	98.55	99.70
	Normal	1	336		98.53	99.70	98.55

The CNN-LSTM model incorrectly classified only 6 of the 684 data for the right hemisphere EEG signals and reaches the highest accuracy of 99.12%. The sensitivity of the depression and normal class are 98.55% and 99.70% respectively. The accuracy of the model for the left hemisphere EEG signals is 97.66%. The sensitivity of the depression and normal classes are 97.03% and 98.27%, respectively. It can be noted from the results obtained in the above that, CNN-LSTM model yielded the highest performance in detecting the depression using EEG signals. Besides, our experimental results indicate that, right hemisphere (Fp2-T4) EEG signals show a higher performance than the left hemisphere EEG signals. The trained CNN-LSTM model took approximately 0.005 s to classify a single EEG input data of 2000 samples.

10-fold cross validation tests

The other common technique used in the evaluation of models in the field of machine learning is k-fold cross-validation. In this technique, the data is randomly divided into k equal parts. k-1 parts are used in the training phase of the model and the remaining part is used in the testing phase. This process repeats until all parts are evaluated in the test phase. In this study, k = 10 is selected and the data are randomly divided into 10 equal sections. Figure 7 shows the graphs of the performance values obtained by the 10-fold cross validation test for both EEG signal groups.

The performance criteria for the right hemisphere EEG signals are above 98% for all folds and average accuracy value is 98.94%. The CNN-LSTM model performed using left hemisphere EEG signals showed slightly lower performance than right hemisphere EEG signals. The average accuracy value of this model is 97.82%. Table 8 presents the overall performance and confusion matrix obtained using 10-fold cross validation with both EEG signals.

The CNN-LSTM model, using right hemisphere signals in the 10-fold tests, misclassified only 19 out -of 2250 depression data. But 38 out of 2420 depression data are incorrectly classified using left hemisphere EEG data. Thus, 10-fold cross validation for right and left hemisphere EEG signals have yielded accuracy of 98.95% and 97.76% respectively. These results are comparable with the experimental results obtained using the random splitting technique. The performance obtained using right hemisphere with random splitting is better than the 10-fold cross validation test and the performance of the 10-fold cross validation for left hemisphere is slightly higher.

An EEG signal applied to the input of the trained CNN-LSTM network is passed through the CNN and LSTM layers, respectively, and the classification step is performed on the feature maps obtained from these layers. Figure 8 shows the output of a sample depression EEG signal obtained from CNN and LSTM layers.

Discussion

In this study, a hybrid deep learning based automatic depression detection system was proposed. Summary of automated depression systems developed using deep learning techniques with EEG signals is given in Table 9.

It can be seen from Table 9 that the accuracy and sensitivity values of the proposed method are higher than the previous studies. Acharya et al. [29] obtained 95.49% accuracy for right hemisphere EEG signals, while we have obtained 99.12% and 98.95% accuracy using the same database with random-splitting and 10-fold CV, respectively. Similarly, Acharya et al. [29] achieved 93.54%

Table 7 Performance values obtained during testing the model with left hemisphere (Fp1-T3) EEG data

	Classes	Predicted		Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
		Depression	Normal				
Actual	Depression	327	10	97.66	98.19	97.03	98.27
	Normal	6	341		97.15	98.27	97.03

Fig. 7 The graphs of CNN-LSTM model using 10-fold cross validation: **a** right hemisphere EEG signals, **b** left hemisphere EEG signals
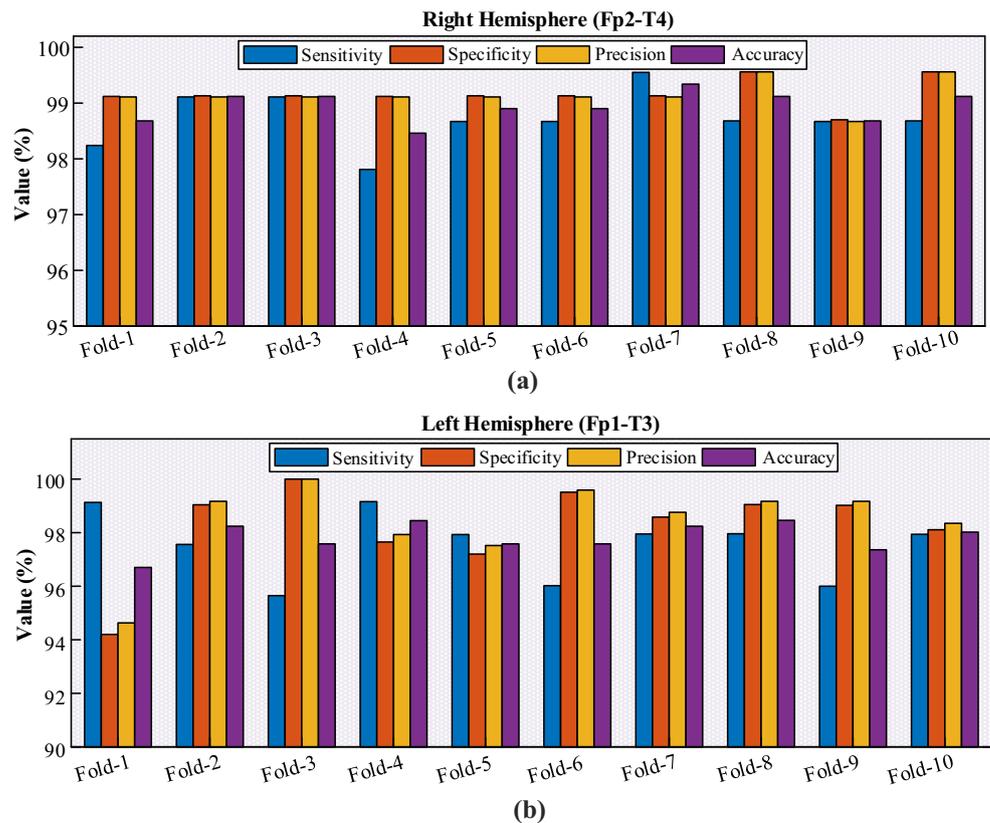
accuracy for the left group, but we have achieved 97.66% and 97.66% with random-splitting and 10-fold CV, respectively. Our right hemisphere accuracies are higher than the left as reported by Acharya et al. [29]. This is because the activation of frontal cortex of right hemisphere is higher during depression than left hemisphere [47]. Hence, right hemisphere EEG will contribute more than the left hemisphere.

The most important advantage of this study is its high performance in detecting depression by using both local characteristics and long-term dependencies of the EEG signals. The CNN networks learn local properties while LSTM network learns sequences from these features. In few state-of-the-art studies given in Table 1, wavelet [28, 44, 45], HOS [24], and non-linear [46] feature extraction techniques have been used. These approaches are complex, time consuming and require experience. But in our study, this feature extraction is performed by the model itself. In addition, the proposed deep detection model consists of multiple layers instead of shallow classifiers such as SVM and ANN is presented.

Hence, this proposed CNN-LSTM model has achieved remarkable performance with single-channel EEG data obtained from right and left hemispheres of the brain. Therefore, CNN-

Table 8 Overall performance values obtained during 10-fold cross validation with EEG data

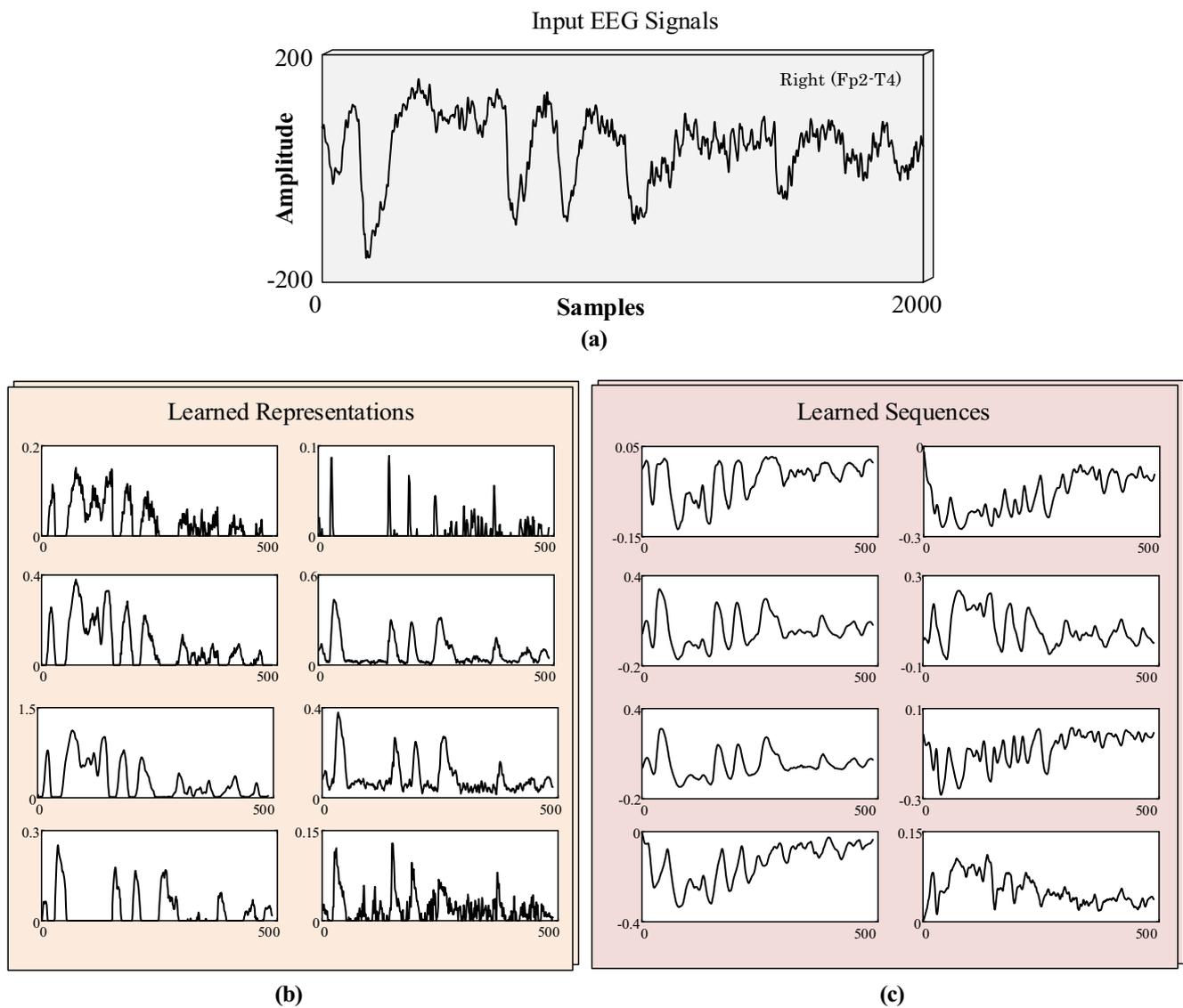|			Predicted Classes		Performances (%)			
			Depression	Normal	Accuracy	Precision	Sensitivity	Specificity
Right (Fp2-T4)	Actual Classes	Depression	2231	19	98.95	99.16	98.72	99.17
		Normal	29	2271		98.74	99.17	98.72
Left (Fp1-T3)		Depression	2382	38	97.76	98.43	97.38	98.19
		Normal	64	2066		97.00	98.19	97.38

Fig. 8 Output obtained at CNN and LSTM when the original depression EEG signal is fed: **a** original depression EEG signal, **b** features obtained at the output of CNN and **c** sequences obtained at the output of LSTM

LSTM model is accurate and robust in detecting the depression using EEG signals. The proposed model detects unknown EEG signals fast and accurately. Therefore, the proposed model is useful and can be easily implemented for clinical applications.

The main drawback of this study is that, we have used few subjects (15 normal and 15 depression). In addition, the developed model is computationally intensive. In future, we intend to extend this work, using more number of subjects taken from diverse background and the computational complexity can be reduced using graphical processing units (GPUs). In future, we intend to improve the results applying more advanced deep learning approaches with more dataset.

Table 9 Summary of automated depression systems developed using deep learning techniques with EEG signals

Study	EEG Signals	Method	Accuracy (%)	Sensitivity (%)
Acharya et al. [29]	Right (Fp2-T4)	• 13-layer CNN	95.49	94.99
	Left (Fp1-T3)	• 10-fold CV	93.54	91.89
The proposed	Right (Fp2-T4)	• CNN-LSTM	99.12	99.11
	Left (Fp1-T3)	• Random splitting (70, 15,15)	97.66	97.67

Additionally, the CNN-LSTM layers will be evaluated using classifiers such as SVM.

Conclusion

A novel depression detection system based on EEG signals is presented. This model consists of a combination of LSTM network that is effective in learning long-term dependencies present in the CNN architecture, which is powerful in extracting the local features. The proposed CNN-LSTM network is developed using EEG signals obtained from the right and left hemispheres of the brain of 30 subjects. Our proposed model is able to detect the depression with an accuracy of 99.12% and sensitivity of 99.11% from the right (Fp2-T4) side hemisphere EEG signals. However, more robust models can be developed using huge database obtained from diverse races. The developed model can be used to detect the early stage of depression and other neurological disorders using EEG signals.

Compliance with ethical standards

Conflict of interest   All authors declare that there is no conflict of interest in this work.

Ethical approval   All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. We have obtained the ethical approval for depression data from Medical College Calicut, Kerala, India.

Informed consent   Informed consent was obtained from all individual participants included in the study.

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