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DepHNN: A novel hybrid neural network for electroencephalogram (EEG)-based screening of depression

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ABSTRACT

Depression is a psychological disorder characterized by the continuous occurrence of bad mood state. It is critical to understand that this disorder is severely affecting people of multiple age groups across the world. This illness is now considered as a global issue and its early diagnosis will be effective in saving the lives of many people. This mental disorder can be diagnosed with the help of Electroencephalogram (EEG) signals as an analysis of these signals can indicate the prevailing mental state of the patients. This paper elaborates on the advantages of a fully automated Depression Detection System, as manual analysis of the EEG signal is very time consuming, tedious and it requires a lot of experience. This research paper presents a novel EEG based computer-aided (CAD) Hybrid Neural Network that can be identified as DepHNN (Depression Hybrid Neural Network) for depression screening. The proposed method uses Convolutional Neural Network (CNN) for temporal learning, windowing and long-short term memory (LSTM) architectures for the sequence learning process. In this model, EEG signals have been obtained from 21 drug-free, symptomatic depressed, and 24 normal patients using neuroscan. The model has less time and minimized computation complexity as it uses the windowing technique. It has attained an accuracy of 99.10% with mean absolute error (MAE) of 0.2040. The results show that the developed hybrid CNN-LSTM model is accurate, less complex, and useful in detecting depression using EEG signals.

1. Introduction

As estimated by the World Health Organization (WHO), depression is one of the most prominent and second major disabilities causing mental illness affecting around 322 million people worldwide [1]. As per the records, there is an increment of 18% in the number of people suffering from depression in the last decade wherein the percentage of female patients is much higher than males [2]. It is a disease whose symptoms can be severe, mild, or moderate. People suffering from depression may experience several emotions as guilt feeling, lower mood state, low concentration, lack of interest in regular activities, low self-esteem and it can even lead to harboring suicidal thoughts [3–5]. There are innumerable factors as lack of awareness, untrained medical care providers, lack of resources, and mostly incorrect diagnosis that led to the staggering 50% of the patients suffering from depression remains untreated for the condition [5]. This illness can be treated easily if diagnosed timely and properly, so a computer-aided solution based on a Hybrid combination of LSTM+CNN with very little computation complexity and high accuracy can help in effective diagnosis.

EEG has been explored as an effective biomarker and diagnosed tool [6–8] for the detection of neurological disorders in comparison to others because of its non-invasive and economical nature. EEG records brain electrical signals with the reference of time as shown in Fig. 1, these signals are much complex and messy in nature. Hence,it is very difficult to analyze such signals manually [9]. In last few years, many machine learning [6–8,10–14] and deep learning [15–19,11,20–30] tools have been explored using EEG signal for detection of several neurological diseases as Alzheimer's [31], Epilepsy [32,33], Parkinson's [34,35], Seizure [36,37], Schizophrenia [38] Creutzfeldt-Jakob [39] and Emotion detection etc. Therefore, this paper also utilizes EEG signals as the biomarker and proposes a Computer-Aided Detection system for the diagnosis of depressive disorder. This is really an important field because of the fact that depression is a complex and multifaceted issue till date, EEG Signal along artificial intelligence techniques have a great potential to mitigate the depression detection issues.

The structure of the paper can be summarized as follows: Section 2 represents the review of prior research work in the detection of depression using EEG Signals. In Section 3, the dataset used in the study

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and Deep learning model for depression is introduced. In Section 4, the Proposed DepHNN model for depression detection is presented. Section 5 presents the results and comparison with other studies on the same dataset. Finally, in Section 6 conclusion is given.

2. Prior research work and contribution

2.1. State of art work

There have been several attempts for Depression Detection from last decade. Table 1 gives an overview of some very popular studies related to Depression Detection System using EEG signals. [40] presented a model with the combination of Wavelet-Chaos method, Higuchi's–Katz's Fractal Dimension (HFD–KFD) [41] and Enhanced Probabilistic Neural Network (EPNN) for diagnosis of Major Depression Disorder (MDD) with an accuracy of 91.3%. [42] extracted non-linear features and used Logistic Regression Classifier for differentiating normal and depressed classes and attain accuracy of 90.05%. [43] performed wavelet packet decomposition on EEG signals and extracted non-linear features and entropy features. Then these features were fed into Probabilistic Neural Network (PNN) classifier to categories normal and depressed patients which reported accuracy of 98.20%. [44] investigated various non-linear feature extraction methods and proposed an index for depression detection. They have used the SVM classifier and reported an accuracy of 98%. [45] used a combination of wavelet entropies, energy features, and Support Vector Machine classifier with Radial Basis Kernel Function (SVM RBF) that reported accuracy of 88.9%. [46] extracted features from the linear predictive coding (LPC) methodology and reported an accuracy of 94.3%.

All the above-mentioned studies have used handcrafted features where features have to be selected using some machine learning algorithms or nonlinear analysis [48,49]. It was a very complex task to choose appropriate feature set manually but then [25] proposed a deep learning-based 13-layer CNN model and [47] developed a 11-layer CNN-LSTM model to automatically classify normal and depressed patients with much better accuracy. The deep learning method doesn't require any feature set as it automatically and iteratively learns from available EEG dataset and it can classify normal and depressed subjects. Such Deep Learning methods have been applied to several applications in recent past and showed very good performance on larger dataset [15–18], [25–30]. CNN is primarily used for image processing and it has also showed very promising results in the biomedical fields too as in the early diagnosis of Alzheimer's disease [31], Depression [50,40], Medical imaging field [51–53], Seizure detection, early-stage Creutzfeld-Jakob disease and Autism detection. There have been some obstacles such as lack of trained health professionals and non-availability of laboratory tests for the diagnosis of depression. The present paper focuses on developing an effective system that supports the automatic diagnosis of depression using EEG signals. In this system, EEG signals are initially processed and then analyzed by passing through a deep neural network for classification.

Table 1
Methods proposed in literature for depression detection system using EEG signals.

Authors and Year	Dataset	Method
Ahmadlou et al. [40], 2012	12 Normal, 12 Depressed	Enhanced PNN
Hosseinifard et al. [42], 2013	45 Normal, 35 Depressed	Logistic Regression
Faust et al. [43], 2014	15 Normal, 15 Depressed	PNN
Acharya et al. [44], 2015	15 Normal, 15 Depressed	SVM
Bairy et al. [45], 2016	14 Normal, 16 Depressed	SVMRBF
Bairy et al. [46], 2017	15 Normal, 15 Depressed	Bagged Tree
Acharya et al. [25], 2018	15 Normal, 15 Depressed	CNN
Ay et al. [47], 2019	15 Normal, 15 Depressed	CNN-LSTM

2.2. Research gaps addressed in the paper

Several methods and datasets have been proposed/used in the literature for the diagnosis of depressive disorder. The main findings or research gaps of these studies are listed below:

1. In several studies, [54,41–46], many handcrafted linear or non-linear features as wavelet entropies, DWT, etc. and clinical features have been extracted [55]. The main drawback of this manually features selection is that the selection process can have imputation on the performance of classification model.
2. Datasets used in almost all the above studies or research accommodated relatively less number of subjects and that too when the subjects were stimulated with the controlled task.
3. The CNN model proposed by [25] presented the advantage of automatic feature selection with high accuracy over previously available machine learning approaches and it uses 13 neural layers. [56] stated that LSTM networks can deliver better results than CNN for EEG signals because EEG signals are highly complex and nonlinear time series in nature. That LSTM based model proposed by [56] showed false prediction rate (FPR) of 0.11–0.02 for seizure prediction.
4. Deep neural models proposed in the literature are a bit complex. Therefore, such a deep model requires expensive system configuration to train and classify.

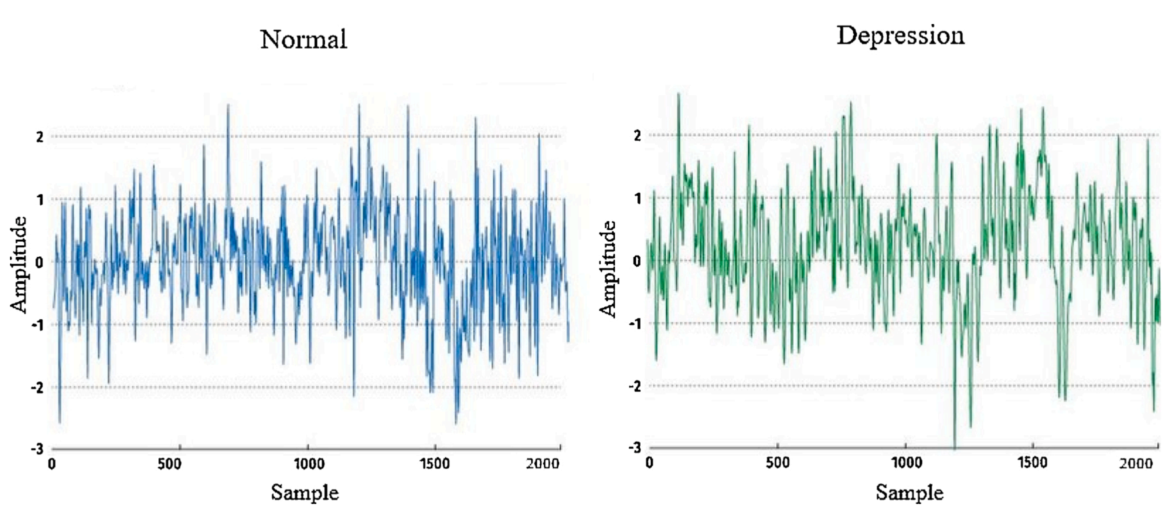

Fig. 1. Normal EEG and depressed EEG.

2.3. Novel contribution of the paper

1. In this paper, a Hybrid CNN-LSTM based Deep Learning model is proposed for depression detection. The proposed model explores LSTM network with CNN layers where CNN layer stride over the time series EEG input signals for windowing and LSTM block provides sequence learning. Hence, it is a complete model that enables learning on both long-term dependencies and local features for EEG signals.
2. The proposed DepHNN is a high performance (less time and computation complexity) and automatic detection model which can be used in the detection of depression disorder effectively.
3. A different and comparatively larger dataset with 24 normal and 21 depressed patients are used to train and test the model.
4. Windowing is used as a part of pre-processing so that model can be trained in relatively less time.
5. This paper has proposed a model with relatively less number of hidden layers, hence it has relatively less complexity.

3. Our vision of depression detection using EEG

3.1. Deep learning model for depression

CNN has demonstrated promising results in extracting features from stationary data as images, notwithstanding, one of the major concerns with CNNs is that it can't assess temporal or earlier data in the time-series signals. However, LSTM can be effectively utilized to extract and process the temporal information [56]. So, a better solution considering the Hybrid combination of both CNN and LSTM can be utilized to process the EEG signal (Time-Series signal). Fig. 2 shows a schematic diagram of our proposal for depression detection with help of EEG signal. In this model, EEG signals from brain electrical activity have been used for the detection of depression. Initially, Pre-processed EEG data has been applied to the CNN layer which transforms the time-series EEG data into cross-sectional data using windowing, and then the feature output from the CNN model is provided to LSTM block [57]. LSTM block performs sequence learning on the signals coming from the CNN model and this learning capability of the LSTM model is utilized to study the significance of each feature in the ultimate conclusion making. The output of the LSTM block is applied to fully connected layers to help in automatic detection of depression. Thus, a hybrid combination CNN-LSTM-Fully connected layer has been used in this study for the automatic detection of depression.

3.2. Dataset and preprocessing of EEG signal for depression detection

The dataset of EEG signals were obtained from the psychology department, University of Arizona, USA [58]. Participant's data were obtained with written informed consent that was approved by the University of Arizona. The selection of Participants was done based on mass survey scores of the Beck Depression Inventory (BDI). The EEG signals were taken from $N = 24$ control (14 female) participants with a BDI score of less than 7 and $N = 21$ (14 female) depressed participants with a BDI score greater than 13. All participants were of age group 18–25 with no history of trauma or seizures and no current psychoactive medication. The EEG signals were taken using 64 scalp electrodes and sampled at a rate of 500 Hz. Artifacts such as eyeblinks were removed with the help of Independent Components Analysis and the Fast Fourier Transform method was used to extract time-frequency information from the raw EEG signals. The windowing method was used as a part of pre-processing as it is a smart way to process a time-series data used in a deep learning-based model [59]. In this process, the reshaping of complete information is done with the window of fixed size in such a way that can provide possible necessary information at a given point of time to get accurate prediction and then the effect of its response can be checked on the model.

4. Proposed model for EEG based depression detection

The CNN model simply strides over the data in different hidden layers but here output is not fed back to the network. Therefore, CNN models are quite poor in learning sequential information but good in extracting temporal features as discussed in the previous section.

To overcome this problem, a Hybrid model is proposed in this paper using CNN and LSTM both. Since, LSTM being a part of RNN, is used for sequential data learning because it not only learns from the training but also remembers what it has learned to predict the next element in the sequence. As a part of the process, the output is fed back to the network. So, LSTM learns long-term dependencies and processes these features in a sequential manner (sequence learning). The proposed approach is

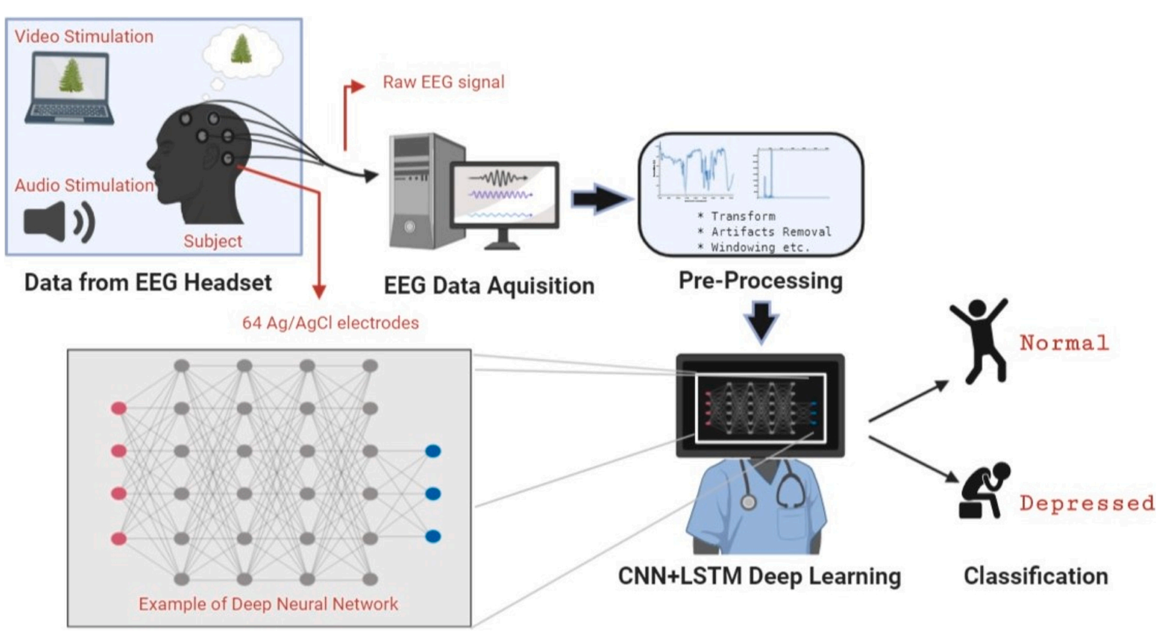

Fig. 2. Depression detection system using EEG signals.

shown in Fig. 3.

4.1. Feature extraction using CNN

The main objective of using CNN is to extract important features from input EEG signals to train the algorithm. CNN is mainly a combination of neural network and convolution process [25]. Convolution process is performed by sliding the specific kernels over the input data to get the feature map. The convolved output is generated using the following equation:

$$y(t) = (x * t) = x(w)k(t - w)\mathrm{d}w \tag{1}$$

where *y*, *x*, and *w* denote the output feature map, input data, and filter respectively. In this proposed model as shown in Fig. 3, 1 convolution layer and 3 fully connected layers have been used. As there are 64 channels, the window size is 20, and the batch size is 40, for the convolution layer, several different architectures have been investigated by varying the kernel size, and then kernel of 64 × 5 has been chosen which has been proved to allow for capturing information at 4 Hz and above from EEG signals [60]. These filters are being convolved with the matrix of input EEG signal data to obtain significant features. A rectified Linear Unit (ReLU) is employed as an activation function which is useful after the convolution layer to increase the robustness of the algorithm. ReLU takes *x* value for the positive inputs and makes 0 for negative inputs as shown in the equation below:

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

Then, the extracted features are generated after ReLU.

4.2. Learning model with LSTM

The LSTM architecture was proposed by Hochreiter and Schmidhuber [60] in 1997 for sequence learning. EEG signals are time-series signals as they record brain activity over a certain period. Therefore, sequence signal learning to model short term and long term memory is required. Recurrent neural networks (RNN) are only suitable for modeling short term memory but redundant in the case of long term memory. The major challenge while training neural networks in backpropagation is its vanishing gradient. This vanishing gradient problem makes it tedious to learn neural networks, so LSTM architecture is used to overcome the problem as this remembers input information for a long time and it can also decide which data is to be remembered.

LSTM architecture uses specific hidden units called memory cell as shown in Fig. 4, which remembers the previous input for a long time. This architecture comprises multiple functions like sum, multiplication, sigmoid and hyperbolic tangent which are being used during backpropagation to update the weights. Fig. 4 shows the sequence learning over EEG signals. Let there are total *N* local features, $x_1, x_2 \ldots x_N$, which are extracted from above defined CNN model. The X_t is input signal feature extracted from CNN model for time t, long term memory value S_{t-1}, short term memory value h_{t-1}, ignore factor i_t, forget factor f_t, S_{t-1} f_t is the output of forget gate, $\widetilde{S}_t i_t$ is the output of input gate, S_t is the output of remember gate and h_t is the output of use gate.

4.3. Architecture of proposed hybrid model: DepHNN

The architecture of proposed Hybrid 6-layer CNN-LSTM model is shown in Fig. 5. In this model initially, as convolution operation is performed on the input signal to obtain the 1st layer (output neurons of 64 × 5), and then ReLU layer is used as an activation function. Layers 2 and 3 are used for sequence learning, so LSTM architecture is used. Layer 4 and 5 are fully-connected layers connected to 16 fully-connected neurons and layer 6 is the final layer with 2 outputs neurons that classify normal and depressed patients. This model has used Huber's loss for backpropagation to update the weight matrix. Each layer of the proposed CNN-LSTM model and parameter associated with each layer is explained in Table 2.

5. Results and discussion

The proposed model was trained and tested on a computer with Intel i7 (2.30 GHz processor) and a 12 GB RAM DDR4. The implementation and results were carried with Python using Keras libraries.

A backpropagation algorithm is employed for the training of the model with the batch size of 64 and for improving the efficiency of the training, ADAM (Adaptive moment estimation) optimizer is used to update the weights of the network. For training, validation, and testing, data is randomly divided using the widely used random splitting technique. In this paper, the complete dataset is divided into 70% training, 20% validation and 10% test set. This process is widely used in deep networks where training and validation dataset is used to train the model and test data is used to test the model. We have used 9248 files for training, 2563 for validation and 1000 for testing.

Table 3 shows the classification performance of various Deep Learning models trained on the same dataset using different combinations of layers. It can be seen that the proposed hybrid DepHNN model outperforms the other models in classifying depressed and healthy subjects. Model_1 consists of 2 LSTM layers along with the windowing method took a minimum time of 103 s to complete an epoch of training but gives a maximum loss of 0.34 and Model_2 with of 3 LSTM layers and windowing method took 158 s to complete an epoch of training which has less loss of 0.2. So, if the number of dense layers is increased instead of LSTM layers then training time is reduced to 108 s, and loss is also reduced to 0.27 as given by Model_3 in comparison with Model_1 or Model_2. Model_4 consists of 4 LSTM without using any CNN layer and windowing method which gives less loss of 0.19 but it takes a maximum time of 213 s to complete an epoch of training on the same dataset.

The classification performance of various models has been investigated with different numbers of Dense layers and kernel size as shown in the Figs. 6 and 7. The proposed model with 3 Dense layers (including output layer) outperforms other models in terms of loss and time taken. Similarly, It is evident from the Fig. 7 that classification performance has been improved by increasing the kernel size. However, it can also be

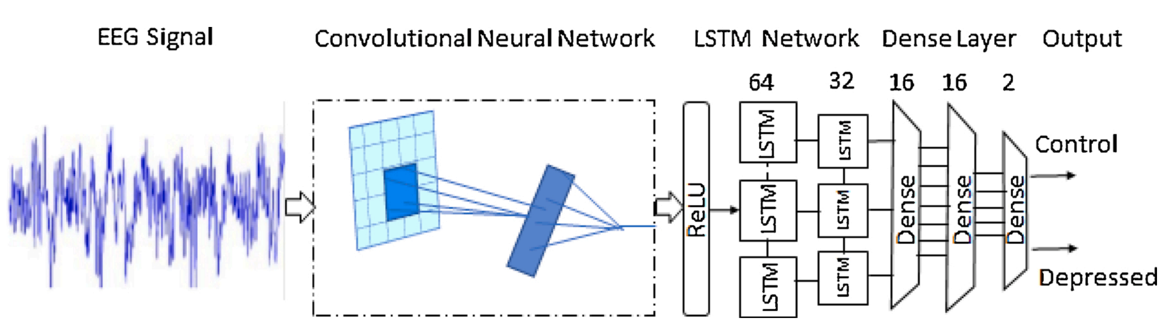

Fig. 3. Proposed hybrid CNN-LSTM approach for depression detection.

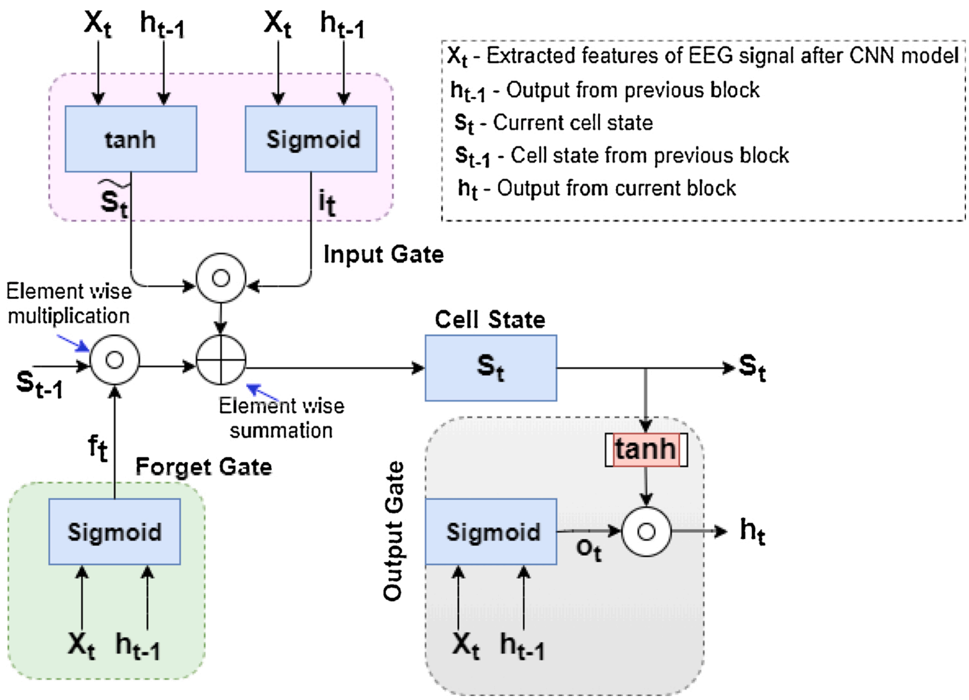

Fig. 4. LSTM Architecture [60].

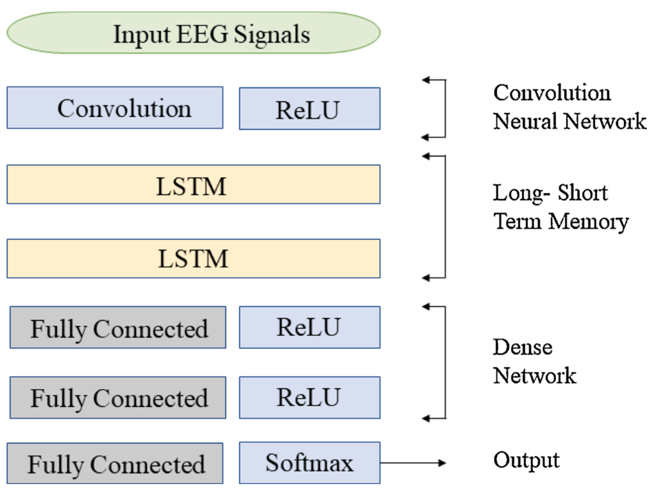

Fig. 5. Proposed architecture.

Table 2
Parameters of proposed hybrid deep network architecture.

S. No.	Name of layers	Kernel	Parameters of layers	Parameters
1	Convolution	64 × 5	Stride = 1, ReLU Activation	384
2	LSTM	None	Unit size = 64, Return Sequence = True	33,024
3	LSTM	None	Unit size = 32, Return Sequence = True	12,416
4	Fully Connected	None	Unit size = 16, ReLU Activation	528
5	Fully Connected	None	Unit size = 16, ReLU Activation	272
6	Fully Connected	None	Unit size = 2, Softmax Activation	34

Table 3
Performance comparison of proposed DepHHN with other designed deep learning models of different architecture.

Model	Layer	Type	Total parameters	Time taken to complete an epoch (s)	Loss
Model_1	1	Convolution	30,225	103	0.34
	2	LSTM			
	3	LSTM			
	4	Dense			
Model_2	1	Convolution	54,210	158	0.2
	2	LSTM			
	3	LSTM			
	4	LSTM			
	5	Dense			
Model_3	1	Convolution	41,154	108	0.27
	2	LSTM			
	3	LSTM			
	4	Dense			
	5	Dense			
Model_4 (without applying windowing	1	LSTM	70,722	213	0.19
	2	LSTM			
	3	LSTM			
	4	LSTM			
	5	Dense			
DepHNN (Proposed Model)	1	Convolution	46,658	112	0.2
	2	LSTM			
	3	LSTM			
	4	Dense			
	5	Dense			
	6	Dense			

seen that a larger kernel size did not further increase the accuracy which is probably because of the more number of parameters or the over-smoothening effect of larger kernel size.

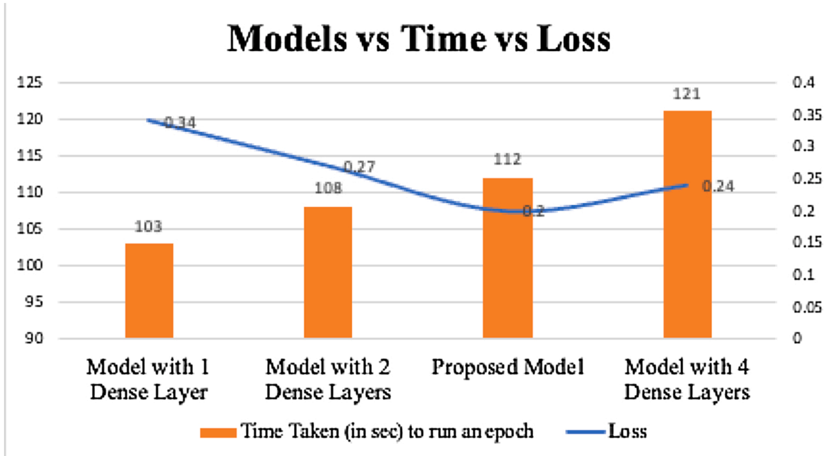

Fig. 6. Performance comparison of proposed DepHNN with other models of different dense layers in terms of loss and time taken to complete an epoch.

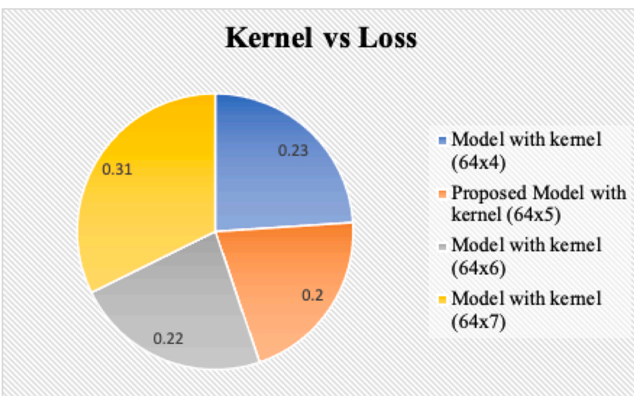

Fig. 7. Loss comparison of proposed DepHNN with other models of different kernel size.

The proposed hybrid CNN-LSTM model is tested using unused 10% test data set after training and validation. The model has a low MAE of 0.2040 as shown in Fig. 8. It is incorrectly classified only 9 of the 1000 data EEG signals and reaches the highest accuracy of 99.10% as shown in Fig. 9. The obtained results show that, the hybrid CNN-LSTM model gives the best performance (greater than 90%) in detecting the depression using EEG signals. Hybrid CNN-LSTM model along with the windowing technique took approximately 112 s to complete an epoch of training on EEG input data that is quite comparable with other previously proposed models for the given machine configuration. So, it shows much less time and computation complexity in comparison to previously proposed deep learning models.

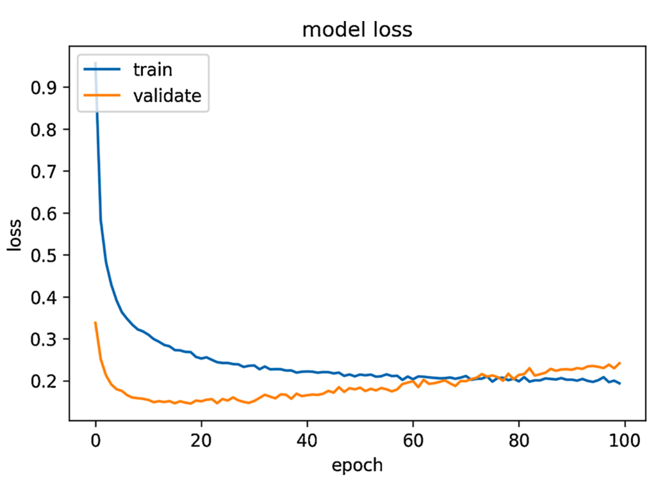

Fig. 8. Loss values for the proposed model.

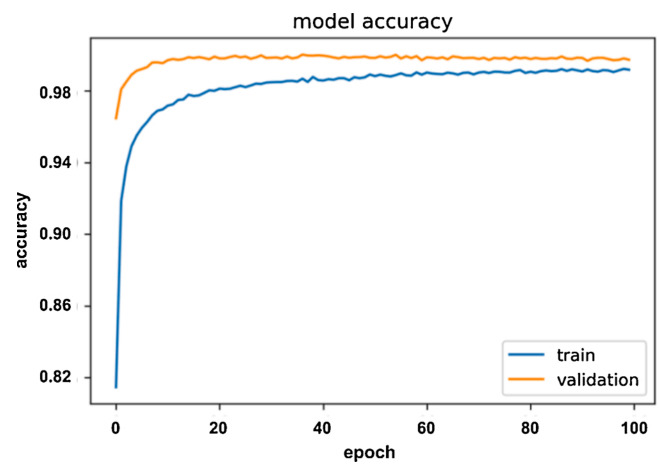

Fig. 9. Accuracy values for the proposed model.

The performances in terms of accuracy obtained using EEG data are summarized in the confusion matrix as in Table 4. The results obtained are recorded in Table 4 and it shows that the 0.5% of the normal EEG signals are misclassified as depressive EEG signals and 0.4% of the depressive signals is wrongly categorized as normal EEG signals. It includes the average diagnostic performances obtained using the proposed hybrid CNN-LSTM model and the number of correctly identified and wrongly identified normal and depressive EEG signals. A high classification performance in terms of accuracy (greater than 90%) is achieved for EEG data.

The proposed work is compared with previous similar work on automated detection of several neurological diseases with the help of CAD and using EEG signals and the results are shown in Table 5. The proposed has excellent performance in terms of accuracy with compared to existing deep learning systems. For an appropriate comparison, the dataset used in this proposed model has also been utilized for the training of the model used by [25] and it shows the best possible accuracy of 95.2% and took 137 s to complete an epoch that is more than the time taken by proposed DepHNN model. These studies proposed several models using deep learning or machine learning classifiers using various feature extraction techniques such as clinical features [24], entropies [18,20], nonlinear features [5,19,11,22], statistical analysis

Table 4
Performance values obtained during testing the model for EEG data.

Confusion matrix						
Original	Prediction					
		Normal	Depression	Accuracy	Precision	f1-Score
	Normal	452	5	99.1%	99%	0.99
	Depression	4	539			

Table 5
Comparison of various studies related to neurological applications using EEG signals.

Author &Year	**Dataset**	**Neurological application**	**Method**	**Accuracy (%)**
Bairy et al. [45], 2016	14 Normal, 16 Depressed	Depression Detection	SVMRBF	88.9
Bairy et al. [46], 2017	15 Normal, 15 Depressed	Depression Detection	Bagged Tree	94.3
Acharya et al. [15], 2017	5 Normal, 5 Epileptic	Seizure Detection	CNN (13 Layers)	88.7
Spampinato et al. [61], 2017	6 Subjects	Discriminate Brain Activity	CNN	86.9
Alhagry et al. [62], 2017	32 Subjects	Emotion Recognition	CNN-LSTM	85.65
Acharya et al. [25], 2018	15 Normal, 15 Depressed	Depression Detection	CNN (13 Layers)	93.5
Oh et al. [63], 2018	20 Normal, 20 PD	Parkinson's Disease	CNN (13 Layers)	88.25
Tsiouris et al. [56], 2018	24 Subjects	Seizure Prediction	LSTM	99.6
Ay et al. [47], 2019	15 Normal, 15 Depressed	Depression Detection	CNN-LSTM	97.66
Li et al. [64], 2019	27 Normal, 24 Depressed	Depression Detection	ConvNet	85.62
Oh et al. [65], 2019	14 Normal, 14 schizophrenia	schizophrenia Detection	CNN (11 Layers)	81.26
DepHNN	**24 Normal, 21 Depressed**	**Depression Detection**	**CNN (6 Layers)**	**99.1**

[27], and relative wavelet energy [18]. These approaches are time-consuming and complex as they employed difficult feature extraction and reduction methods.

On the other side deep learning methods used in [25] and [15,61–63,47,64,65] do not require any separate feature extraction methods as here the feature extraction is performed by the model itself. In contrast, the main advantage of this study is that it shows good performance with the average configured system in detecting depression, in comparatively lesser time by using both local characteristics and long-term dependencies of the EEG signals as the CNN networks gives important features while LSTM network learns sequences from these features.

The DepHNN model uses 45 subjects and gives an accuracy of 99.1% with it has an added advantage of being automatic model in comparison with an accuracy of 97.66% proposed by [47] using CNN-LSTM method. Therefore, the DepHNN model is highly efficient, accurate, fast, and robust in detecting depression using EEG signals. This model can be used in clinical settings as a tool to diagnose depression automatically.

6. Conclusion and future research

This paper presents a hybrid model DepHNN with CNN and LSTM architecture and this model uses LSTM that introduces long-term dependencies in CNN architecture. It is pivotal to know that the CNN architecture does not require any feature extraction method as this model can itself learn from local features during the training of the algorithm. This proposed model is developed using total 45 patients (24 normal and 21 depressed). It can classify normal and depressed patients with very high accuracy of 99.1% and it gives a very low error rate of 0.2040 in less time with an average configured computer system.

In the future, this model can be updated or improved to diagnose the severity of depression and its different stages. This model can be used as a complementary tool or second opinion in the diagnosis of depression made by clinicians. The proposed model could be integrated in Internet of Medical Things (IoMT) network for continuous monitoring by healthcare provider and is also useful to take some preventive actions in case of critical condition of the patents. However, a more accurate and robust model can also be developed using a larger dataset and to detect other neurological disorders at the early stages.

Conflict of interest

None declared.

Declaration of Competing Interest

The authors report no declarations of interest.

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