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A Hybrid Neural Classifier for Depression Screening Using Electroencephalograms (EEG)

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Abstract-Depression seems to be a psychiatric condition marked by recurrent episodes of depression. It is very crucial to realise that people of all ages in different parts of the world are being seriously affected by this condition. The early detection of this sickness will help to save many lives because it is now recognised as a global problem. Electroencephalogram (EEG) signals can be used to diagnose this mental disease since they can be analyzed to reveal the patients' current mental state. The benefits of a completely automated depressive detection scheme are discussed in detail in this study since manual analysis of the EEG data is time-consuming, laborious, and takes a great deal of expertise. This study introduces a new Electroencephalography computer-aided hybrid computational model for depression screening. The suggested approach makes use of windowing and long-short term memory (LSTM) architectures for sequence learning as well as CNN for temporal learning. The EEG data used in this model were acquired using neuroscan from some drug-free, symptomatic depressive patients, as well as few healthy individuals. The windowing approach is used by the model, which reduces calculation complexity and saves time. It gives more than 99 percent accuracy. The findings demonstrate the usefulness and accuracy of the hybrid CNNLSTM model for identifying depression in EEG data.

Keywords-Mental health, Mental illness, EEG, Depression etc.

1. Introduction

Depression is among the most common and second-leading causes of mental disease, as per estimates from the World Health Organization (WHO), impacting over millionsof people across the globe [1]. According to statistics, there has been approx. 20% uptick in the population of persons experiencing depression over the past ten years, with a much larger percentage of female patients than male patients .It is an illness with varying degrees of severe, acute, and mild symptoms. People who are depressed may feel a variety of feelings, including guilt, a poor mood, difficulty concentrating, a loss of interest in routine tasks, low self-esteem, and it may even cause them to entertain suicide ideas [2]. Numerous problems, including inadequate medical education, a lack of resources, and frequently inaccurate diagnosis, have contributed to the startling many people with depression who are not receiving treatment for their ailment [3]. A computer-aided method relies on a synergistic system of LSTM andCNN with minimal computational complexity and computational accuracy can aid in the accurate diagnosis of this ailment, which can be readily treated if detected early and correctly.

Due to its non-invasiveness and low cost, EEG has been investigated as a useful marker and screening tool [4][5] for the identification of neurological diseases. As we know EEG captures brain electrical impulses with time as a reference. These signals are still quite complicated and disorganized. Therefore, manually analyzing such signals is highly challenging [6].The detection of several neurological diseases, such as Alzheimer's [7], Epilepsy [8], Schizophrenia [9], Creutzfeldt-Jakob [10], and Emotion detection, among others, has been explored using EEG signals by a number of machine learning [11][12] and deep learning [12-19] tools in recent years.In order to diagnose depressive condition, this article also uses EEG waves as a biomarker and suggests a computer-aided approach to detect. Because depression continues to be a complicated and diverse problem, this field is extremely essential. Artificial intelligence approaches used in conjunction with EEG signals have the potential to significantly reduce the difficulties associated with detecting depression.

2. Previous studies and contributions

In the past some years, there were various attempts to detect depression. A summary of several well-known researches on the use of EEG data in depression detection techniques is provided in Table 1. In order to diagnose Major Depressive Disease (MDD) with an efficiency of 91.3 percent, [20] used the Wavelet-Chaos approach, Higuchi's- Katz's Fractal Dimension (HFD-KFD), and Expanded Probabilistic NN. [21]achieved accuracy of 90.05 percent by extracting non-linear characteristics and using a Logistic Regression Classifier to distinguish between the healthy and depressed classes. On EEG recordings, [22] conducted wavelet packet extraction and obtained non-linear and entropy properties.The Probabilistic Deep Neural (PDNN) classifier was then given these characteristics to categorise normal and depressed patients, with accuracy of 98.20 percent. [23] examined several non-linear feature selection methods and put forth an index for depression identification. They reported a 98 percent accuracy using the Support vector machine classifier. Wavelet entropies, energy characteristics, and a SVM classifier with Radial Basis Kernel Function (SVM RBF) were combined by [24] to provide a result with an accuracy of 88.9 percent. [25] demonstrated an accuracy of 94.3 percent using characteristics collected from the linear predictive coding (LPC) approach.

All of the aforementioned investigations employed handmade characteristics, which had to be chosen using nonlinear analysis ormachine learning techniques [28]. Manually selecting the right feature set was a very difficult process, but [17] presented a deep learning-based CNN 13-layer model, and [26] produced an 11-layer CNN-LSTM model to more accurately categorise normal and depressed individuals.

The deep learning approach can distinguish between participants who are normal and those who are sad without the need for a feature set since it learns automatically and repeatedly from the existing EEG dataset. Such Deep Learning techniques have recently been used in a number of applications and demonstrated excellent performance on bigger datasets. CNN is primarily used for image processing, but it has also demonstrated very promising results in the biomedical fields, including early Alzheimer's disease diagnosis [7], depression diagnosis [29], medical imaging field diagnosis [30–32], seizure detection, slightly earlier Creutzfeldt-Jakob disease detection, and autism diagnosis.

Authors and Year	Methods Used	Accuracy
Acharya et al. [23], 2015	SVM	93.5
Bairy et al. [24], 2016	SVMRBF	88.9
Bairy et al. [25], 2017	Bagged Tree	94.3
Acharya et al. [17], 2018	CNN	88.7
Ay et al. [26], 2019	CNN-LSTM	97.66

Table 1-Methods for depression identification utilizing EEG signals

There have been several challenges, including the absence of laboratory testing and a shortage of medical personnel with the necessary training to diagnose depression. The goal of the current study is to create a system that facilitates the automated detection of depression using EEG data. In this system, EEG waves are first processed before being analyzed and classified using a DNN.

3. Research Gaps

For the identification of depressive illness, a number of techniques and datasets have already been suggested or utilised with in literature. The following is a list of the major conclusions or knowledge gaps from these studies:

i. Various handmade linear as well as non-linear characteristics, such as wavelet entropies, DWT and many more. And clinical characteristics have been retrieved in several researches [20-24]. The biggest disadvantage of these manually chosen features is that this might impute to the efficiency of the classification algorithm.

j. Subject counts in practically all of the aforementioned studies or research were rather low, even when the volunteers were given a controlled task to complete.

k. CNN model suggested by author in [17] includes thirteen network layers and has the benefit of automated feature selection with excellent accuracy over earlier machine learning techniques. Author claimed that because EEG signals are very complex and nonlinear time series in nature, LSTM Deep networks can produce superior results to CNN for these signals. The Long short - term memory model put forward by [33] demonstrated a falsified prediction rate (FPR) for seizure prediction.

l. The literature suggests some really complicated deep neural models.As a result, training and classifying such a deep model demands expensive system architecture.

4. The paper's original contribution

i. A Composite CNN-LSTM oriented DL model for stress detection is suggested in this study. In the suggested model, CNN layers stride across time - series data EEG input signals providing windowing while LSTM blocks offer sequence learning. CNN layers are explored along with LSTM networks. As a result, it is a full model that permits learning for EEG signals' local properties as well as long-term dependence.

ii. The suggested hybrid computational model is really a highly efficient (less computation complexity and time required) and automated tracking model that can be utilised to diagnose depressive disorder effectively and efficiently.

iii. To train as well as validate the model, a new and significantly bigger dataset of healthy patients and depressive patients was employed.

iv. To help the model be trained more quickly, windowing is done as component of the pre-processing procedure.

v. This research suggests a model that is substantially less complicated since it has fewer hidden layers than other models.

5. How we see utilizing EEG to diagnose sadness

5.1Deep learning depression model

Despite the fact that CNN has shown promising results even in features extracted from pictures of stationary data, one of the main issues with CNNs is that they might evaluate spatial or earlier information in the time series analysis signals. However, the temporal information may be successfully extracted and processed using LSTM [33].

Therefore, a better method for processing the EEG information may be used, taking into account the Hybrid mixture including both CNN and LSTM (Time-Series signal). A schematic representation of our suggestion for detecting depression using the EEG data is shown in Fig. 1. Therefore in model, depression has been identified using EEG information from brain electrical activity. Pre-processed EEG data is first given to the CNN layer, which uses windowing to convert time-series EEG signal data to cross-sectional data. The CNN model's feature output is then delivered to the LSTM block.

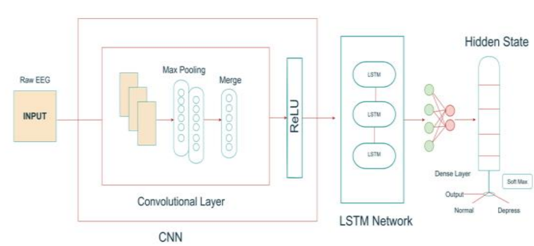

Fig-1 Detecting Depression using EEG data

The sequence learning function of the LSTM model is used to examine the importance of each feature in the final conclusion-making process. The LSTM block conducts sequence learning also on signal received from the Convolution Neural Network Model.

Fully linked layers are given the LSTM block's output to aid in the automated identification of depression. In order to automatically diagnose depression, a composite CNN-LSTM coupled layer has been situated in this work.

5.2 EEG signal preparation for depression identification

Independent Components Analysis was used to eliminate artefacts like eye blinks, and the Fast Fourier Transform technique was utilised to retrieve time-frequency data from raw Brain activity. The windowing approach, which is a clever way to process time-series data utilised in a deep learning-based model, was employed as part of the pre-processing [34]. In this method, the entire information is reshaped using a window with a specified size in order to supply any information that may be required at a certain moment in order to obtain an accurate forecast, after which the impact of its reaction may be evaluated here on model.

6. A model that is suggested for detecting depression using EEG.

This CNN model only passes through the data in various hidden layers; however, the network is not informed of the results here. As a result, as was covered in the previous section, CNN models are fairly bad at learning sequential information but quite strong at extracting temporal aspects.In order to solve this issue, a hybrid approach combining CNN and LSTM is suggested in this study. Since LSTM is a component of RNN, it is utilised for sequential data learning since it not only picks up new information from training but also retains it so it can anticipate what will come next in the sequence. The method includes feeding the network with the output.

As a result, the LSTM analyses these characteristics sequentially after learning long-term dependencies (sequence learning)

6.1. CNN feature extraction

The primary goal of utilizing CNN is to train the algorithm by removing significant characteristics from incoming EEG signals. CNN primarily combines the convolution method with neural network.

The proposed model, shown in Fig. 2. For the convolution layer, several different architectures have been investigated by varying the kernel size.To extract important characteristics, these filters typically convolved with the incoming EEG signal information matrix. After the convolution layer, a rectified linear unit (ReLU) is used as an activation function to improve the algorithm's resilience.

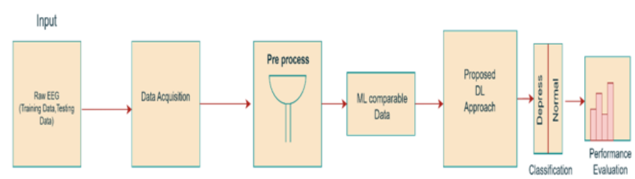

Fig. 2. Proposed hybrid CNN-LSTM approach for depression detection.

6.2 The proposed hybrid computational model architecture

Above Figures depicts the suggested mixed CNN-LSTM model's design. In this model, the first layer is created by performing a convolution operation on the input signal, and the ReLU layer is then employed as an activation function. The weight matrix of this model has been updated using Huber's loss for backpropagation.

6.3 LSTM-based learning model

In 1997, Hochreiter and Schmidhuber [35] proposed the LSTM architecture for sequence learning. Since EEG signals track brain activity over time, they are time-series indicators. In order to mimic short and long-term memory, sequence pattern learning is necessary. Recurrent neural networks (RNN) are unnecessary for modelling long-term memory and only useful for modelling short-term memory. The vanishing gradient is the main difficulty when training neural networks for back propagation.The disappearing gradient issue makes it difficult to train neural networks, thus LSTM architecture is employed to get around it since it can choose which input data should be remembered and remember it for a long period.As shown in above fig, the LSTM design employs specialised hidden units called memory cells, which have a long memory for prior input.Several functions, including sum, multiplication, sigmoid, and hyperbolic tangent, are included in this design and are utilised in backpropagation to update the weights.

7. Findings and analysis

Python was used for the implementation and results, along with Keras packages.64 batches of the model are trained using a backpropagation approach, and the network's weights are updated using the ADAM (Adaptive Moment Estimation) optimizer to increase training efficiency. Data is randomly split using the well-known random splitting approach for training, validation, and testing. The entire dataset is split into three parts for this study: 75 percent training, 15 percent validation, and 10 percent test set.Deep networks frequently employ this method where test data is used to validate the model after training and validation datasets are utilised to train the model.

The performances of the classifier of multiple Deep Learning models were trained on the very same dataset using various layer combinations. The suggested composite proposed model performs better than that of the other models in identifying depressed and healthy people, as can be demonstrated. It can be seen that increasing the kernel size would not further improve accuracy, which really is likely due to the additional parameters or oversmoothing effect of the larger kernel size.After training and validation, the proposed mixed CNN-LSTM model is examined using an underused 10% of the testing dataset. The model achieves the best accuracy of 99.20 percent, as shown in Fig. 3.

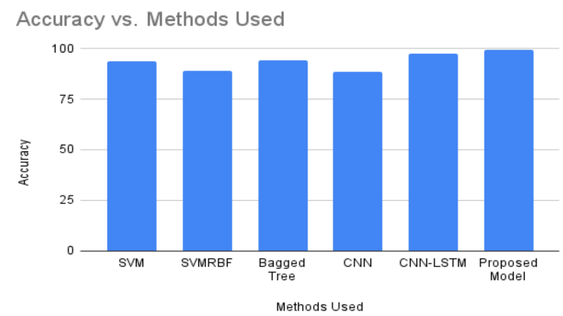

Fig. 3. Accuracy values for the proposed model

The findings collected demonstrate that the mixed proposedmodel performs best (more than 90%) in identifying depression in EEG data. This is pretty comparable to other already suggested models. As a result, it demonstrates significantly lower computational and temporal complexity than initially proposed deep learning methods.Table 2 summarises the accuracy results achieved using EEG data. It also provides the number of successfully and incorrectly recognised normal and depressed EEG signals as well as the average diagnostic performances attained using the suggested hybrid CNN-LSTM model. For EEG data, a high classification performance in terms of accuracy (higher than 90%) is attained.The findings of comparing the proposed study to earlier comparable research on the automated identification of various neurological illnesses using EEG data and CAD are given also. When compared to current deep learning systems, the suggested performs excellently in terms of accuracy. For an adequate comparison, the dataset used for training the model employed by [17] was also used. This model exhibits the greatest achievable accuracy of 95.2. These research put forth a number of models that make use of convolutional or ML classifiers and a variety of feature extraction methods, including clinical features ,entropies asymmetric features ,statistical data analysis [18], and comparative wavelet energy .These strategies took a lot of time and involved complicated feature extraction & reduction techniques.However, basic feature extraction is handled by the model itself in [17] and given other papers;therefore there is no need for further feature extraction techniques. The main benefit of this study, in contrast, is that it demonstrates good performance with the average configured system in detecting depression in comparably less time by utilizing both local features and lengthy dependencies of both the EEG signals as the Convolutional neural network networks provides key aspects while the LSTM network understands sequences from all these features.

Using 45 subjects, the proposed model provides correctness of 99.2% and has the further benefit of being an automated model as opposed to the correctness of 97.66% reported by [26] using the CNN-LSTM approach.

The proposed model algorithm can therefore diagnose depression using EEG data with great efficiency, accuracy, speed, and robustness. The automated diagnosis of depression using this approach is applicable in clinical settings.

Dataset	Methods Used	Accuracy
30 people	SVM	93.5
30 people	SVMRBF	88.9
30 people	Bagged Tree	94.3
30 people	CNN	88.7
30 people	CNN-LSTM	97.66
45 people	Proposed Model	99.20

Table 2: Accuracy results achieved using EEG data by various Methods

8. Conclusion and future research

With CNN as well as LSTM design, proposed composite model presented in this work employs LSTM to inject long-term dependencies into the CNN architecture. It is crucial to understand that the CNN model does not need any feature extraction techniques since this model may learn from local information while the algorithm is being trained. The development of this suggested model involved 45 people in total .With an averagely setup computer system, it can categorise healthy and depressed people with an accuracy of 99.2%.

The model can be upgraded or enhanced in the future to identify the level of symptoms and its various phases. When a physician diagnoses depression, they might utilize this model as an additional tool or second opinion. The suggested model may be included into an Internet of Medical Things (IoMT) system for continuous patient monitoring by healthcare providers. It can also be helpful for taking certain preventive measures when a patient is in a severe situation. To identify additional neurological problems early on, a larger dataset may also be used to create a model that is more reliable and accurate.

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