Empowering Mental Health: CNN and LSTM Fusion for Timely Depression Detection in Women

Original Scientific Paper

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Abstract *– Depression is a mental illness that manifests as persistent melancholy, a loss of interest in routine activities, trouble focusing, poor memory, and a lack of energy. It is a widespread mental health condition that can affect people of any age or gender. Depression is more common in women than in men. In order to identify early indicators of depression in women, this study uses a deep learning-based model utilizing convolutional neural networks and Long Short-Term Memory. With the help of a dataset of left and right hemispheric electroencephalogram data, the suggested model was trained and assessed. The suggested method entails preprocessing the electroencephalogram data, which is feature-extracted using a convolutional neural network, and sequence modeling using a Long Short-Term Memory network. With the help of Electroencephalogram data from women with and without depression, the model was trained and assessed. The results show that the suggested method successfully identified depression in women using Electroencephalogram data with excellent accuracy, sensitivity, and specificity. When it came to identifying female depression, the model had an accuracy of 99.02% on the left hemisphere and a right hemisphere accuracy of 98.06%. The study demonstrates that employing advanced deep learning techniques on electroencephalogram data enables accurate and sensitive identification of depression in women. This highlights the potential for early intervention in mental health disorders, particularly in populations with a higher depression prevalence.*

Keywords: *Early depression detection, EEG signals, mild depression, Long Short-Term Memory, Feature selection, Convolutional Neural Networks*

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1. INTRODUCTION

Psychoanalytic ideas of depression [1] first appeared around the beginning of the 20th century, emphasizing the importance of unconscious conflicts and early experiences. Subsequently, with studies into the role of neurotransmitters [2], genetics, and brain architecture in depression, biological explanations developed. Depression is now understood to be a complicated condition with a variety of causes and treatments. Depression can be treated with psychotherapy [3], medication [4], and lifestyle modifications (such as regular exercise and a nutritious diet). The significance of tackling societal factors that affect mental health, such as poverty, prejudice, and trauma, is now becoming more widely acknowledged [5]. A mental health condition called depression, commonly referred to as major depressive disorder, affects a person's emotions, thoughts, and behavior. Although it can strike at any age, this prevalent ailment typically manifests in early adulthood. Depression has historically been associated with moral failure or weakness, and those who experience it are frequently stigmatized and shunned.

1.1. CAUSES OF DEPRESSION

As depression is a complicated disorder, its root causes are still unclear. Depression is probably brought on by a confluence of hereditary, environmental, and psychological factors. The following are some typical reasons for depression:

- Biological factors: Particularly, biological components may be quite important in the emergence of depression. Depression may be exacerbated by imbalances in brain neurotransmitters such as serotonin [6] and dopamine [7]. Depression tends to run in families, so genetics may also be involved. Depression may also be exacerbated by abnormalities in neurotransmitters such as serotonin, norepinephrine [8], and dopamine. These chemicals control mood, and when they are out of balance, it can result in depressive symptoms. Hormonal imbalances, persistent pain, anomalies in the structure of the brain, and chronic sickness [9] are some additional biological variables that might contribute to depression. It is crucial to remember that while biological variables can play a part in the onset of depression, they are not the only contributing element.
- Environmental factors: Depression development may also be influenced by environmental variables. Depression risk factors include things like traumatic experiences [10], ongoing stress [11], and social isolation. Depression can be brought on in those who are vulnerable by traumatic events including losing a loved one, experiencing physical or mental abuse, or going through a significant life transition. Persistent stress, like that brought on by work-related stress or financial anxiety, can also help depression develop. Feelings of hopelessness and despair can result from social isolation [12], which can also cause depression. Loneliness and a lack of social support are two examples of social isolation. Furthermore, being exposed to chemicals or pollutants in the environment might harm mental health and hasten the onset of depression [13]. It is crucial to understand how environmental variables may contribute to the onset of depression and to take action to address and manage these factors in order to avoid or treat the illness. This may entail reaching out to friends and family for support, limiting exposure to stressors, and engaging in self-care practices like meditation or exercise.
- Psychological factors: Depression might also occur because of psychological reasons. For instance, unfavorable cognitive habits, including ruminating, criticizing, and having poor self-esteem, might help depression develop and persist [14]. A feeling of hopelessness and helplessness, which are frequent signs of depression, can result from negative self-talk and persistently dwelling on unfavorable occurrences. Moreover, some psychological qualities, including neuroticism [15], may make someone more susceptible to depression. Negative emotions are more powerful and frequent in neurotic people than in non-neurotic people, which might hasten the onset of depression.
- In addition, negative life events like abuse, neglect, or childhood trauma can raise one's risk of developing depression later in life. These events can increase a person's sense of worthlessness and powerlessness, which increases their risk of developing depression [16]. Depressive disorders can also develop as a result of a lack of social support and harmful coping strategies like substance abuse and avoidance. Developing effective treatment strategies, such as cognitive-behavioral therapy (CBT) [17] and mindfulness-based therapies that target negative thought patterns and assist people in creating healthy coping mechanisms to manage depression symptoms, requires an understanding of the psychological factors that contribute to depression.
- Hormonal factors: Depression can also be influenced by hormonal changes, such as those that take place during pregnancy, menopause, or the menstrual cycle [15]. Moreover, hormones might contribute to depression, especially in women. Depression can be exacerbated by changes in hormone levels brought on by the menstrual cycle, pregnancy, and menopause. Similarly, fluctuations in hormone levels during pregnancy might bring on feelings of depression. Many new moms experience postpartum depression, a common mood illness that is also thought to be brought on by hormonal changes following childbirth. Finally, some women may have symptoms of depression during menopause [18] due to the drop in estrogen levels. Depression may also be exacerbated by hormonal imbalances brought on by illnesses like hypothyroidism or hyperthyroidism. When there is an imbalance in the thyroid hormones, which are essential for controlling the body's metabolism and energy levels, depression symptoms can result. The symptoms of sadness can also be exacerbated by hormonal imbalances brought on by specific drugs or medical procedures, such as hormonal birth control or chemotherapy [19]. In order to create efficient treatment plans that address the underlying hormonal imbalances, such as hormone replacement therapy or drug management, it is crucial to understand the hormonal aspects that contribute to depression.
- Substance abuse: Addiction to drugs or alcohol [20] is another potential factor in depression. This is because of a variety of things, such as the harm that substance abuse does to the brain and the emotional toll that addiction takes. Abuse of substances can cause chemical imbalances in the brain, disturb the balance of neurotransmitters, and result in depressive symptoms. Synapses from a healthy person and a depressed person are shown in Fig. 1. A sense of hopelessness and despair can also be produced by the cycle of addiction and substance misuse, which can aid in the onset of depression.

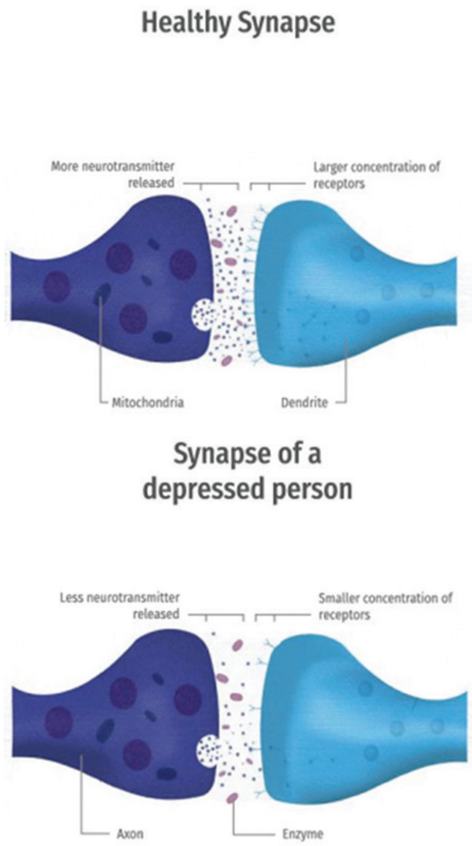

Fig. 1. Synapse of Healthy person and Depressed Person

1.2. TYPES OF DEPRESSION

There are several different types of depression, each with its own specific symptoms and causes. Here are some of the most common types:

- Major depressive disorder (MDD): MDD, commonly referred to as clinical depression, is defined by a person's loss of interest in formerly liked activities as well as persistent emotions of melancholy and hopelessness. Treatment for MDD is frequently necessary because it can make daily tasks difficult.
- Persistent depressive disorder (PDD): Chronic depression, or PDD, lasts for at least two years. Although the symptoms of depression in people with PDD are less severe than in people with MDD, they can nevertheless be disruptive to everyday living.
- Seasonal affective disorder (SAD): SAD is a form of depression that typically develops in the winter and is brought on by seasonal changes. Low mood, lack of energy, and increased tiredness are SAD symptoms.
- Postpartum depression (PPD): Postpartum depression (PPD) is a kind of depression that affects new moms. PPD symptoms include depression, anxiety, and a hard time bonding with the infant.
- Bipolar disorder: Extreme mood swings, such as those that can range from episodes of depression to episodes of mania or hypomania, are the hallmark of bipolar disorder, a mood illness.
- Psychotic depression: A severe form of depression known as psychotic depression includes psychotic symptoms like hallucinations or delusions.
- Situational depression: Situational depression is a form of depression that is brought on by a particular event, like the death of a loved one or the loss of a job.

The paper begins with an introduction discussing the historical context and multifactorial nature of depression, emphasizing the importance of timely detection, particularly in women. It delves into various causes and types of depression, highlighting biological, environmental, psychological, hormonal, and substance-related factors. Following the introduction, a comprehensive literature review is presented, summarizing recent research on depression detection using machine learning and deep learning techniques. The methodology section describes the proposed approach for depression detection using EEG signals, detailing the CNN-LSTM model architecture and dataset used. Results and discussions analyze the performance of the model in detecting depression from EEG signals, including accuracy, sensitivity, and comparison with previous studies. The conclusion summarizes the findings, highlighting the efficacy of the proposed method for early detection of depression in women and discussing potential future research directions, such as utilizing larger and more diverse datasets and exploring multimodal data for improved diagnosis.

2. LITERATURE REVIEW

Burdisso et al. [21] introduce SS3, a brand-new supervised learning model for text classification, to serve as a generic foundation for addressing issues with early depression risk detection. The SS3 is intended to address three of the most difficult aspects of ERD: explainability, support for early classification, and incremental classification of sequential data. The work has limitations because the authors used words as the fundamental building blocks rather than higher-level building elements like sentences and paragraphs.

Su et al. [22] utilized long short-term memory (LSTM) and six machine learning (ML) models to forecast several depression risk indicators as well as the likelihood of depression in the older population over the following two years. The prediction accuracy of the model was assessed using decision curve analysis (DCA) and receiver operating curves (ROC). For early diagnosis and intervention, the suggested LSTM+ML model-based decision support system may be particularly beneficial for physicians, nurses, and community medical professionals. The method's need to progressively increase the retrospective waves employed in the LSTM model is one of its limitations. The high-dimensional and time-series data on risk factors for depression in the elderly can be successfully captured by the LSTM+ML model.

Zheng et al. [23] suggest a graph attention model for depression detection that is embedded with multi-modal information. In addition to teaching acceptable embeddings for knowledge graph nodes, this method makes use of medical information to enhance classification and prediction performance via the knowledge attention mechanism. The suggested approach greatly outperforms other leading state-of-the-art approaches in terms of classification and prediction performance, with guaranteed robustness with each modality of multi-modal data, according to experimental results on real-world datasets. Their approach may obtain the knowledge-attention representation vector using learned medical embeddings and a deep learning-based network, which primarily aids the detection model's performance. The findings may not be applicable to other populations or nations because the study only examined a particular population (elderly individuals in China).

Islam et al. [24] suggested employing a convolutional neural network (CNN) for a computer-aided detection (CAD) system (ConvNet). The authors employed transfer learning to build the architecture of ConvNet since the CAD system used in clinical practice and the architecture of ConvNet that was developed through trial and error should both be constructed on the foundation of local databases. The technique is used to diagnose depression without the use of harmful procedures or drugs. Only a few electroencephalogram (EEG) channels were employed in the investigation, which may not have been enough to gather sufficient information for a thorough analysis.

Facebook can be used as a tool for assessing and identifying serious depression among its users, according to Shah et al. [25], who have demonstrated this potential. The purpose of this study is to analyze depression using Facebook data that was gathered from an online open source. The authors suggest using scalable and effective machine learning technology to study the impact of depression identification. For the dataset, the authors used Linguistic Inquiry and Word Count (LIWC). The study's use of non-invasive techniques to gather information from social media platforms lessened the strain and expense of conventional data collection techniques. Due to the possibility that user-sensitive information may be present in social media data, the study raises ethical questions surrounding privacy and confidentiality.

Chiong et al. [26] have suggested a model that may identify depression from user posts. The training data were used to train deep learning algorithms, while the test data were used to evaluate their performance. With the use of this deep learning technique, authors have attempted to overcome the constraints of conventional machine learning, which only allows for text classification. The study showed the potential for early depression detection using deep learning techniques, which could result in early intervention and treatment, thereby lessening the severity of the condition and improving outcomes. The study showed great accuracy in the diagnosis of depression, indicating that the deep learning methodology may be a potential way for social network data depression identification. Users could not have mentioned all symptoms of depression or may not have used some keywords associated with depression; therefore, the study may not have gathered all pertinent information about depression.

In order to suggest a generalized strategy for depression diagnosis using social media texts, Katchapakirin et al. [27] study several text preprocessing and textual-based feature methods coupled with machine learning classifiers, including single and ensemble models. The authors first train and test the machine learning models using two publicly available, labeled Twitter datasets, and then they assess the performance of the learned models with three non-Twitter depression-class-only datasets. According to experimental findings, the suggested method may successfully identify depression in social media texts even when the training datasets don't include specific keywords (like "depression" and "diagnosis") and when unrelated datasets are used for testing. In contrast to other feature sets, the study's text-based methodology can collect more in-depth and complex information regarding depression. The study might have only used a few feature extraction techniques, which could have reduced the approach's accuracy.

In order to create a depression detection algorithm for the Thai language on Facebook, where people utilize it as a platform for exchanging ideas, emotions, and life events, Alghowinem et al. [28] used natural language processing (NLP) approaches. Findings from 35 Facebook users showed that the degree of depression may be predicted by their behavior on Facebook. The findings of the trial indicate that depression might be predicted using Facebook behavioral data, including messages and actions. However, because Facebook has restricted their ability to acquire personal information and the procedure for doing so has grown more challenging, the sample size of this paper is quite small. As a result, not all significant aspects may be included in the study's findings. Also, as the language-related elements had to be translated from Thai to English in order to analyze the process, there may have been some mistakes as a result of the translation process because some crucial sentimental polar words may have been lost.

Arora et al. [29] analyze the frequently used features and their impact on the classification outcomes in order to provide an interpretation of the depression detection model. The created framework gathers and chooses the 38 feature selection algorithms of various categories' most promising characteristics for modeling depression detection. In order to create more accurate and effective models, the paper employs feature selection techniques that can help identify the most crucial elements for depression identification.

The framework's aggregated features are generalized by the authors using various datasets. Despite the fact that the paper's main focus is interpretability, the feature selection techniques may not fully explain how the models produce predictions.

Lam et al. [30] offer a method of separating depression- and anxiety-related health tweets from all other mixed tweets, which puts us one step closer to determining the health state of a living environment. It's a new platform for patient contact, with many of them taking part in decision-making for better treatment outcomes. Many crucial actions are carried out after the retrieval of the health tweets.

Genevieve et al. [31] focus on machine learning ways to automatically identify depression from clinical interviews, utilizing the models that have been trained on multimodal data. The authors propose a method that incorporates a data augmentation procedure based on topic modeling using a transformer and deep CNN for acoustic feature modeling.

Chiu et al. [32] provide a method for automatically detecting sadness that involves examining a person's environment at home, their behavior, and the social media posts they make. Recurrent neural networks are used in the proposed method to compute each person's post-representation. Next, using deep neural networks, the representations are integrated with additional content-based, behavioral, and living environment variables to forecast the individual's diagnosis of depression.

The existing literature primarily focuses on utilizing either CNN or LSTM networks for depression detection from EEG signals, but there is a noticeable gap in research exploring the fusion of these two deep learning architectures. This research gap prompted my interest in investigating the potential synergistic effects of combining CNNs and LSTMs to improve the accuracy and reliability of depression detection from EEG data. The man's contributions to the proposed work are as follows:

- Develop a novel approach utilizing CNN and LSTM fusion with EEG data for the timely detection of depression in women.
- Evaluate the performance of the proposed CNN-LSTM model in accurately identifying depression from EEG signals, aiming to provide a non-invasive and effective method for early detection of depression in female individuals.

3. METHODOLOGY

EEG signals are utilized in this study for automatic depression identification in women. CNNs are utilized for feature extraction from the EEG data, capturing spatial patterns and local dependencies within the signals. These extracted features are then fed into LSTM networks, which specialize in learning temporal dependencies, enabling the model to capture long-range dependencies in the EEG data over time. Additionally, the study utilizes Keras, a deep learning library in Python, to implement the CNN-LSTM architecture, ensuring the computational efficiency and scalability of the model.

The feature maps and output of CNN are supplied to the LSTM as inputs, and these signals are subjected to sequence learning. The LSTM outputs are transmitted through fully connected layers. Fig. 2 illustrates the study's methodology in a block diagram format.

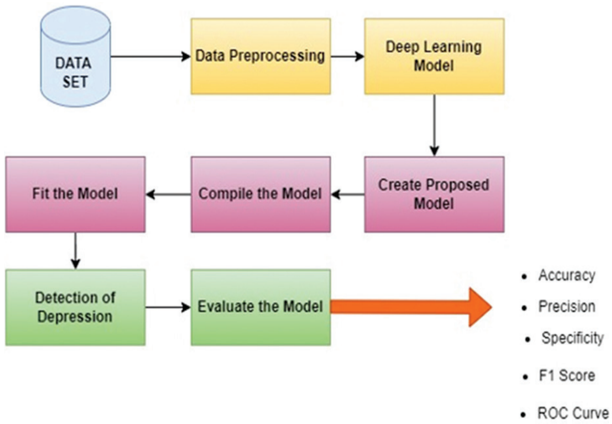

Fig. 2. The block diagram of the proposed architecture

While learning sequential information is difficult for the CNN model, it is good at extracting temporal aspects. Sequential information is generally used in the context of CNNs to describe data that has a temporal or sequential structure, such as speech signals, movies, or sensor data. Convolutional filters are applied to the sequence by the CNN, which searches for patterns at various scales. The patterns or traits that a CNN has trained to recognize and extract from the time dimension of incoming data are referred to as temporal features. CNNs often identify temporal features in sequential or time-series data, such as speech signals, movies, or sensor data. The CNN scans the input data for patterns at various time scales by applying convolutional filters across the temporal dimension. The local features of the input EEG signals are learned by CNN (representation learning), the long-term dependencies are learned by LSTM, and these features are processed sequentially by LSTM (sequence learning).

The CNN network is made up of numerous layers of connected neurons, each of which is in charge of identifying particular aspects of the input image. Edge detection is normally carried out in the first layer, with more intricate feature detection carried out in later layers. Pooling layers, which minimize the spatial size of the feature maps to increase the network's computational efficiency, are also used by CNNs. A fully connected layer serves as the network's final layer and maps the output of the convolutional layers to the class labels of the input images. The mathematical action that a CNN takes when processing an input picture or signal is represented by this equation.

$$Y_c(t)=(X_c*W_c)(t)=\int X_c(\tau)W_c(t-\tau)\,D_\tau \quad (1)$$

Where impulse response is W_c, input signal is X_c, and $Y_c(t)$ denotes the output signal at time t. The output signal y is created by convolving the input signal X_c with a filter or kernel W_c. By integrating the input signal $\int X_c(\tau)$ and the filter $W_c(t\text{-}\tau)$ throughout the input signal domain, one may determine the outcome of the convolution operation at each point in time t.

$$F_c(k)=max(0,k) \quad (2)$$

Where

$F_c(k)$ is a function that returns the highest value between b and a, and k is the input to the ReLU function. $Y_c(t)$ is the output of the ReLU function, given an input x. If the input value is positive, this method returns k; if it is negative, it returns 0. Because it is computationally effective and reduces the vanishing gradient issue in deep neural networks, the ReLU function is preferred over other activation functions like sigmoid. The behavior of some types of neurons in the brain that only fire when the input signal exceeds a particular threshold is modeled by the ReLU function, which is also biologically inspired. The new inputs for the following layer will be the extracted feature maps. The MaxPooling1D layer employs the maximum pooling strategy to minimize the size of the input. To prevent the suggested network from having an overfitting issue, we additionally applied the dropout approach. Because it enables the model to learn from data sequences like time series, sentences of natural language, and DNA sequences, sequence learning is a crucial step in deep learning. Transformers in DL models with LSTM networks are made to identify patterns and dependencies in data sequences. With the aid of sequence learning, the model may take the features from each element in the sequence and use them to forecast the next element or categorize the entire sequence. Deep learning models may accurately predict or classify data even when it is complicated and noisy by including temporal information. The vanishing gradient problem, which makes it challenging to train the prior layers and learn the network, is the main issue encountered while training artificial neural networks with back propagation.

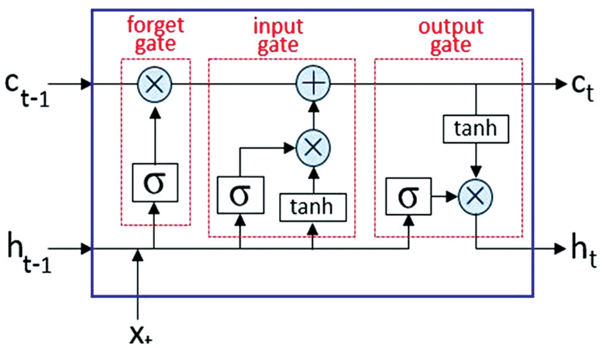

Fig. 3. Architecture of LSTM

Unlike the RNN architecture, the LSTM architecture shown in Fig. 3 has unique memory cells for storing the previous input for a considerable amount of time.

3.1. DESCRIPTION OF DATASET

We used the identical normal and depressive EEG signals in this analysis as those used by Acharya et al. [34]. The left and right halves of the brains of 15 healthy patients and 15 depressed subjects were used to collect the EEG data. A 50 Hz notch filter was used to remove power line noise, while at 256 Hz, the EEG signals were captured. Experts painstakingly removed muscle and eye movement-related artifacts from the EEG readings. The EEG data from 30 patients were divided into two groups: normal and depressed classes for the left and right hemispheres, respectively. It consists of 4318 normal EEG records and 4798 depression records.

Table 1. Details of the EEG Dataset

Class	EEG signal of right hemisphere hemisphere	EEG signal of left hemisphere	Total
Depressed	2398	2400	4798
Normal	2159	2159	4318
Total	4557	4559	9116

In this study, automatic depression identification is carried out using EEG signal samples of the brain. The data are randomly split into training and testing groups when using the random splitting technique. As shown in Fig. 5, the dataset for each group in this study is split into 80% training sets and 20% test sets. The deep learning model is trained using the training datasets. The data that the model never used during training makes up the test set. As a result, test data can be used to more effectively observe the trained model's test performance. 4557 data files were collected from the right hemisphere. We have utilized 3645 of these files for training and 912 for testing. Similar to this, there are 4559 files overall in the left hemisphere's data. 911 files were used for testing after 3648 were used for training. Python is used to implement the model, together with the Keras deep learning tools. Fig. 4 displays examples of a few signal samples found in the data.

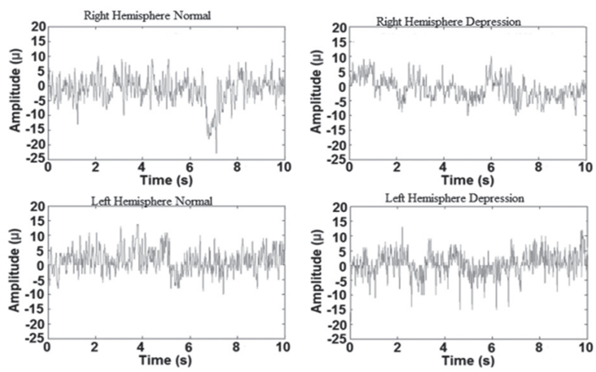

Fig. 4. Sample EEG signal

Table 2 list the parameters and the layers used in this approach. Using the values obtained using the brute-force method, the model's filter number and parameter selection, such as kernel size is carried out.

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Table 2. Details of the proposed CNN-LSTM model

Layers	Type	Output shape
0	Inputs	8 x 512
1-6	Time-distributed convolutional block	8 x 256 x 32
7-12	Time-distributed convolutional block	8 x 128 x 32
13-18	Time-distributed convolutional block	8 X 64 X 32
19-24	Time-distributed convolutional block	8 x 32 x 32
25	Time-d distributed flattened	8 x 1024
26	Time-distributed fully connected	8 x 32
27	Time-distributed batch normalization	8 x 32
28	Time-distributed dropout 50%	8 x 32
29	LSTM	32
30	Batch normalization	32
31	Dropout 50%	32
32	Fully connected	16
33	Batch normalization	16
34	Dropout 50%	16
35	Outputs	4

4. RESULT AND DISCUSSION

For right- and left-hemisphere EEG data, independent experimental tests were carried out. The normal and depression classes were included in the training set of the CNN-LSTM model. We ensure that overfitting does not take place during training by monitoring the model's performance. At the conclusion of training, the right hemisphere EEG signal model had achieved an accuracy of 98.06%, and the loss value had dropped from 0.42 to 0.03. Also, each epoch of training took an average of 52 seconds. By the end of the 25th epoch, the left hemisphere EEG signal model's training performances had attained an accuracy of 99.02% during training with a loss of 0.04.

Table 3. Obtained performance values

	Accuracy	Precision	Specificity	F1-Score
Using EEG of Right Hemisphere	98.06	98.01	98.45	99.01
Using EEG of Left Hemisphere	99.02	98.23	98.49	99.41

Only six input data points for the right hemisphere EEG signals were incorrectly classified by the CNN-LSTM model, which achieves 98.06% accuracy. The sensitivity of the normal class is 99.70%, whereas the sensitivity of the depressed class is 98.55%. For left-hemisphere EEG signals, the model's accuracy is 97.66%. The classes for depression and normal have sensitivity values of 96.02% and 97.19%, respectively. It is clear from the results of the preceding analysis that the CNN-LSTM model performed best at identifying depression in EEG signals. Also, according to the results of our investigation, left hemisphere (Fp2-T4) EEG signals perform better than right EEG signals. The trained CNN-LSTM model classified a single EEG input in about 0.005 seconds. The experimental results demonstrate the efficacy of the proposed CNN-LSTM model in detecting depression from EEG signals. Specifically, the model achieved high accuracy rates of 98.06% and 99.02% for right and left hemisphere EEG signals, respectively. This indicates the model's robust performance in accurately classifying depression status based on EEG data. Additionally, the sensitivity values for both depression and normal classes further validate the model's effectiveness in correctly identifying individuals with depression while minimizing false positives. The performance graph of the proposed model is shown in the below figure.

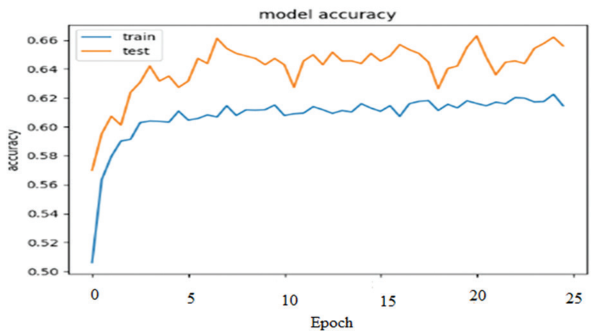

Fig. 5. Performance measure Accuracy plot

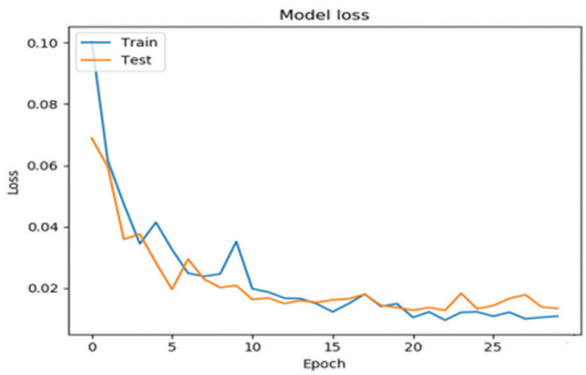

Fig. 6. Performance measure Loss plot

Also, ROC curves were used to evaluate the model. ROC curves are widely used in healthcare decision-making and are regarded as a powerful measure of a diagnostic test. They are extremely helpful for developing classifiers and visualizing their performance. On the X-axis of the ROC curve are graphs showing the false positive rate, and on the Y-axis are plots showing the real positive rate. The ROC for the depression detection algorithm is shown in Fig. 7.

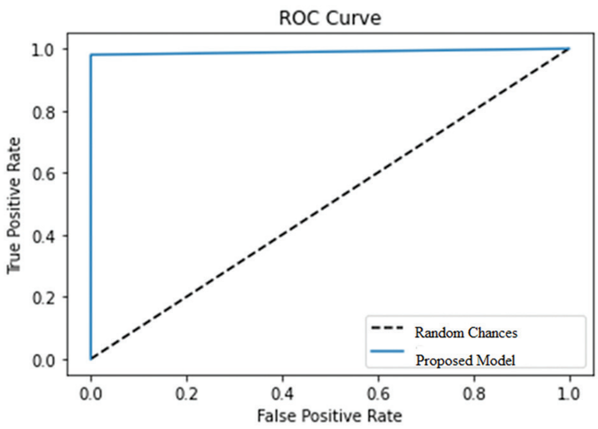

Fig. 7. ROC of the proposed system

It is evident that the new method has higher accuracy than the earlier investigations. The accuracy of Acharya et al. [33] for right hemisphere EEG signals was 95.49%, whereas our accuracy using the same database was 99.02 and 98.06%. Although the LSTM network learns sequences from these attributes, the CNN network learns local properties. A few cutting-edge investigations have used feature extraction approaches. These methods demand expertise, are difficult, and take a lot of time. Yet, in our investigation, the model itself does the feature extraction. In addition, a deep detection model that uses layers rather than simple classifiers like SVM and ANN is proposed. As a result, the CNN LSTM model is reliable and accurate at identifying depression from EEG signals. The suggested model quickly and precisely detects unidentified EEG signals. As a result, the suggested model is practical and simple to apply for clinical applications. The biggest flaw in this study is the small number of participants—15 healthy individuals and 15 depressed individuals. The developed model also requires a lot of computing. A future study will expand on this research by adding more people from various backgrounds and utilizing graphics processing units (GPUs) to simplify the computation. Further improvements will be made using more sophisticated deep learning techniques and more datasets. Moreover, classifiers like SVM will be used to evaluate the CNN-LSTM layers.

Table 4. Comparison of the proposed method with other methods

Reference	Methodology	Accuracy
[34]	CNN	87.95%
[35]	CNN	92.66%
[36]	CNN+LSTM	98.54%
[37]	DepAudioNet	66.07%
[38]	Time series classification	91.67%
Proposed	CNN+LSTM	99.02%

The results corroborate findings from previous studies, indicating the viability of utilizing deep learning models such as CNN and LSTM for depression detection from EEG signals. The high accuracy and sensitivity achieved by the proposed CNN-LSTM fusion model align with the working hypothesis, affirming its potential as an effective tool for the early identification of depression in women. These results suggest that integrating CNN and LSTM networks can enhance the discriminative power of EEG-based depression detection models, thus contributing to advancements in mental health screening methodologies.

5. CONCLUSION

In summary, the work suggests a unique method for detecting depression in women early on by combining CNN and LSTM with EEG data. The suggested model showed excellent accuracy in identifying female depression using EEG data. Deep learning models have a number of benefits over conventional diagnostic techniques for using EEG data to identify depression. It offers unbiased assessments of brain activity, enabling more accurate mental health disorder diagnosis and monitoring. In order to provide remote diagnosis and monitoring of mental health disorders, the proposed model can be connected with telehealth systems. The comparatively tiny dataset utilized for model training and testing is one of the study's drawbacks. In order to enhance the generalizability of the model, future research should take into account utilizing larger and more varied datasets. More research into the use of multimodal data for a more precise diagnosis of mental health disorders such as speech or facial expressions would be intriguing. These findings suggest that the CNN-LSTM approach offers a promising and reliable method for the early detection of depression in women. Thus, the proposed method can be deemed acceptable for clinical application, providing a valuable tool for mental health screening and intervention. Future research could explore integrating additional modalities, such as speech or facial expressions, with EEG data to develop a more comprehensive diagnostic tool for mental health disorders.

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