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ACNN-LSTM: A Novel Deep Learning Approach for Decoding Depression from Resting-State EEG

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Abstract: Depression is a widespread psychological disorder that significantly impacts individuals. The conventional diagnostic approach through doctor-patient communication lacks objectivity and precision. The development of a more accurate and balanced technique for the detection of depression is critical. Due to its ability to effectively describe brain activity, resting electroencephalography (rEEG) is a valuable technique for investigating brain differences between healthy controls and patients with depression. This study examined the rEEG data from 95 healthy controls and 119 individuals with depression. This study constructed the brain's functional network and extracted linear spectral power density parameters from the rEEG data using correlation. Extracting distinctive features for identifying depression in rEEG data remains challenging due to the absence of crucial multichannel and temporal contexts in most existing methods. This research proposes taking advantage of an attention-based convolutional neural network with Long Short-Time Memory (ACNN-LSTM) to enhance its ability to identify of depressive disorders by extracting more selective features from rEEG signals. The ACNN-LSTM being presented incorporates a channel-wise attention mechanism to dynamically assign weights to different electrodes. A Convolutional Neural Network (CNN) is used to extract the important spatial details from the encoded rEEG data. An LSTM combines extended self-attention to examine the time-frequency trends in rEEG data by evaluating significance based on built-in similarities in the signals. The proposed model demonstrated strong performance with an accuracy of 97.34% in distinguishing between depression and healthy controls using 10-fold cross-validation. According to our research, the front and occipital lobes—particularly the Fp1 and Fz locations and the O1 and O2 positions with the oscillations of beta and alpha—play the largest roles in the detection of depressive disorders.

Keywords: Depressive disorder, 19_Channel resting EEG data, Feature extraction, Attention mechanism, LSTM.

1. Introduction

As a result of the current COVID-19 outbreak, anxiety, depression, and panic have become more commonplace. Depression is projected to overtake heart disease as the second most frequent disease by 2020. It is essential to identify depression in its early treatable stages to perhaps prevent the suicide of a patient. [1]

One significant factor is the absence of physiological markers for mental illnesses. EEG is a real-time representation of human brain function associated with emotions, along with other physiological information. It is characterized by advanced temporal resolution, simplicity of operation, reduced acquisition and upkeep expenses, and compact apparatus. EEG can be used as an objective analytical tool to diagnose depression in its early stages and prevent it from progressing to a severe and irreversible state.

An EEG examines the human brain's electrical functioning using electrodes placed on the scalp. EEG data is usually collected up to hundreds of electrodes positioned at different locations on the scalp. EEG equipment used in cognitive neuroscience studies typically includes Three to 128 electrodes. EEG signals typically represent two categories of brain functions: rest state and event-related processes. [2] Resting-state EEG can precisely represent the functioning of human brain systems. Previous studies

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have shown that the spectral features and spatial features (functional connectivity) of rEEG are crucial in identifying depressive disorder. In the resting state, EEG doesn't record active tasks but is still a useful tool for diagnosing and treating disorders because it shows how two groups of neurons interact and how functionally connected they are. [3,4]

Appropriate longitudinal investigations are necessary to discover the components linked to depression. Longitudinal studies suggest that a lower intelligence quotient (IQ) score is linked to a higher likelihood of depressive disorders. [5] Individuals with an IQ below 85 may be more likely to suffer from financial difficulties and stress, perhaps increasing their risk for mental health issues. [6]

Spatial and temporal resolutions are essential metrics when working with brain imaging strategies. Spatial resolution pertains to the capacity to differentiate between two distinct brain regions. Temporal resolution is the capacity to differentiate between two events occurring in the brain at distinct times. [7] Emotional characteristics in EEG can be derived from the three domains of time, frequency, and time-frequency domain. Differential entropy (DE) features improve the capture of emotional states in EEG recordings. [8] EEG can uncover distinct frequency oscillations with precise temporal resolution. Oscillations in delta (δ), theta (θ), alpha (α), beta (β), high beta (η), and gamma (γ) frequencies are known to offer insights into depressive disorder. Patients with depression showed more complexity in EEG oscillations ranging from 0.5 to 40 Hz when their eyes were closed in comparison to healthy control subjects. [9]

The frequency oscillations indicate the brain's activity and condition, with the high and low band coefficients utilised to evaluate different states of mind. New neurobiological markers, including the spectral power distinction, are necessary for accurately diagnosing depression. Using the ratio method to assess spectral power offers a more efficient brain position that is simpler to calculate than nonlinear EEG characteristics.

Alpha oscillation represents cerebral relaxation, sleep, and specific emotions. Beta oscillation is linked to anticipation, anxiety, and internal controls, while theta oscillation indicates emotional processing. [10] Most of this research relies on coherence features derived from multi-electrode EEG data. It is uncertain whether combining single and multi-electrode features can enhance the categorization of depressed patients and normal controls. Recent research suggests a connection between brain functional connectivity and certain psychophysiological conditions characterised by cognitive impairment. This study aims to identify and evaluate abnormalities in depressed patients by analysing changes in both power spectral density (PSD) and functional connectivity between different brain areas in EEG recordings.

Because the treatment is given to depressed individuals based on the classification result, the reliability of the EEG signal classification is another key research challenge that needs to be addressed. A further problem for researchers is the fact that there is always a trade-off between the complexity of the computation and the accuracy.

Traditional machine-learning techniques have been applied using manually specified EEG characteristics to detect MDD intelligently. Resting-state EEG complexity, spectral power, and detrended fluctuations were chosen as features and fed into a linear regression (LR). They discovered significant increases in β and γ spectral powers in groups with major depressive disorder (MDD) and attained a classification accuracy of 90%. [11] Combining EEG data and extracting linear and nonlinear features from each modality led to the creation of a multimodal depression recognition model. The features were then used to classify the data using K-Nearest Neighbour, Decision Tree, and SVM algorithms. The KNN classifier achieved a classification accuracy of 86.98%. [12]

It is still challenging to extract more distinguishing signals for EEG analysis in environments where depression is present. Deep neural networks are becoming increasingly popular in the field of electroencephalogram (EEG) detection as a result of their remarkable classification performance and the feature extraction methods that they employ. [13] Thus, an effective deep-learning system that extracts characteristics and classifies unprocessed EEG signals is essential.

Deep neural networks are gaining popularity in EEG detection due to their exceptional classification performance, along with feature extraction approaches. The integration of CNN and RNN to capture spatial and time characteristics from EEG inputs, [14] CNNs are typically used for extracting spatial information from EEG signals; however, they overlook the significance of features across many channels. [15] An RNN examines the temporal features of EEG signals but does not consider the significance of various EEG samples.

Based on the previously described research, it can be observed that CNNs and LSTMs fail to consider the significance of distinct spatial, spectral, and temporal regions. The complete use of EEG signal data across several areas remains an immense challenge. So here this study examines the temporal characteristics of specific time segments by utilizing LSTM networks and self-attention strategies to focus on various EEG samples. Channel-specific attention and enhanced self-attention could uncover extra spatial and temporal characteristics.

1.1 Problem statement

- Most of the methods we looked at here used standard machine learning methods for extracting features, which need to say how many features should be taken for the best classification accuracy. Finding the best way to use all the data found in the different parts of EEG readings remains not easy.
- The literature reviews deep learning models for classifying depressive disorder use long-term sample signals from EEG data, which don't do a great job of capturing how sample features change over time.
- The significance of various spatial, spectral, and temporal features is overlooked by CNN and LSTM.

1.2 Objectives

This work's main contribution can be stated in the following way:

- Following the phases of convolution, attention mechanisms are implemented on the temporal segments' spatial and spectral features to allocate distinct weights to various brain locations and frequencies.
- The proposed method ACNN-LSTM have implemented a segmented time step signal with a reduced duration of one second to extract temporal regions from the EEG signal more effectively.
- The Logistic Regression Elastic Net Classification technique is used to discover EEG spectral bands and electrodes that distinguish depressed people from healthy controls.

2. Materials and proposed method

2.1 EEG dataset description

Data was collected prospectively from clinical records, psychological assessment tests, and quantitative EEG (QEEG) examinations at the Boramae Medical Centre in Seoul, Korea, from January 2011 to December 2018. Two psychiatrists and two psychologists reviewed the initial diagnoses in electronic medical documents and mental assessments done following QEEG from March 2019 to August 2019 to clinically confirm the primary diagnosis. Moreover, this study included a Healthy Control (HC) sample (n = 95) and a sample with depressive disorder (n = 119). [16]

2.2 EEG acquisition

EEG Installation and Parameters over five minutes eye closing state rEEG data were gathered with a Neuro scan with 19 channels, a sampling rate of 500-1000Hz, and 0.1-100 online filters. The analysis commenced by down sampling the EEG data to 128Hz. [16] Nineteen channels were chosen in coordination with a mastoid reference channel according to the international 10–20 system: FP1, FP2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1, and O2. The distance between the FPz and Fz electrodes defined the ground channel.

2.3 EEG pre-processing & statistical data analysis

EEG data preliminary processing involves eliminating noise to enhance the accuracy of neural signals and transforming the data into a more practical format for subsequent analysis and research. Independent Component Analysis (ICA) is a technique used to detect and eliminate artifacts. The filters are designed to ensure that they do not alter or distort the signals in any manner. High-pass filters with a cut-off frequency typically below 0.5 Hz are employed to eliminate very low-frequency components, like those associated with breathing. High-frequency noise is reduced by employing lowpass filters set at a cut-off frequency of around 50–70 Hz.

Participant age, gender, years of education, and their impacts were incorporated into the model for adjustment in subsequent analyses. Moreover, IQ is a significant factor that may exhibit an association with QEEG, which may be attributed to psychiatric symptoms. [16]

2.4 Feature extraction

2.4.1. Spatial and temporal feature extraction

Following pre-processing, various temporal and frequency domain characteristics were extracted to serve as inputs for the proposed technique. Features were retrieved from each time-step in both the time and frequency domains. Time-domain characteristics comprise mean, variance, and standard deviation. The frequency-domain features extracted include relative band power in six frequency bands: δ (1–4 Hz), θ (4–8 Hz), α (8–12 Hz), β (12–25 Hz), η (25–30 Hz), and γ (30–40 Hz).

2.4.2. Fast fourier transform (FFT)

The rEEG data was processed by advancing in 19-point increments with a 70% overlap, revising the FFT, and employing a 19-point window that slid the 128-demonstrate cross-spectrum for the entire modified rEEG record.

$$\psi = rFFT(EEG[19\_channel]) = \begin{cases} [x[0], Re(x[1]), lm(x[1]), \ldots, Re(x[m/2])], n\ even \\ [x[0], Re(x[1]), lm(x[1]), \ldots, Re(x[m/2]), n\ odd \end{cases}$$

Where

$$z[j] = \sum_{f=0}^{m-1} EEG[19\_channel, f]\ exp\left(-i.\frac{j.f.2\pi}{m}\right) \quad (1)$$

for j = {0, . . ., m − 1}, we obtain the frequency domain representation of EEG [$19\_channel$]. [17]

2.4.3. Coherence

EEG coherence and phase were calculated for all 171 intra-hemispheric and inter-hemispheric pairs of electrode combinations. [18] The term $COH_{xy}(f)$ represent the coherence on frequency band f, while $Q_{xx}(f)\ and\ Q_{yy}(f)$ denote the average auto power spectrum, which measures the energy or activity at various frequencies. $Q_{xy}(f)$ represents the average cross power density. It quantifies connectedness by considering the combined energy shared between two places at a particular frequency, encompassing both in-phase and out-of-phase activities. Here, f represents the frequency of channels x and y.

$$COH_{xy}^2(f) = \frac{|Q_{xy}(f)|^2}{Q_{xx}(f)Q_{yy}(f)} \quad (2)$$

The process of calculating coherence involves initially determining the power spectra for x and y, followed by computing the normalized cross-spectra. The coherence value ranges from 0 to 1. A coherence value around 1 indicates a robust linear relationship between the EEG waves. Coherence was calculated for every possible pair of the 19 channels over the 6 frequency bands: δ, θ, α, β, η ,and γ. The study obtained 1026 coherence features from each participant's EEG data, consisting of 171 pairings of functional connectivity over 6 frequency bands.

2.4.4. Power spectral density (PSD)

Owing to the limited amount of EEG data, a parametric technique is the only way to obtain an accurate estimate of the genuine spectrum. The PSD is determined using Fast Fourier transformation (FFT) applied to the autocorrelation signal.

$$PSD = \frac{1}{2\pi}\int_{wl1}^{wl2} PS_x(w)dw \quad (3)$$

$$PS_x(w) = \lim_{t\to\infty}\left[\frac{E[F_x(w)^2]}{2T}\right] \quad (4)$$

To determine the overall power of a signal with infinite energy/power over time, one can calculate it by integrating or summing the spectral components over time. The Fourier spectrum output of the input signal is denoted as F(w), with wl1 representing the lower frequency and wl2 representing the upper frequency of the power spectral output.

2.4.5. Functional connectivity (FC)

The brain functional connectivity networks based on EEG involve vertices represented by EEG electrodes and edges representing correlations between pairs of EEG signals from different channels. This study chose 19 channel electrodes and analysed the performance of EEG connectivity features retrieved from brain networks built with the vertices of an 18-channel system. To quantify the relationships between pairs of EEG data from distinct channels, Pearson’s correlation coefficient is employed.

$$\rho_{i,j} = \frac{cov(i,j)}{\sigma_i\sigma_j} \quad (5)$$

Eq. (5) cov(i, j) denotes the correlation with i and j, and σ_i and σ_j represent their standard deviations.

2.4.6. Channel extension & self attention

Channel-wise attention overcomes other approaches by modifying the significance of various channels in a feature map, enabling the extraction of essential information. The channel-wise attention looks at the benefits of enhancing the links between feature channels. In particular, a compact module was proposed to use the inter-electrode relationship of a feature outline [19] and channel-wise attention were integrated for imagine labelling. [20] By incorporating channel-wise attention into a CNN, the spatial and spectral information contained in

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multichannel EEG signals can be explored to extract more distinctive spatial co-ordinates among the electrodes. For EEG classification tasks, one common approach is to divide a single EEG trial into many input samples to increase the training dataset size. Many techniques overlook to consider the significance of various EEG samples. We apply the self-attention approach to investigate the temporal relationships between EEG recordings. [21]

2.5 Proposed method - ACNN-LSTM

The ACNN-LSTM model includes an attention mechanism extended self-attention mechanism and overall architecture for this work (Fig.1). We use the attention mechanism to investigate the significance of various electrodes in multichannel EEG signals. Two subsequent convolutional layers are used to extract features from the input data sequence.

Attention methods are utilised in each temporal slice's spatial and spectral dimensions following the convolutional layers of the CNN. This allows for distinct weights to be allocated to various brain areas and frequency bands (Fig.2). By incorporating channel-wise attention into a CNN model, the relevance of different channels in multichannel EEG signals can be explored, leading to the extraction of more discriminative spatial information. $PS = \{\mathrm{PS}_1, \mathrm{PS}_2, \ldots, \mathrm{PS}_m\}$ represents EEG samples that have undergone pre-processing, where $\mathrm{PS}_i = [ps_1, ps_2, \ldots, ps_m]$. Each EEG sample is denoted as es_i denotes the j^{th} electrode of EEG sample es_i, and m is the total number of electrodes in each sample. Mean pooling is employed initially on each electrode rEEG sample in order to obtain statistics that are specific to that channel.

$$\overline{es} = [\,\overline{es_1}, \overline{es_2}, \ldots, \overline{es_m}\,] \qquad (6)$$

Where $\overline{es_j}$ $(j = 1, 2, \ldots, m)$ represents the average of the j^{th} channel. The channel-wise attention system utilises dual fully-connected tiers with a non-linear in between: a dimensionality-reduction region with frequency $\mathcal{W}_1$ and a dimensionality-emerging region with frequency $\mathcal{W}_2$ and biases b_1, b_2. This approach aims to decrease model complexity and enhance generalizability.

$$v = softmax\big(\mathcal{W}_2.(\tanh(\mathcal{W}_1.\overline{es} + b_1) + b_2)\big) \qquad (7)$$

$$ch_j = v_j * es_j \qquad (8)$$

Also utilise a CNN to enhance the extraction of spatial details from EEG signals. The CNN consists of k convolution kernels, with each kernel having a

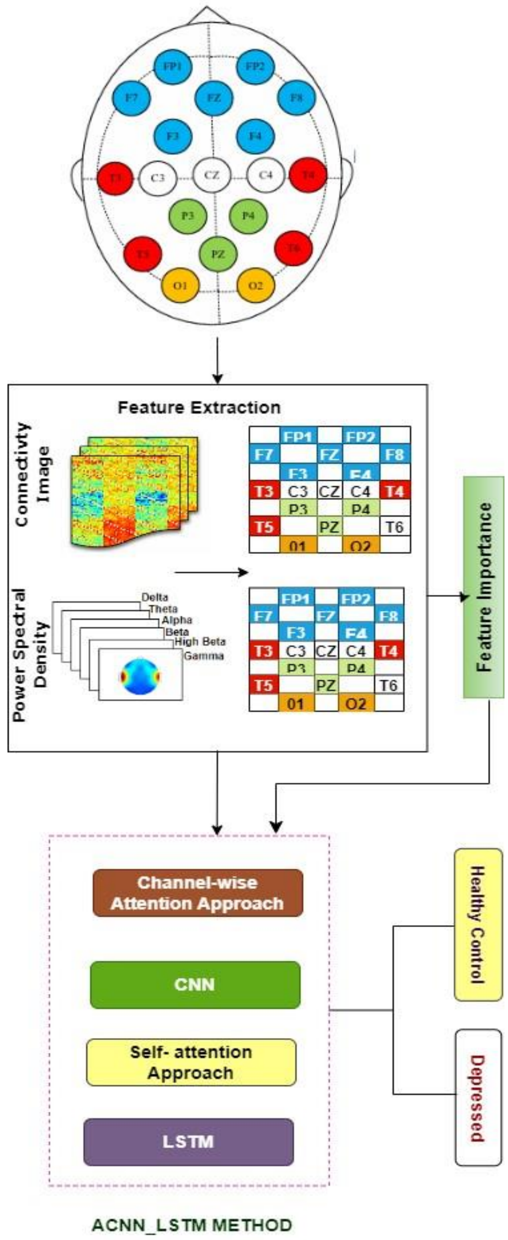

Figure. 1 Overall architecture diagram for 19_channel rEEG predict depressive disorder and healthy controls

height equal to the number of electrodes. The purpose of the kernel dimensions is to examine the temporal characteristics of the EEG data. In the convolution operations, we employ the exponential linear unit (ELU) activation function, which is more effective than the other activation function that is typically used [22].

Following that, we add a pooling layer to cut down on the number of parameters and get more features. Following pooling, the mathematical

representation is designated as $\{\mathrm{P}_i | \mathrm{P} = MaxPool(\mathrm{Ch}'_{i,}), i = 1 \ldots m\}$

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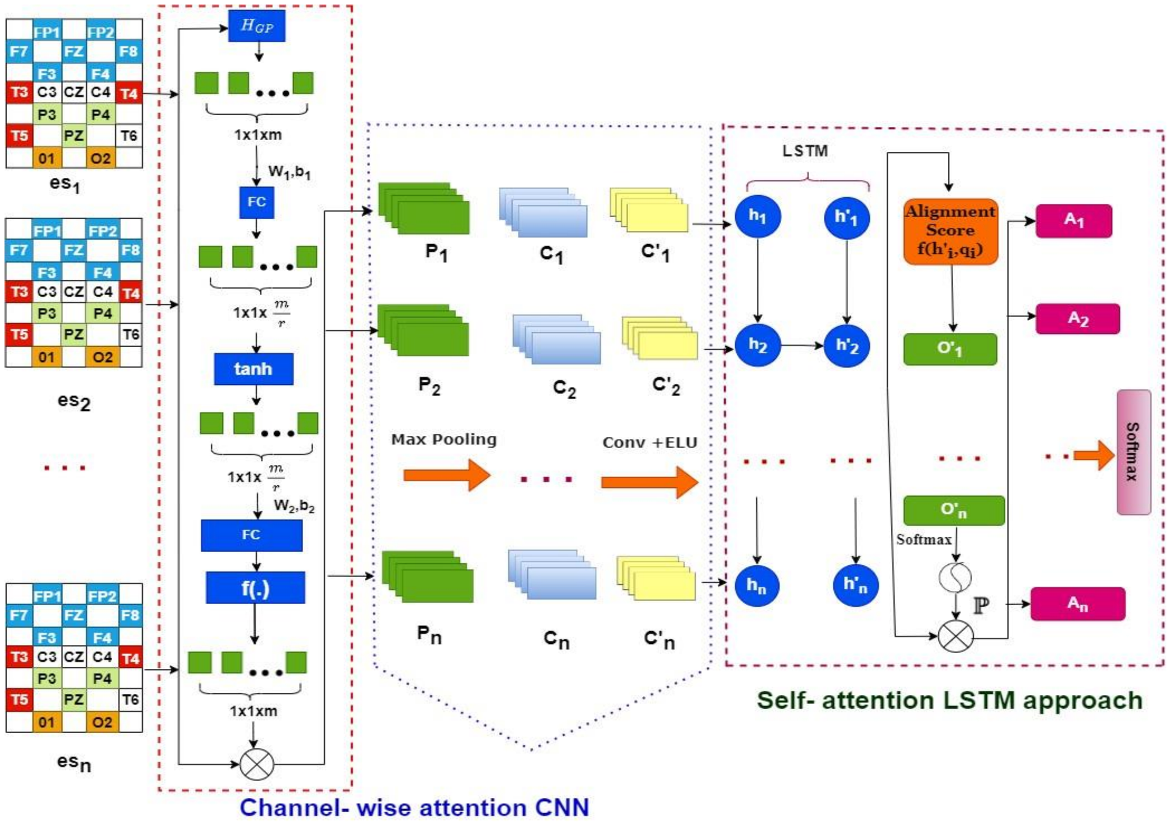

Figure. 2 Architecture diagrams for ACNN_LSTM with attention framework

The LSTM unit utilises four distinct functions: sigmoid (σ), hyperbolic tangent (tanh), multiplication (.), and addition (+), to facilitate weight updates in the backpropagation process shown in Fig. 3. The sigmoid was chosen as the activation function because it tended to send its results 0 or 1. The purpose of the forget gate is to remove irrelevant data from the environment. The hidden layer of the prior state and the current input are weighted combined by the system, which subsequently uses a sigmoid function to process the data. Next, we build the mask that the addition gate will use to select which data to include in the current context. Output gate determines the necessary information for the present hidden phase.h_{t-1} is the previous hidden state, x_t is current input, $\mathcal{W}$ is weight matrix and b is bias

First Step is forget gate

$$fg_t = \sigma\left(\mathcal{W}_f.[h_{t-1}, x_t] + b_f\right) \tag{9}$$

Input Gate

$$i_t = \sigma(\mathcal{W}_i.[h_{t-1}, x_t] + b_i) \tag{10}$$

$$\tilde{c}_t = \tanh(\mathcal{W}_{\mathcal{C}}.[h_{t-1}, x_t] + b_{\mathcal{C}}) \tag{11}$$

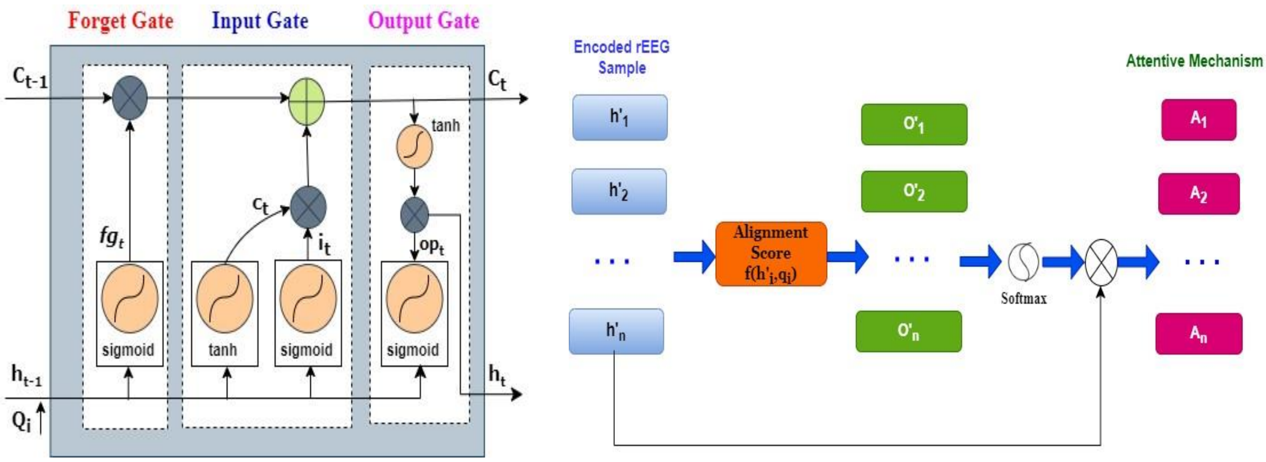

Figure. 3 LSTM and self-attention mechanism

Update the cell memory

$$c_t = fg_t . c_{t-1} + i_t . \tilde{c_t} \tag{12}$$

Output Gate

$$\mathrm{op}_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{13}$$

$$h_t = \mathrm{op}_t . \tanh(c_t) \tag{14}$$

This method considers both the distinctive temporal information that LSTM offers and the inherent similarities in each EEG sample that extended self-attention captures. Applying a self-attention approach to allocate weights to individual rEEG samples based on their inherent significance. It can enhance the description of the precise meaning by calculating the similarity within each sample from several perspectives. The resulting o'_i can be viewed as a vector representing the score of features from the ith sample h'_i. q_i is the pattern vector that is aligned and created from the feature vector h'_i.

$$o'_i = f(h'_i, q_i) = \mathcal{W}^T(\mathcal{W}_1 h'_i + \mathcal{W}_2 q_i + b_1) + b \tag{15}$$

Let $P = \{\mathbb{P}_1, \mathbb{P}_2, \ldots, \mathbb{P}_m\}$represent the probable outcomes of all samples. The probability of the ith rEEG sample is denoted as

$$\mathrm{P}_i = \frac{\exp\left(o'^{T}_i . h'_i\right)}{\sum_{i=1}^{m} \exp\left(o'^{T}_i . h'_i\right)} \tag{16}$$

Finally, A is equal to one-fourth of the $\{\mathrm{A}_1, \mathrm{A}_2, \ldots, \mathrm{A}_m\}$ sum of notes the attributes obtained by the enhanced self-attention approach. The following formula can be used to calculate the ith attentive feature that the enhanced self-attention process has extracted:

$$\mathcal{A}_\mathrm{i} = \mathrm{P_i} . \mathrm{h'_i} \tag{17}$$

The SoftMax classifier executes gathered features as input to identify the depressive disorder.

$$\mathrm{Z} = \mathrm{softmax}(\mathcal{W}\mathcal{A} + \mathrm{b}) \tag{18}$$

Variable	Description
ψ	Revising FFT
$COH^2_{xy}(f)$	Coherence of channel x and y
$Q_{xx}(f)$ and $Q_{yy}(f)$	Average auto power spectrum
$Q_{xy}(f)$	Average cross power density
$PS_x(w)$	Power of a signal over time
$wl1, wl2$	Lower and upper frequency
$\mathrm{F}(w)$	Fourier spectral input
$\rho_{i,j}$	Correlation coefficient
$\sigma_i\sigma_j$	Standard deviations
cov (i, j)	Covariance
es_m	EEG sample of m electrodes
b, b_1, b_2	Biases
$\mathcal{W}_1, \mathcal{W}_2$	Dimensionality reduction and increasing parameter with frequency
v	Channel-wise attention approach
ch_j	EEG channel feature extract via CNN with an attention mechanism
fg_t, i_t, op_t	Forget gate, input gate, output gate
h_t, c_t, x_t	Hidden state, Update the cell, current input
Tanh, sigmoid	Activation function

3. Results and discussion

3.1 Experimental results

EEG signals with 214 samples were collected from 95 healthy individuals and 119 individuals with depressive illnesses to accurately forecast depression. The deep learning model is evaluated using random splitting and 10-fold cross-validation procedures (Table 1). To evaluate the efficacy of each proposed model, the resulting evaluation measures are used:
Precision (P): TP/(TP+FP)
Recall (R): TP/ (TP+FN
F-measure =2∗ (P ∗ R) / (P + R)
Accuracy: TP+TN/(TP+FP+FN+TN)

3.2 ACNN – LSTM

The ACRNN model is mainly trained on a training set containing normal and depression classes. We monitor the model's performance on both training

Table 1. Confusion matrix for predicting depressive disorder

		Actual	
		Depressive Disorder	Healthy Control
Predicted	Depressive Disorder	True Positive (TP)	False Positive (FP)
	Healthy Control	False Negative(FN)	True Negative (TN)

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and validation sets to prevent overfitting during training. The accuracy and loss numbers suggest that overfitting did not occur during training.

3.3 Validating proposed model

The ACRNN model included a channel-wise attention mechanism, a CNN, and an LSTM network with extended self-attention. It was created to assess the efficacy of channel-wise attention and self-attention operations in the original paradigm. Assessment of the suggested model using k-fold cross-validation. This study utilises k values of 5 and 10.

The performance requirements for detecting depressive disorder using EEG signals exceed 90% for both 5 and 10 folds, with the 10-fold accuracy score surpassing the 5-fold accuracy at 97.34%. The ACRNN model demonstrated strong performance and high accuracy in identifying EEG data, slightly outperforming the machine learning model (Fig.4).

We assess the efficacy of LSTM and standard machine learning classification algorithms in recognising depressive disorder and healthy control EEG signals using the input form of feature extraction. Common machine learning classification techniques for comparison are support vector machine (SVM), logistic regression Elastic Net (LR-EN), and random forest (RF) their classification accuracy is inferior compared to deep learning (Table 2). By conducting a comparative analysis, we can determine that the highest-performing classification system could lose accuracy by potentially ignoring essential attributes and incorporating irrelevant ones. Therefore, these methods are challenging, time-consuming, and require the developer to have professional expertise. These diagnostic methods do incorporate sequence learning, which is essential for fully understanding a signal that expect better accuracy compare to machine learning.

Table 2. Evaluating the performance of machine learning and a proposed model using 10-fold and 5-fold cross-validation.

Evaluating Model	**Methods**	**Pre-cision**	**Re-call**	**F1-Score**	**Acc-uracy**
10 - Fold Cross Validation	LR-EN	89.12	83.24	86.31	82.1
	SVM	80.16	85.45	82.16	76.25
	RF	77.28	85.32	84.25	77.56
	LSTM	94.21	95.24	94.53	93.71
	ACNN-LSTM	97.34	98.35	96.53	97.34
5 - Fold Cross Validation	LR-EN	79.23	81.24	80.52	80.41
	SVM	72.43	71.65	71.86	70.84
	RF	74.24	73.26	71.51	73.51
	LSTM	90.57	87.68	90.65	89.87
	ACNN-LSTM	93.52	95.12	93.24	91.36

The ACNN-LSTM model achieved a 15% increase in accuracy compared to the classification model due to the channel-wise attention mechanism emphasising spatial characteristics across different channels. The ACRNN enhanced the average recognition accuracy by 3% compared to LSTM by integrating channel-wise techniques to extract spatiotemporal information from EEG signals.

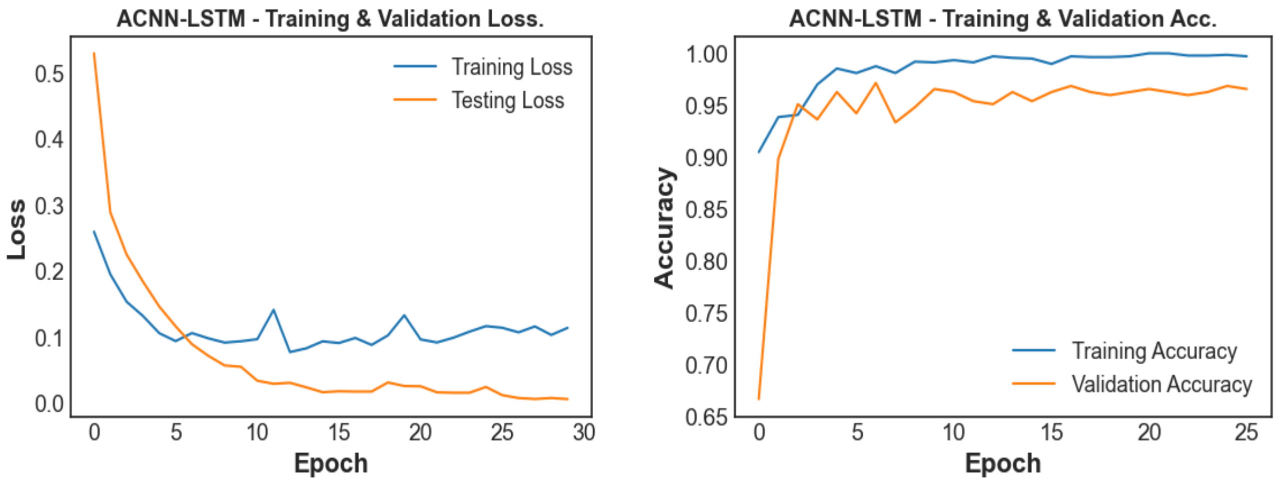

Figure. 4 Proposed ACRNN model: (a) Accuracy of depressive disorder prediction from EEG signal and (b) Loss values in diagnosing depressive disorder

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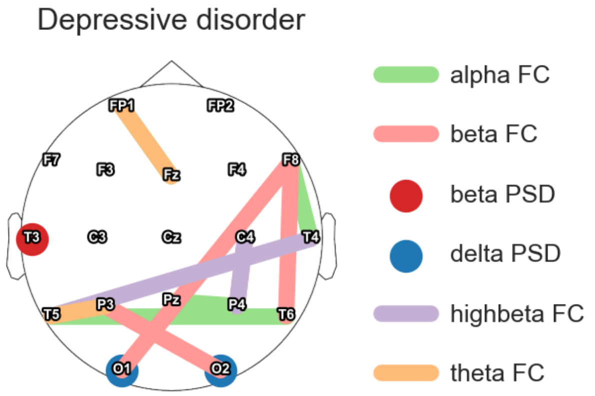

Figure. 5 Strong channel connectivity analyse the depressive disorder

3.4 Best feature combination

The beta band exhibits superior mean classification accuracies in comparison to the alpha and theta bands, indicating that the beta band is more strongly associated with the state of depression. According to previous research, there are substantial distinctions between depressed individuals and healthy controls. As reported by researchers, depression is associated with a substantial increase in beta power within the beta frequency band. [23]

In this instance, the channel location (Table 2) is validated using 10-fold cross-validation; the electrode FC is computed precisely 10 times. The proposed model would incorporate this specific feature in order to enhance precision and decrease the dimensions of the features and electrodes. The accuracy of coherence and correlation was marginally enhanced by the functional connectivity matrix (Fig. 5) utilised in this study, approaching that of one band of frequencies for the FC and PSD.

3.5 Functional connectivity

This work emphasises the role of electrodes and functional connections in improving the accuracy of the proposed model. Fig. 6 displays the top 15 important features for predicting depression utilising the coherence of 19 electrodes and 6 bands of Power Spectral Density (PSD). The significance of delta O2, delta O1, and beta T3 as PSD electrodes has been highlighted in prior investigations. The previous study found heightened activation in the frontal lobe, temporal lobe, parietal lobe, and occipital lobe in patients with major depressive disorder. [24]

The disparity between the healthy control group and individuals with depressive disorders was primarily observed in the frontal region (FP1 and Fz), parietal region (P3, P4, and Pz), temporal lobe (T3, T4, T5, T6), and occipital lobe (O1, O2). The study showed that patients with depressive disorder exhibited significantly greater coefficients in the delta band in the occipital lobe and the beta band in temporal regions in the Power Spectral Density (PSD) feature.

Fig. 5 Electrode pairs with functional connectivity are identified to diagnose depressive disorder effectively. Electrodes T3, O1, and O2 represent channels with increased weight. Electrodes on the right hemispheric side accurately predict depressive disorder.

3.6 Comparative analysis

This work has an advantage over previous similar studies in that it compares the machine and deep learning models and examines the significance of spatial, temporal, and spatial information concurrently and interactively with CNN-LSTM through the use of an attention mechanism. The large dataset size used to train the networks might be viewed as the primary benefit of the research. As a result, Table 4 shows that this study achieved the greatest results at this point in identifying patients with depressive disorders and healthy controls. However, the outcomes demonstrated that employing two deep learning models improves recognition precision. The results in detail were presented in Table 4.

Table 3. Comparative study between proposed ACNN -LSTM and existing method with different features and dataset

Author	Feature	Method	Dataset	Accuracy (%)
S. Liu et al [11]	Spectral and Non linear	Linear SVM	30 MDD 26 healthy control (HC)	89.04
H. Cai et al[12]	Linear and Non - linear feature	KNN	86 depressed patients and 92 HC	86.98
D. Zhang et al [14]	Spatial and temporal features	CNN and RNN	108 subjects	98.31
Li et al [25]	Spectral, spatial, and temporal feature	CNN	15 MDD 15 healthy	85.62
Proposed Method	Spectral, spatial, and temporal feature	ACNN LSTM	119 depressed patients and 95 HC	97.34

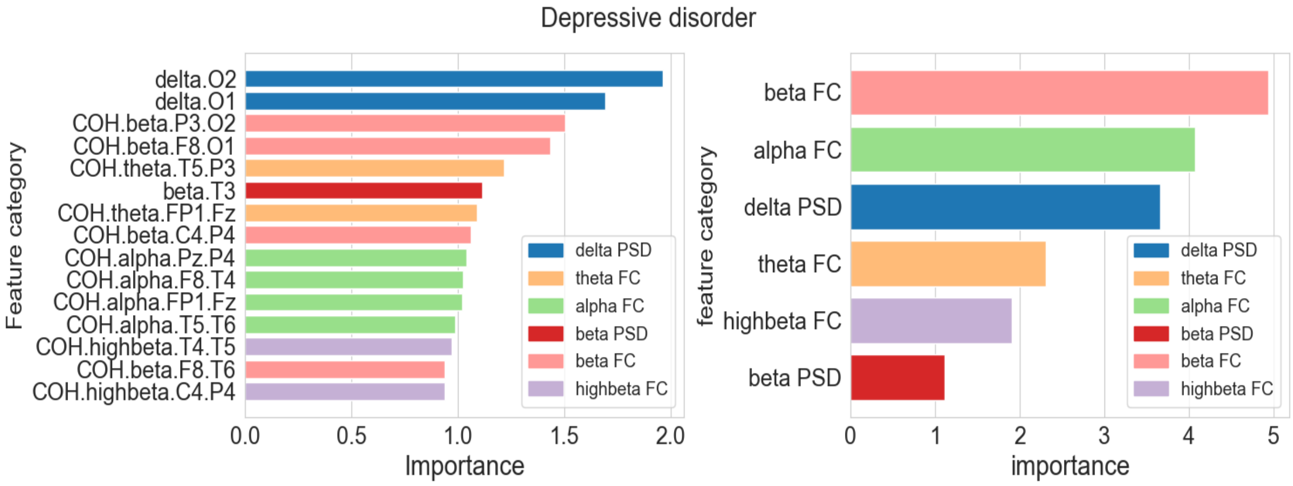

Figure.6 Feature importance of spatial and spectral analysis

According to Table 4 the accuracy of selecting characteristics manually and classifying them using machine learning is not satisfactory. To improve accuracy and lower the loss function value, deep learning techniques also incorporate two independent deep learning approaches. In this work, CNN using the ELU activation function outperforms ReLU. An essential component in optimising accuracy is feature selection. The channel-specific attention method extracts all spatial and spectral characteristics from each electrode of the rEEG sample, while the self-attention method extracts time segments with the shortest time slice to extract all EEG data information. The proposed model is evaluated using a 10-fold cross-validation method that improves accuracy and avoid overfitting.

3.7 Discussion

We investigated how to enhance feature extraction by considering individual differences using channel-wise attention mechanism, and the significance of temporal relationships in the early detection of depression. ACNN-LSTM demonstrated superior performance in 10-fold cross-validation compared to other models, especially when using varied activation functions. This mechanism, along with a self-attention operation, enhanced the extraction of spatial changes while improving accuracy and electrical brain activity over time. It also reflected changes in electrical activity based on electrode position and corresponding brain regions.

This study provides specific proof that PSD, Coherence, FC, and demographic factors are viable biomarkers for analysing complexity differences in depression. Research has indicated that the beta and alpha bands may exhibit enhanced discriminatory power and provide more precise detection of depressive disorder.

Classification of EEG using 128 or 64 electrodes is prohibitively expensive for some clinics to implement. [25] The electrodes FP1, FP2, F3, O2, and T3 showed a significant difference between individuals with mild depression and healthy. Prior research has established that the right hemisphere exhibited superior emotion recognition capabilities, with the right hemisphere being particularly adept at processing negative emotions. It has been established that MDD can impact both hemispheres; however, the manifestation of efforts was more prevalent on the right side. Numerous studies have identified distinct variations in the frontal and parietal lobes between controls who are despondent and those who are healthy.

4. Conclusion

The proposed modal rEEG spatial, spectral, and temporal rEEG features enhance the detection performance of depressive disorder when compared to state-of-the-art approaches. This study aims to validate the ACNN-LSTM model's accuracy rate of 97.34% and enhance its performance using the k-fold cross-validation technique. Based on this premise, the Logistic Regression Elastic Net Classification was subsequently employed to determine that beta and alpha functional connectivity, as well as delta frequency bands in the brain, exhibited a strong correlation with depressive disorder. The beta connectivity with right hemispheric electrodes demonstrated the highest detection accuracy of 97.10%. In the future, there is potential for the model to undergo upgrades or enhancements in order to effectively diagnose depression throughout multiple stages and with varying levels of severity. Furthermore, we conducted experiments on several iterations of machine learning and neural networks to analyse spatial and spectral-temporal characteristics.

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Our findings indicate that the ACNN-LSTM model outperforms other models in detecting depressive disorders.

Conflicts of Interest

Authors declare no conflict of interest.

Author Contributions

Annapoorani was the primary author who contributed conceptualization, technique, data collection, implemented the concept, collected results and writing—original draught. Lakshmi reviewed the work, suggested changes and verified the results.

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