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Original Article

Deep Learning Based Depression Analysis using EEG and ECG Signals

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Abstract *- In covid -19 situation, most people suffer from stress. Continuous stress can lead to severe psychological and even physical disorders. To detect depression manually is time-consuming, tedious, and requires expertise. The present system detects and analyses depression based on EEG and ECG signals. The system layout strategies and calculations include extraction and choice strategies for classification, deteriorating techniques, and combination methodologies. The EEG and ECG features are extracted and sent for classification. The ST segment, P wave, and QRS wave are extracted from ECG signals as features. The most prominent features analyzed from EEG signals are Hjorth activity (HA), standard deviation, entropy, and band power alpha. The Long Short-Term Memory (LSTM) autoencoder and RNN deep learning model approach were used for depression analysis.*

Keywords *- Deep learning, Depression analysis, Feature extraction, LSTM autoencoder, Recurrent Neural Networks.*

1. Introduction

Depression and its analysis tend to assist physicians in diagnosing and monitoring depression. The challenges addressed are (a) EEG signals-based depression detection and (b) ECG signals-based depression detection can assist in the diagnosis and monitoring of the disorder. Electroencephalography (EEG) is used therapeutic test that identifies irregular electrical movements in the brain. Remarkable advances in neuroscience, sensor innovations, and productive flagging computations have facilitated the transition from clinically designed diagnostics and investigations to personalized therapeutic applications. The literature shows that the daily use of EEG for monitoring and tracking health has a promising future. Traditionally, depression has been treated primarily by medical, psychological, and physical methods. Acupuncture is a new treatment for depression without drug addiction, with few side effects and low cost.

In clinical practice, mainly qualitative psychological measures are currently used to assess the therapeutic effects of depression. The Self-Assessed Depression Scale (SDS) is time-wasting and complex, and the assessment results are closely related to the patient's mental state during administration.

In this present system, both EEG and ECG signals are considered for depression analysis. The Butterworth filter is used for preprocessing to remove artifacts from signals and send them to the feature extraction process. The spectral entropy and instantaneous frequency features extracted from ECG signals and the Hjorth activity (*HA*), standard deviation, entropy and band power alpha are the most prominent features extracted from EEG signals. These features are sent to the LSTM autoencoder with RNN as the classifier. The performance of this present system is compared based on the algorithms adopted and the accuracy obtained after testing them on PhysioNet datasets. The existing methodology attains an accuracy of 84% for ECG signal and 96% for EEG signal. However, the present system's measured accuracy is 97%.

2. Literature Review

A review of the work carried out by the researchers in the area of depression detection and its analysis is done in detail. Cognizance of that work is presented here.

Yibo Zhu et al. [8] discussed Major Depressive Disorder (MDD) which has shown an adverse impact on actual recuperation in an assortment of clinical occasions (e.g., stroke and spinal string wounds). The review fostered a prescient gloom appraisal strategy utilizing practical close infrared spectroscopy (fNIRS), which may be quickly incorporated or executed simultaneously with actual recovery undertakings. The top 5 standard elements brought about a characterization exactness of 93%, responsiveness of 85%, and explicitness of 92% utilizing the XG Boost classifier. This work identified mean oxy hemodynamics.

Oleksii Komarov et al. [5] elaborated Daily Sampling System (DSS) carried out as a cell phone uses, whichever joins a bunch of self-appraisal levels for assessing varieties in the enthusiastic state and rest quality all through a complete scholastic form as well as examining every day scores of the members consistently inserted to the Depression data and participated in relaxing-condition EEG information collecting following report consummation. The study collected 1835 everyday tests and 94 consolidated EEG databases from 18 college understudies (matured persons from 23 to 27 years) and 80 % reaction proportion in presenting the day-by-day information during a scholarly semester.

Marcel Trotzek et al. [7] addressed the early location of sadness using machine learning models; we can detect sadness in messages on a social platform. An artificial neural network (ANN) that uses user-level semantic metadata is analyzed and classified. A troupe of the two methodologies is displayed to accomplish cutting-edge outcomes in a current early location task. Moreover, the famous ERDE score as a metric for early recognition framework is inspected exhaustively. Extra tests are essential to find a better way of coordinating the metadata.

Purude Vaishali Narayanrao et al. [25] discussed a depression detection technique in which a dataset is collected through questionnaires provided to the person using various platforms. The classifiers are Decision Trees, support vector machine (SVM), Logistic Regression and KNN. The system attains 90% accuracy. The limited database is the drawback of the system. From social media, Twitter uses tweets Machine Learning algorithm is used for depression detection. Keywords are extracted from tweets. It used Python and Bayes' classifiers to detect whether a person is depressed.

Wheidima Carneiro de Melo et al. [10] introduced a deep learning design for precisely anticipating gloom levels through dissemination learning. It depends on another assumption misfortune work that permits to assess of the essential information appropriation over melancholy strengths, where outcomes upsides of the circulation were upgrades to move toward the ground levels truth. This approach can deliver exact expectations of melancholy levels significantly undermark vulnerability. AVEC2013 and AVEC2014 datasets are used.

Bryan G. Dadiz et al. [9] presented the characterization model of recognizing sorrow in light of neighbourhood double example (LBP) surface highlights a picture handling approach for design acknowledgement on pictures. The face picture is trimmed from a tape recording nine and extricating Formally dressed LBP highlights in each and every edge.

A piece of the grouping is to execute Principal Component Analysis (PCA) eigenvalues from the first highlights to see the impacts. System accuracy is 81% using an SVM classifier with a radial basis function as the kernel. Some parts of the background were also captured by segmenting faces from video images using the Viola and Jones method. Here a recommendation for this uses a more robust segmentation method to better isolate the absolute part of the face from further noise.

Mandar Deshpande et al. [12], Twitter feeds for depression-focused sentiment analysis. The message from Twitter is classified as true or false based on a curated word list to detect depressive trends. For classification, SVM and Naive-Bayes classifiers were used. The results are presented using key categorical parameters, including F1 score, precision, and confusion matrix. More than 10,000 tweets were collected for the training and test database from Twitter API. A data split into 80% for training, and 20% for testing was chosen. Naive Bayes is a commonly used method for text classification that is effective on multinomial data. Also, an SVM classifier is used.

Chiara Visentini et al. [2], the lambda-based architecture of the suggested system for tracking depressive symptoms. This study receives textual, visual, and audio data; it stores them; then, using real-time calculations (in the "speed-time layer"), it determines the person's mood and suggests the best activity based on the findings of the observation process.

Jian Shen et al. [17], The three-electrode invasive EEG acquisition device was used in this study to collect resting EEG data with eyes closed of the scalp electrodes located at Fp1, Fpz, and Fp2, which are closely related to emotion, allows for the presentation of a novel method for the detection and diagnosis of depression using pervasive EEG. Pervasive EEG data from 170 subjects—81 depression patients and 89 healthy individuals were gathered throughout the experiment while they were at rest with their eyes closed.

Sumaiya Tarannum Noor et al. [23], This model featured a feature extraction method to forecast heart issues. The ST segment and QRS wave, extracted from ECG signals, can be used in a web application to determine whether someone is experiencing hyperacute, acute, or chronic stress.

This model predicts normal, aberrant, and PVC heartbeats using an RNN and an LSTM autoencoder. An RNN model for categorizing regular, irregular, and PVC heartbeats is based on deep learning. This technique served as a classifier for us. To forecast aberrant and PVC heartbeats, the model employs a dataset of heart rates. We have used 5000 ECG samples for the dataset.

Changye Zhu et al. [19], about 700 postgraduate students participate from April 2012 to June 2012. During this duration, all students there, the preprocessing strategy comprises selecting qualities, Z-score normalization and lessening measurement. After preprocessing information, we must decide on and extricate vital highlights closely associated with the condition. These highlights are the critical variables for recognizing web users' status. Two strategies are utilized to extricate highlights during this arrange DFT and K-means.

Lang He et al. [4] The speech capabilities have beneficial statistics for analyzing melancholy. Various melancholy popularity tactics were proposed withinside the Depression Recognition of the image with sound emotion defiance and experimentation with the help of databases AVEC2013, AVEC2014, AVEC2016, and AVEC2017. Three Regression strategies evolved using the AVEC2013 and AVEC2014 facts sets, and the type technique considered the AVEC2016 and AVEC2017 facts. It employs the AVEC2013 and AVEC2014 facts sets. As overall performance is calculated, mean absolute error (MAE) and root mean square error (RMSE) are used for the depression prediction.

Juan Bueno-Notivol et al. [1], Studies had been protected if: (1) pronounced cross-sectional facts on the superiority of melancholy in the course of the COVID-19 outbreak, (2) they had been centred on society primarily depends on total samples (3) they defined a technique used to evaluate or diagnose melancholy; (4) the full-textual content changed into available. A current meta-analysis of 12 more studies found Prevalence of integrated depression within the developing population of COVID-19 was 25%. Suggests the most significant reason behind depression prevalence heterogeneity within the studies included during this meta-analysis is that the scale employed in the analysis. High and also the lowest of them. Use PHQ-9 and SDS scale.

Raid M. Khalil et al. [16], The author explained a system to identify abnormal signals of ECG in cardiovascular patients. Appropriate thresholds for the parametric statistic were selected to see ST depression from deviant ECG data. Additionally, they used a cross validation approach that supported the coefficient of correlation between ECG data for ST depression and other failure patterns to define the prime threshold for this method. A spread of machine learning algorithms is available to produce ideal results. Regarding the results obtained, it turns out that SVM classifiers can be selected and developed to achieve very high accuracy.

Le Yang et al. [26], Here automatic depression model prediction using classification and characteristic sorting methods using linear and non-linear HRV measurements. They used SVM-RFE and a statistical filter because of the classification algorithm. An RNN with an LSTM autoencoder is employed to create the model. One model uses an RNN technique, incorporating a more straightforward approach than a CNN.

Shamla Mantri et al. [14], Output Rephrased Text A group of 16–60-year-old patients. They were taken for patients with regular people and depression. Brain signals are obtained at rest for five minutes from electrode positions using the standard 10-20 Electrode Placement System. The signal is sampled at a rate of 256Hz and notched at 50Hz to eliminate mains interference. EEG signals extracted different frequency bands as δ up to 4 Hz, θ up to 8 Hz, α up to 13 Hz, and Beta β up to 30 Hz—using the Bandpass Butterworth filter.

FFT and DFT are used for feature extraction. EEG signals were classified using ANN and SVM. The performance of this method is evaluated based on term sensitivity, selectivity, and classification accuracy. The concept of windows is used to analyze EEG signals due to its non-stationary nature. Overall specificity and accuracy were used to classify standard and depression signals using four bands. The SVM used the FFT to provide 84.00% accuracy.

A literature survey reveals that 84% accuracy using ECG and 94.6% using EEG signal is reported at national and international levels.

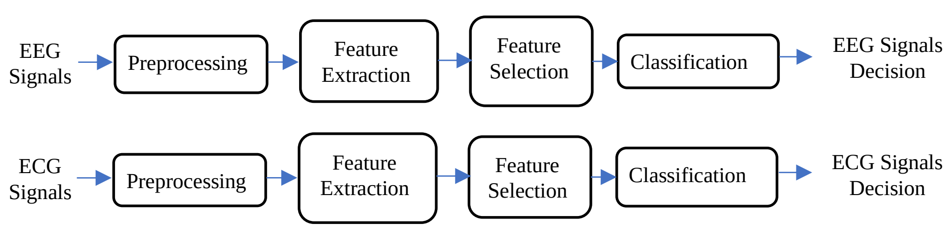

Fig. 1 Depression analysis using EEG and ECG signals

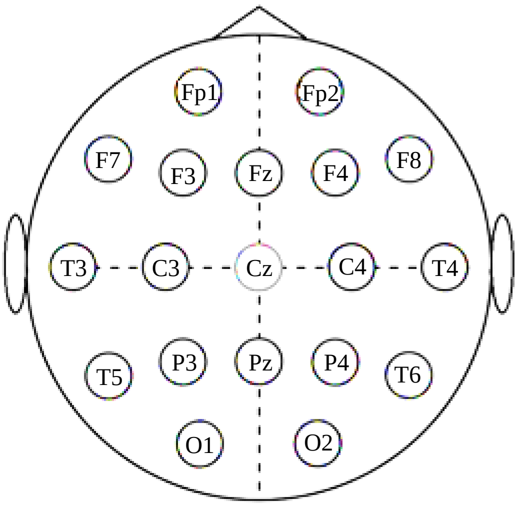

Fig. 2 International 10-20 system for EEG recording

3. Methodology

The present system is designed to get an outcome as depression analysis using EEG and ECG signals. The raw EEG and ECG signals were preprocessed using a Butterworth filter. The features are extracted from EEG as theta, delta, alpha, Beta, and ECG signal as ST segment, P wave and QRS wave separately. The most prominent features are sent to further processing for depression analysis. The LSTM autoencoder with RNN is used for classification. The stepwise methodology to relating depression analysis. The depression analysis system shown in Figure 1 uses EEG and ECG signals. A database was collected from Baramati Hospital with 420 patients.

Step 1: Database

This work uses the 204 EEG signals from the PhysioNet database: ". eeg and. edf "form. Of that, 102 signals are healthy, and 102 are depressed patients. These 102 samples consist of 34 eyes opened, 34 closed, and 34 while doing task conditions.

The ECG datasets are in ". mat" formats. Of the total 8500 ECG signals that 5050 are average person, 700 are depressed, and the remaining are other diseases.

Step 2: Preprocessing

EEG data were recorded per the international 10-20 system shown in Fig 2. One experiment is sliced into three slices, and the middle slice (5 min) is saved for analysis.

The data matrix rearranges the three-channel fragments depending on Fp1, Fp2, T3, C3 and O2 channel order. Each data matrix is applied to the deep learning model as an independent data sample. In previous work, Independent Component analysis (ICA) used for noise removal. The Butterworth filter is used to remove artifacts from signals.

$$|H(j\omega)| = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_c}\right)^{2N}}} \quad (1)$$

Step 3: Feature Extraction

The Fast Fourier transform is used for feature extraction of EEG signals. ECG signal consists of the P-QRS-T waves in one cardiac cycle.

By using wavelet transform, we can extract features of the ECG signal. The amplitudes and intervals determine as features in the ECG signal. ST segments of the ECG signal can observe the depression. The main difference between average and depressed persons is the ST segment in Figure 3.

Step 4: Feature Selection

Activity, Mobility, Complexity. and band power alpha are prominently used to analyze EEG signals for feature extraction.

3.1. Hjorth Activity

The activity parameter represents the signal power, the variance of a time function. This can indicate the surface of the power spectrum in the frequency domain. The following equation represents this:

$$\text{Activity} = \text{var}(y(t)) \quad (2)$$

Where, y(t) represents the signal.

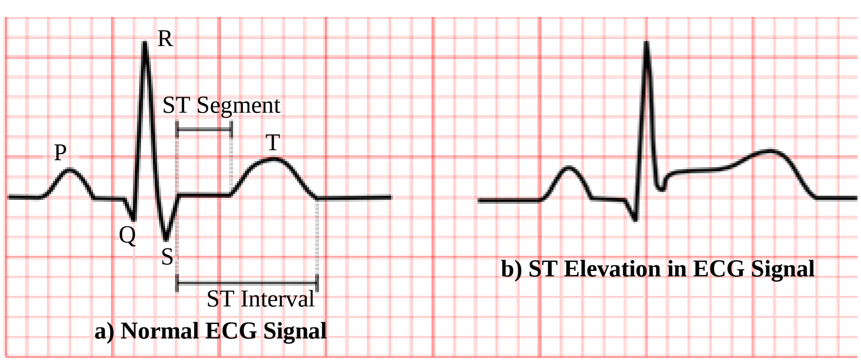

Fig. 3 ECG signal, (a) Normal, (b) Depressed

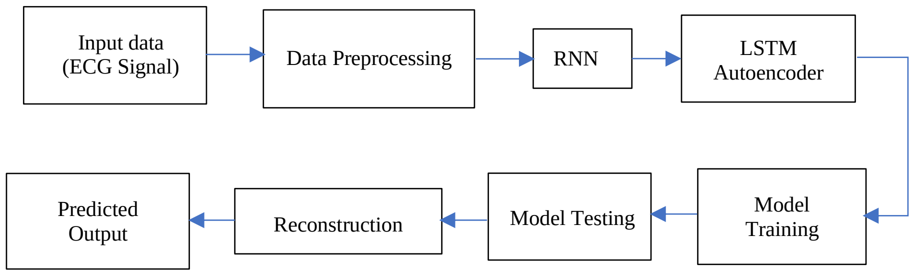

Fig. 4 Architecture of prediction of depression using ECG signals

3.2. Hjorth Mobility

The mobility parameter represents the power spectrum's mean frequency or the proportion of standard deviation.

$$\text{Mobility} = \sqrt{\frac{\text{var}\left(\frac{dy(t)}{dt}\right)}{\text{var}(y(t))}} \tag{3}$$

3.3. Hjorth Complexity

The Complexity parameter represents the change in frequency. The parameter compares the signal's similarity to a pure sine wave, where the value converges to 1 if the signal is more similar. For ECG signals, features are spectral entropy, instantaneous frequency, and arithmetic mean.

$$\text{complexity} = \frac{\text{Mobility}\left(\frac{dy(t)}{dt}\right)}{\text{Mobility}(y(t))} \tag{4}$$

To compute the instantaneous spectral entropy given a time-frequency power spectrogram S(t,f), the probability distribution at time t is:

$$P(t,m)\frac{S(t,m)}{\sum_f S(t,f)} \tag{5}$$

Then the spectral entropy at time t is:

$$H(t) = -\sum_{m=1}^{N} P(t,m)\log 2\, P(t,m) \tag{6}$$

Step 5: Classification

Classification is done by using SVM, KNN, and CNN classifiers in the existing system. These are widely used in the majority of EEG-related studies. The basic LSTM model has the lowest RMSE value compared to other models. Therefore, the LSTM model is suitable for predicting depression from EEG signals.

RNN is a simple approach than CNN. Therefore, the RNN technique is the best solution for classifying the existing methods. It also includes an LSTM autoencoder to improve model performance. The system architecture is depicted in Fig.4. The input is applied from the database, and the input signal, i.e., the ECG signal, is further taken for preprocessing artifacts removal. Then the signal is applied to RNN.

The RNN then learns this data and sends it to the LSTM autoencoder to train the model. After the training, a test is run on the training data to classify and predict normal and depressed heart rhythms. It turns out that an SVM classifier can be selectively developed to achieve very high accuracy.

A standard autoencoder structure contains of two parts. Encoders compress their input; decoders try to recreate it. Output predictions are then obtained from these reconstructed input values.

4. Result and Discussion

4.1. Data Collection

The data acquisition process and EEG collection sites are closely associated with depression. Surface electrodes Fp1, Fp2, F3, F4, C3, C4, T3, T4, T5, P3, and P4 are placed on the scalp according to the International Electrode System 10-20 to record multi-channel EEG data.

For that channel per frame: 32, sampling rate: 128 Hz, and Figure 5. shows that all information about EEG signals is by using different electrodes. Also, electrode Fp1 with eyes closed, eyes opened and in task condition, from that observed information of EEG signal shown in Fig. 6.

The feature extraction of EEG signals was done. A total of eight features are analyzed from that without parameter Hjorth activity (HA), complexity (HC), and mobility (HM) and with parameter as standard deviation, entropy, mean, variance and band power alpha. The Hjorth activity (HA), standard deviation, entropy and band power alpha are most suitable for EEG signals. By using wavelet transform, features are extracted from ECG signals. To classify the depressed or average person by using RNN and Autoencoder techniques.

5. Performance Analysis

Accuracy is used to assess the type overall performance of the system. Sensitivity is a parameter related to the upper potential of a classifier to find good patterns efficiently. Specificity refers to the superior probability of the classifier efficiently catching the worst samples. Recognition accuracy refers to the bare potential of the classifier to efficiently find distinctly labelled samples.

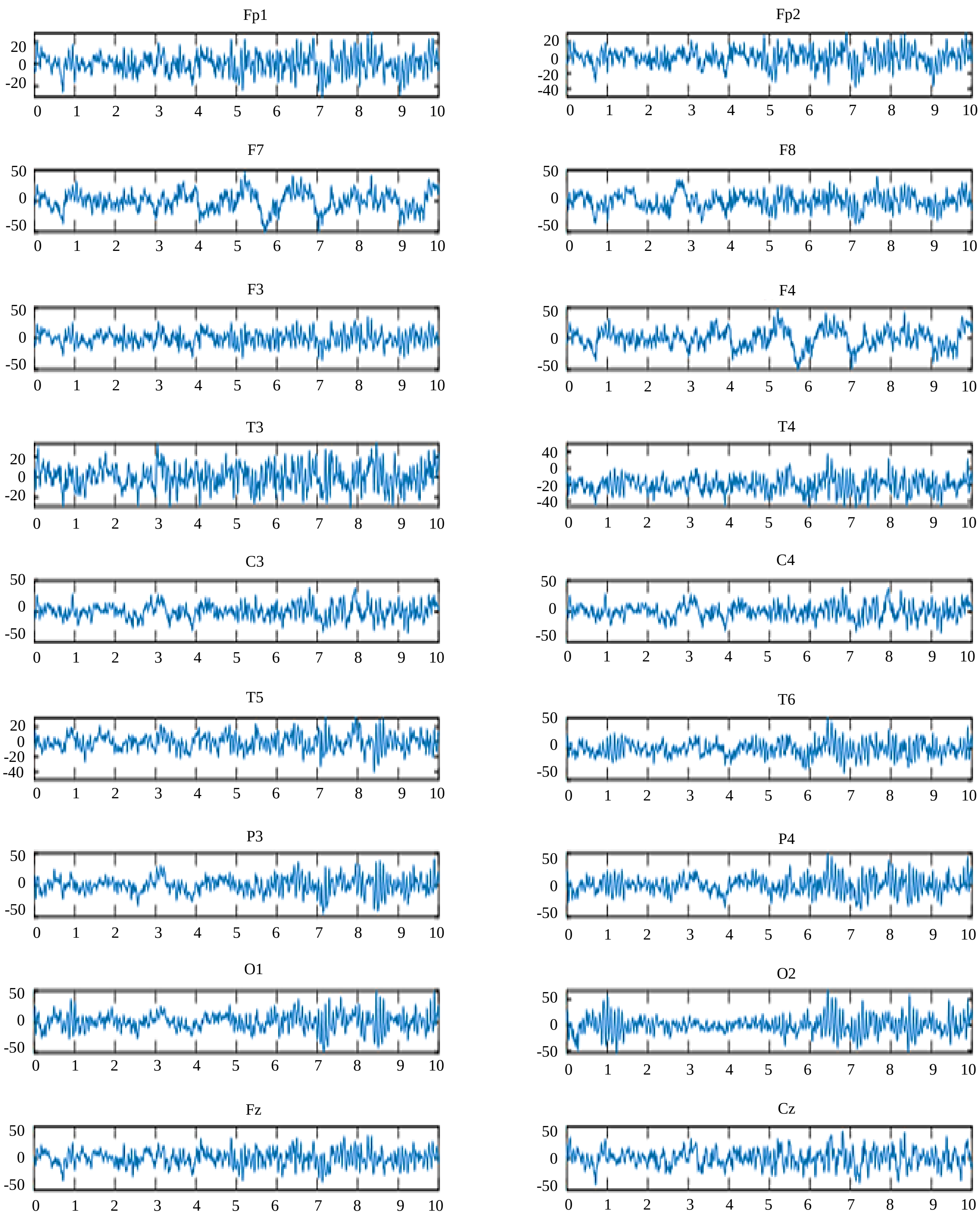

Fig. 5 EEG signal with different electrodes

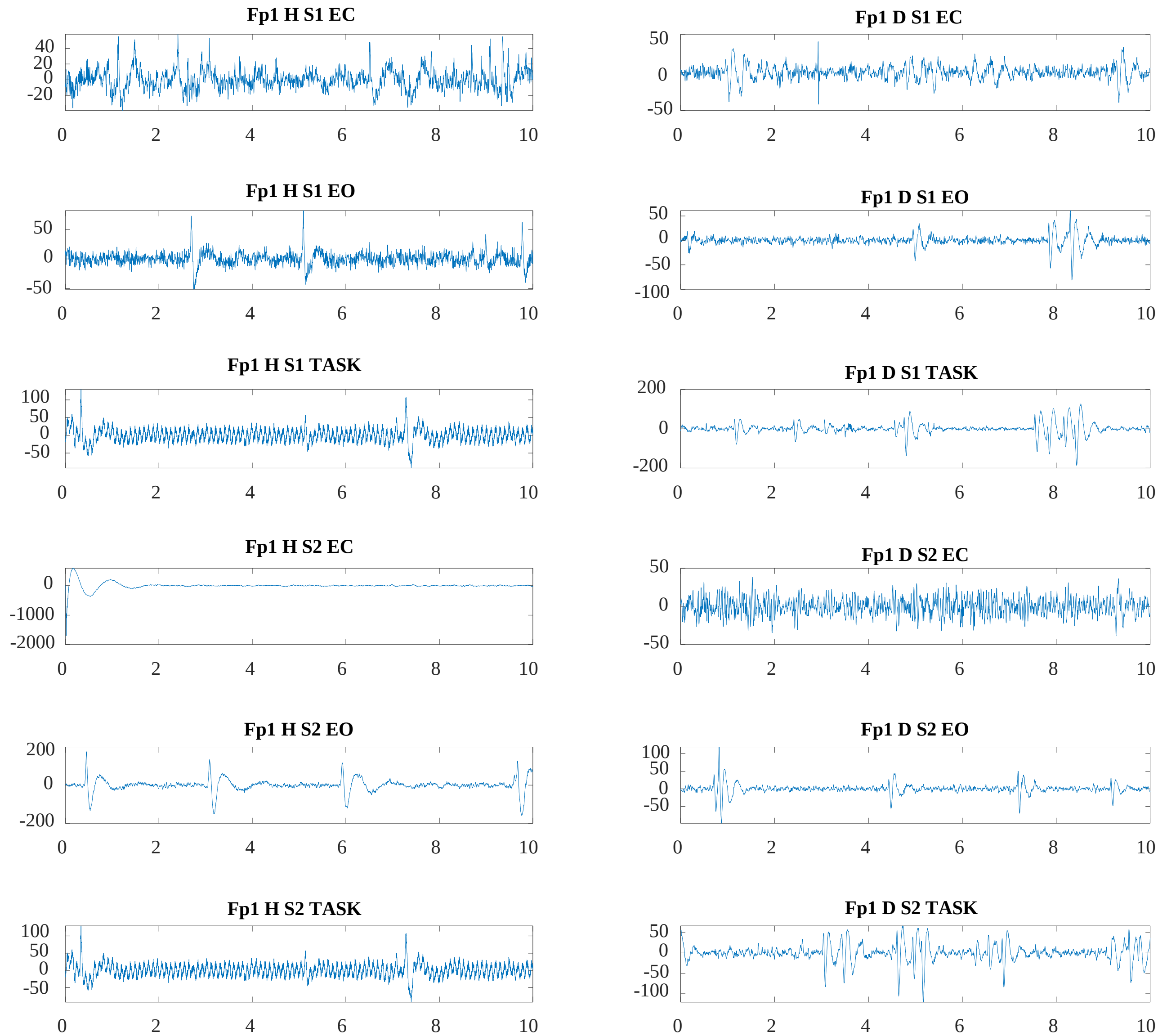

Fig. 6 EEG signal using Fp1 electrode with eyes opened and closed

All these figures are calculated using the following formulas:

$$Accuracy = \frac{tp+tn}{tp+tn+fn+fp} \quad (7)$$

Where tp is true positive, tn is true negative, fp is false positive, and fn is false negative.

$$Sensitivity = \frac{tp}{tp+fn} \quad (8)$$

$$Selectivity = \frac{tp}{tp+fp} \quad (9)$$

$$Specificity = \frac{tn}{tn+fp} \quad (10)$$

The preprocessed ECG signal applied for the classification requires more time, and accuracy is less than 50% to 60%. If the ECG signal extracted prominent features and sent for the classification, then training time requires less and accuracy is improved by up to 98%.

During the training process, the number of iterations improves the accuracy and reduces the loss function depicted in Fig. 7.

Fig. 8 shows the confusion matrix and classification evaluation results of the ECG signal for one-dimensional and two-dimensional sequence input, where D stands for depression and N for normal. A total of 8876 samples for training and 980 for the testing process are taken.

Table 1. Performance parameters of the LSTM model for ECG signals

Parameter	Training Process		Testing Process	
	1-Dimension	2- Dimension	1-Dimension	2-Dimension
1) Accuracy	60 %	91.55 %	58.78 %	85 %
2) Sensitivity	58.6 %	97.45 %	57. 52 %	96.55 %
3) Selectivity	66.24 %	85.33 %	67.14 %	74.28 %
4) Specificity	61.14 %	97.76 %	60.54 %	79.1 %

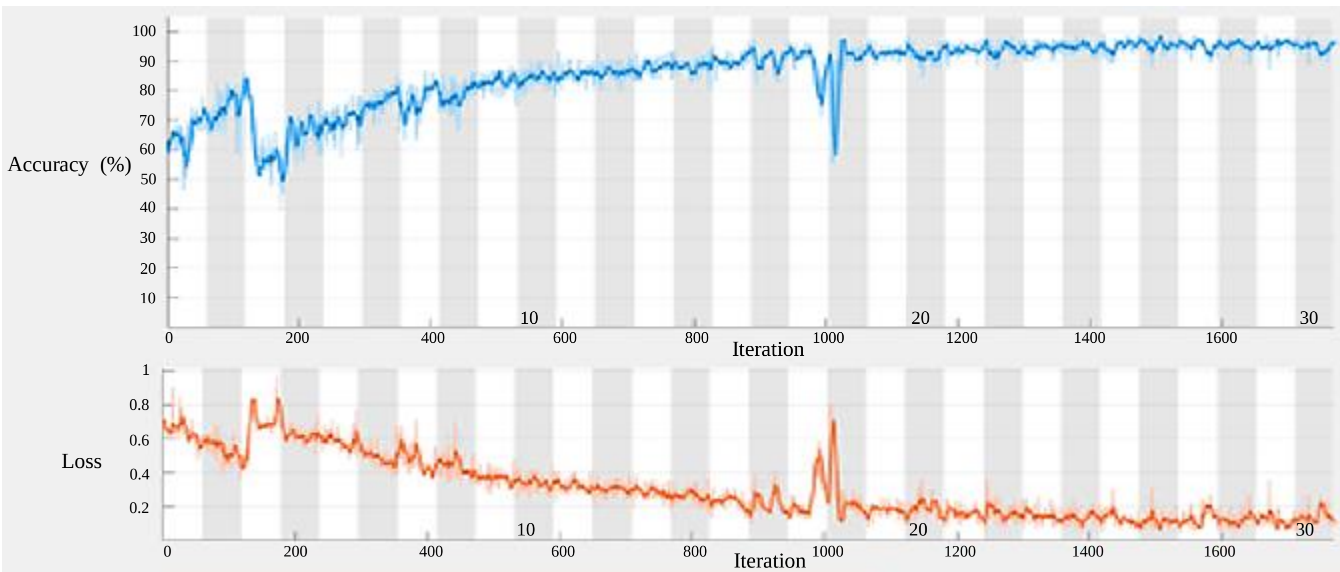

Fig. 7 Accuracy and loss function with no. of iteration during the training process

	D	N
	2940	1498
	2081	2357

(a) 1-Dimension Training Process

	D	N
D	3787	651
N	99	4339

(b) 2-Dimension Training Process

True Class	Predicted Class: D	Predicted Class: N
D	329	161
N	243	247

(c) 1-Dimension Testing Process

True Class	Predicted Class: D	Predicted Class: N
D	364	126
N	13	477

(d) 2-Dimension Testing Process

Fig. 8 Confusion matrix for LSTM (a) 1- Dimension (b) 2- Dimension in training process (c) 1- Dimension (d) 2- Dimension in testing process

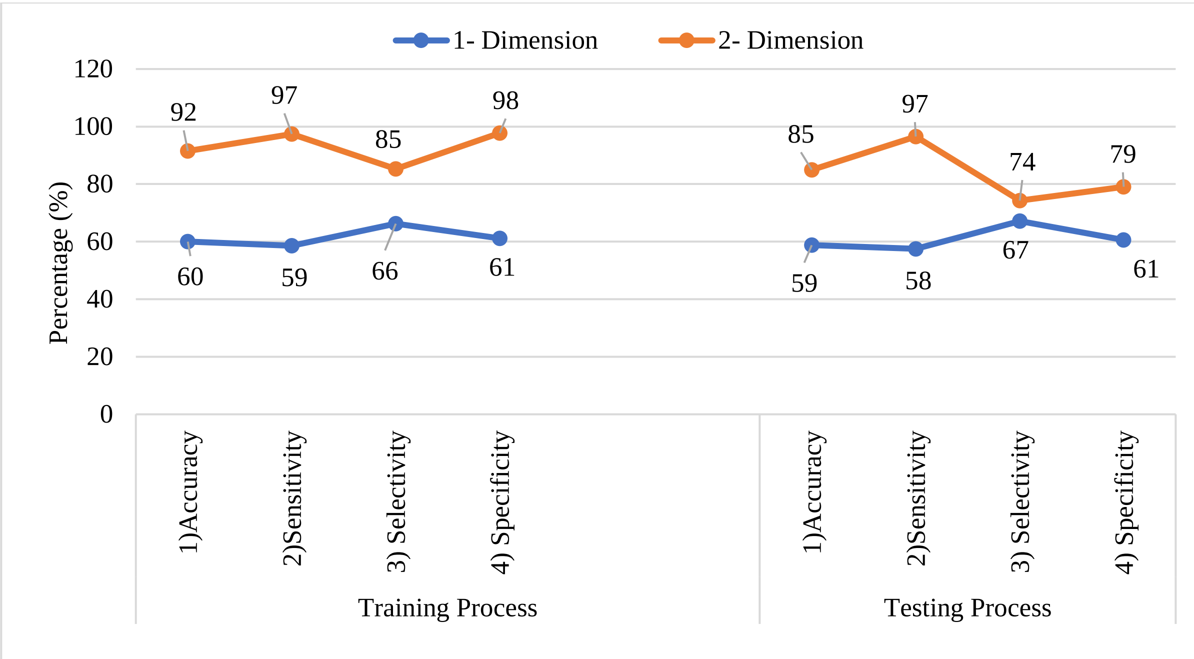

Fig. 9 The performance parameters of classification of ECG signals

Table 1 and Fig. 9 shows the performance analysis of the LSTM model as a classifier used for ECG signals. A comparison of experimental results discovered that performance parameters such as accuracy, sensitivity, selectivity and specificity of two-dimensional sequence input are higher than one-dimensional sequence input to the network.

6. Conclusion

This study tried to find feature extraction methods for depression analysis using EEG and ECG signals. The Hjorth activity (HA), standard deviation, entropy and band power alpha are most suitable for EEG signals and arithmetic mean for ECG signals.

This system uses LSTM autoencoder and RNN with two-dimensional sequence input, providing higher accuracy, specificity, and specificity. The present system attains 97% accuracy for ECG signals.

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