EEG and ECG Signal Based Depression Detection Using Machine Learning

Sanchita Pange[1*], Vijaya Pawar[2]

[1]Department of Electronics and Telecommunication Engineering, AISSM's Institute of Information & Technology, Pune, India.
[1]Department of Electronics and Telecommunication Engineering, Jayawantrao Sawant College of Engineering, Pune, India.
[2]Department of Electronics and Telecommunication Engineering, Bharati Vidyapeeth's College of Engineering for Women, Pune, India.
Email: smpphd20@gmail.com[1], vijaya.kashid@bharatividyapeeth.edu[2]

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ABSTRACT
The COVID-19 pandemic is the century's most memorable event. Stress was a common problem for many during the pandemic. Prolonged stress can cause serious mental and even physical health problems. Manually detecting depression takes a great deal of experience, patience, and time. The current approach uses EEG and ECG readings to identify and analyze depression. The extraction and choosing methods for classification and degrading approaches, as well as combination methodology, are included in the system layout calculations and strategies. After being retrieved, the EEG and ECG features are forwarded for categorization. From ECG signals, the ST segment, P wave, and QRS wave are extracted as characteristics. Hjorth activity (HA), standard deviation, entropy, and band power alpha are the most important characteristics that are analyzed from EEG signals. The Long Short-Term Memory (LSTM) autoencoder and RNN deep learning model approach were used for depression analysis for ECG signals and Support Vector Machine (SVM) and Convolutional Neural Network (CNN) classification methods are used for EEG signals.

Keywords: Depression Detection, EEG and ECG Signals, Feature Extraction, LSTM Autoencoder, Machine Learning.

INTRODUCTION

Electroencephalography (EEG) is the most effective and widely used method for capturing brain activity. Now a days it is extensively used for diagnosis of neurological conditions, including depression, epilepsy, obsessive-compulsive disorder (OCD), seizure prediction, Alzheimer's disease, stroke, Creutzfeldt-Jakob disease, sleep analysis, Parkinson's disease, schizophrenia, and mood state analysis.Globally depression is likely to affect 3.8% of the overall population, with 5.7% of adults over the age of 60 years and 5% of overall adults (4% of males and 6% of women). Depression is main concern as around the world it affected 280 million persons. Across the globe, depression affects 10% of expectant mothers and aspirant mothers. Suicide claims the lives of around 7 Lakhs people annually [23].The study of depression and its analysis often helps doctor to identify and treat depression. The literature survey reveals that use of EEG is beneficial for monitoring and tracking the condition of individuals health and Its future is bright. Traditionally, medical, psychological, and physical approaches have been the mainstays of treatment for depression. Acupuncture is a novel, inexpensive, and low-side effect treatment for depression that does not involve drug addiction.

Currently, clinical practice uses psychological measures, particularly qualitative ones, to evaluate the therapeutic effects of depression. Time-consuming and complicated, the Self-Assessed Depression Scale (SDS) has a strong correlation between the patient's mental state at the time of administration and the assessment's findings.

Both the EEG and ECG signals are taken into account for depression analysis in the current system.It is important to note that, in order to choose the best approach, the suggested system is noise-resistant since noise is eliminated from the EEG signals using the Multiscale Principal Component Analysis (MSPCA). The MSPCA blends wavelets with Principal Component Analysis (PCA), as opposed tousing each of the major elements and the principalKaiser rule selected the components in order to accomplish the highest level of categorization precision.

The additional methods are evaluated in the preprocessing module.conventional techniques such as temporal filtering, spatialfiltering, and discovered MSPCA offers the most effectiveoutcomes in the present work. After The Hjorth activity (HA), standard deviation, entropy, and band power alpha are the most notable features extracted from EEG signals, while spectral entropy and instantaneous frequency features are extracted from ECG signals. The Long Short-Term Memory (LSTM) autoencoder with Recurrent Neural Network (RNN) classifier receives these features in addition. The accuracy and classifiers used for depression detection in the current system, which uses PhysioNet datasets, are the metrics used to assess the system's performance.

LITERATURE REVIEW

A thorough analysis and review of the research conducted by the researchers in the field of depression detection is conducted. This presentation acknowledges that work by looking at papers from the previous nine years.

Major Depressive Disorder (MDD) has been shown to have a negative effect on real recovery in a variety of clinical situations (such as spinal string wounds and strokes), as Yibo Zhu et al. [1] discussed. The review promoted a future-oriented crisis assessment approach that makes use of practical near-infrared spectroscopy (fNIRS) and can be promptly implemented or carried out concurrently with ongoing real recovery projects. Using the XG Boost classifier, the top 5 normal elements produced characterization exactness of 93%, responsiveness of 85%, and explicitness of 92%. This study determined the mean oxygen-hemodynamic.

The Daily Sampling System (DSS), developed by Oleksii Komarov et al. [2], is a mobile application that combines a number of self-assessment levels to evaluate variations in the excited state and rest quality through a comprehensive academic form. It also examines daily scores of the participants who regularly inserted the depression data and took part in relaxing-condition EEG information collection after report completion. The study gathered 1835 daily assessments, 94 consolidated EEG databases, and an 80% response rate from 18 college understudies (adults between the ages of 23 and 27) in order to present the daily data over the course of a semester of study.

Using machine learning models, Marcel Trotzek et al. [3] addressed the early location of sadness and showed that it is possible to identify sadness in social media messages. Using user-level semantic metadata, an artificial neural network (ANN) is analyzed and classified. A combination of the two approaches is demonstrated to achieve state-of-the-art results in an ongoing early location task. Furthermore, a thorough examination is currently conducted on the well-known Early Risk Detection Error (ERDE) score as a metric for early recognition frameworks. To find a better method of coordinating the metadata, more tests are necessary.

Zang Xiaohan et al. [4] The subjects' ECG signals were collected using the multifunctional physiology experiment instrument RM-6280C (Chengdu Instrument Factory, Sichuan, China), with a sampling rate set to 1 kHz. In the experiment, baseline drift was eliminated using a median filter, power frequency interference was eliminated using a notch filter, and EMG interference was eliminated using a low-pass filter. The 5.5-minute data set for this study was split up into epochs, each lasting 5 seconds (or other durations), and each epoch was given a label. They classified and extracted features from ECG segments using a one-dimensional CNN.

Bueno-Notivol Juan et al. [5], Research was shielded if it (1) presented clear cross-sectional data about depression's superiority during the COVID-19 pandemic; (2) focused on society and relied heavily on whole samples; (3) described a method for diagnosing or assessing depression; and (4) made the entire text accessible. According to the most recent meta-analysis, which included 12 additional studies, 25% of the developing COVID-19 population had integrated depression. indicates that the scale used in the analysis is the primary cause of the heterogeneity in depression prevalence among the studies included in this meta-analysis. Use the SDS scale and PHQ-9..

Purude et al. [6] talked about a technique for detecting depression in which a dataset is gathered by giving people questionnaires on a variety of platforms. Decision trees, support vector machines (SVM), logistic regression, and k-nearest neighbor (KNN) are the classifiers used. 90% accuracy is attained by the system. The system's limited database is a drawback. A machine learning algorithm is used to identify depression by analyzing tweets from social media platforms like Twitter. From tweets, keywords are extracted. Python and the Bayes classifier were utilized to determine whether or not the person was depressed.

Through dissemination learning, Wheidima Carneiro de Melo et al. [7] presented a deep learning design for accurately predicting depressing levels. The assessment of the basic information appropriation over depressing strengths, where the results of the circulation were upgraded to move toward the ground truth, depends on another assumption of misfortune work. This method can produce melancholy levels that are

precisely expected while keeping mark vulnerability much lower. The datasets AVEC2013 and AVEC2014 are utilized.
The characterization model of recognizing sorrow in light of neighbourhood was presented by Bryan G. Dadiz et al. [8]. The face image is extracted and cropped from a tape recording. LBP highlights in every edge, dressed formally. Principal Component Analysis (PCA) eigenvalues from the initial highlights are executed as part of the grouping in order to observe the effects. Using an SVM classifier with a radial basis function as the kernel, the system accuracy is 81%. Certain background elements were also captured by applying the Viola and Jones method to segment faces from video images. Here, a suggestion is made to employ a more reliable segmentation technique in order to more effectively separate the face's absolute portion from additional noise.
Twitter feeds for sentiment analysis centered on depression, Mandar Deshpande et al. [9]. Using a carefully selected word list to identify depressive trends, the tweet is categorized as true or false. Both the Naive-Bayes classifier and SVM were used for classification. The confusion matrix, precision, and F1 score are among the important categorical parameters that are used to present the results. Using the Twitter API, more than 10,000 tweets were gathered for the training and test databases. Data was divided into two groups: 80% for training and 20% for testing. For text classification, naive bayes is a popular technique that works well with multinomial data. Moreover, SVM classifier is applied.
The lambda-based architecture of the proposed system for tracking depressive symptoms was described by Chiara Zucco et al. [10]. This research takes in textual, visual, and audio data, stores it, and then uses real-time computations (in the "speed-time layer") to ascertain the subject's mood and recommend the most appropriate activity in light of the observation process's results.
Shen Jian et al. [12], This study used a three-electrode invasive EEG acquisition device to record resting EEG data while the subjects' eyes were closed. the presentation of a novel technique for the detection and diagnosis of depression using pervasive EEG is made possible by the analysis of the scalp electrodes at Fp1, Fpz, and Fp2, which are closely related to emotion. Throughout the trial, 170 subjects—81 of whom had depression and 89 of whom were healthy—had their peripatetic Pervasive EEG data was collected during the experiment while subjects were at rest with their eyes closed from 170 subjects (81 depression patients and 89 healthy individuals).
Noor, Sumaiya Tarannum, and others [13], This model used a feature extraction technique to predict cardiac problems. A web program that uses the extracted ST segment and QRS wave from ECG data may identify whether a user is under hyperacute stress, acute stress, acute stress, or chronic stress. This model uses an LSTM autoencoder and an RNN to predict PVC, aberrant, and normal heartbeats. Deep learning is the foundation of an RNN model that classifies PVC, irregular, and normal heartbeats. The model uses a dataset of heart rates to predict PVC and aberrant heartbeats. For the dataset, they used 5000 ECG samples.
He Lang and others [15] The speech capabilities offer useful statistics for depression analysis. A number of somber popularity strategies were put forth during the Depression. Identification of the image exhibiting defiance and experimentation using the AVEC2013, AVEC2014, AVEC2016, and AVEC2017 databases. Using the AVEC2013 and AVEC2014 fact sets, three regression procedures were developed, with the type methodology taking into account the AVEC2016 and AVEC2017 data. The AVEC2013 and AVEC2014 fact sets are used. In order to forecast depression based on overall performance, mean absolute error (MAE) and root mean square error (RMSE) are utilized.
Muhammad Tariq Sadiqet. al. [16], suggested, an automated multivariate empirical wavelet transform (MEWT)
approach which is straightforward and reliable for decoding.
various motor imagery (MI) tasks approach which is straightforward and reliable for decoding various motor imagery (MI) tasks.
There are makes four primary contributions. Initially, the preprocessing is done using the multiscale principal component analysis method. Second, a unique automated channel selection mechanism is put forth and subsequently validated through in-depth analyses of three distinct approaches for decoding channel combination selection. Third, for the first time in MI applications, a sub-band alignment technique based on MEWT is used to provide joint instantaneous amplitude and frequency components. Fourth, significantlyit is said that lower the computational load and system complexity, a strong correlation-based feature selection technique is used. The sample's sensitivity, specificity, and classification accuracy were averaged and that are 93%, 92.1%, and 91.4%.
Shamla Mantri and colleagues [17], Produced Rewritten Text a group of patients aged 16 to 60. They were prescribed for individuals with depression and normal persons. The conventional 10-20 Electrode Placement System is used to acquire brain signals from electrode placements while the subject is at rest for five minutes. To remove mains interference, the signal is notched at 50 Hz and sampled at a rate of 256

Hz. Different frequency bands were recovered from EEG signals: δ up to 4 Hz, θ up to 8 Hz, α up to 13 Hz, and Beta β up to 30 Hz. applying the Butterworth bandpass filter. For feature extraction, DFT and FFT are utilized. ANN and SVM were used to classify EEG signals. Accurate classification, selectivity, and term sensitivity are used to assess this method's performance.
Literature survey reveals that 93.96% accuracy using ECG signal and 95.3% using EEG signal is reported at national and international level.

Table 1. Comparison with other studies

Author	Methodology	Accuracy (%)	Sensitivity (%)	Specificity (%)
Proposed system	LSTM Encoder (ECG Signals)	93	97	98
	CNN (204 Samples) (EEG Signals)	97.69		
Xiaohan Zang et. al. [4]	CNN (74 patients) (ECG Signals)	93.96	89.43	98.49
Muhammad Tariq Sadiq et. al. [22]	MSPCA, cascade forward neural network CFNN (EEG Signals)	95.3	95.2	96
Gulay Tasci et. al. [21]	KNN (EEG Signals)	83.96	-	-
Shamla Mantri et. al. [17],	FFT and ANN (EEG Signals)	84.00	-	-
Jian Shen et. al [12]	Support Vector Machine (SVM) (EEG Signals)	83.07	-	-

METHODOLOGY

The objective of the current system's design is to use EEG and ECG readings to diagnose depression. The Butterworth filter was used to preprocess the raw EEG and ECG signals. The ECG signal's ST segment, P wave, and QRS wave are extracted independently, as are the features from the EEG's theta, delta, alpha, and beta waves. The most notable characteristics are routed for additional processing in order to analyze depression. For classification, the LSTM autoencoder with RNN is employed.
The methodical approach of connecting depression analysis
The EEG and ECG signals are used by the depression analysis method depicted in Figure 1.

Step 1: Database

For the present system 204 EEG signals are used from PhysioNet database which are in ". edf "form. Out of 204 EEG signals 102 signals are healthy and 102 are of depressed patients. These 102 samples consist of 34 eyes opened samples, 34 eyes closed samples and 34 while doing task.

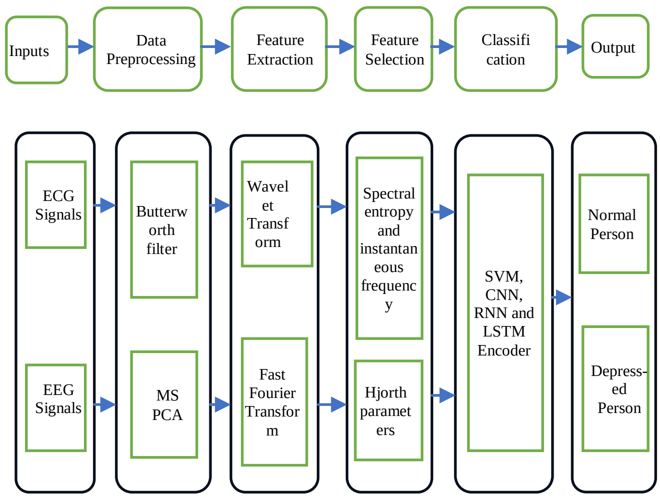

Figure 1. Depression analysis using EEG and ECG signals.

The ECG datasets in ". mat" formats. Total 8500 ECG signals are used in the present work. Out of that 5050 signals are of normal person, 700 are of depressed and remaining are other diseases.

Step 2: Preprocessing

EEG is a painless signal for catching the physiological sign of wave of brain movement. EEG signal recorded is always merged with Artifacts (noise) and sometimes create obstacles for making a true diagnosis.

Initially, the MSPCA method is applied to distinguish noise from the unprocessed EEG data.Combining the features of PCA and wavelet transform results in a hybrid signal denoising algorithm known as multiscale principal component analysis (MSPCA).

The Butterworth filter is used to remove artifacts from ECG signals.

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

Step 3: Feature Extraction

Signals from the brain with left and right sides of it are recorded with and without the eyes. The 30 time-domain-analyzed EEG signal recordings are used to extract average statistical features. Using moving window segmentation, the EEG signal's sample mean values are derived.

The analysis of EEG data by using following features

a) Linear features:FFT, DFT, Band power

b) Nonlinear features:Discrete Wavelet Transform

c) Statistical features:Mean, Median, Variance, standard deviation, Skewness and Kurtosis, Hjorth parameters.

The parameters are Activity, Mobility, Complexity. and band power alpha are prominently used in the analysis of EEG signals for feature selection.

Where y(t) represents the signal.

Hjorth Activity

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

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

Hjorth Mobility

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

$$\mathrm{Mobility} = \sqrt{\frac{\mathrm{var}\left(\frac{dy\,(t)}{dt}\right)}{\mathrm{var}(y(t))}} \quad (3)$$

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.

$$\mathrm{Complexity} = \frac{\mathrm{Mobility}\left(\frac{dy\,(t)}{dt}\right)}{\mathrm{Mobility}(y(t))} \quad (4)$$

ECG signal consists of the P-QRS-T waves in one cardiac cycle. By using wavelet transform we can extract features of ECG signal. The amplitudes and intervals determine as features in ECG signal. The depression can be observed by ST segments of ECG signal. The main difference between normal and depressed person is ST segment shown in Figure 2.

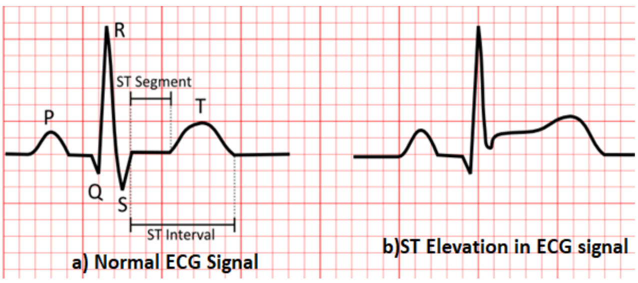

Figure 2. ECG signal, a) Normal b) Depressed

For ECG signals features selected as spectral entropy and instantaneous frequency and its arithmetic mean. To compute the instantaneous spectral entropy given a time-frequency power spectrogram S(t,f), the probability distribution at time t is:

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

Then the spectral entropy at time t is:

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

Step 4: Classification

Order is finished by utilizing SVM, KNN, and CNN classifiers. These are broadly utilized in most of the ECG signal examinations. The fundamental LSTM technique has the most reduced RMSE esteem contrasted with different models. Subsequently, the LSTM model is appropriate for anticipating sorrow from ECG signals. SVM and CNN methods are used for EEG signals.

support Vector Machine

Electroencephalogram (EEG) signals are classified using support vector machines (SVMs), which are widely used in the diagnosis of neurological disorders like epilepsy and sleep disorders. SVM's convex optimization problem allows it to perform well in generalizing to high dimensional data.

A classification technique based on statistical learning theory is the support vector machine (SVM). In a given two-class linearly separable classification problem, support vector machines (SVM) search for a hyperplane that maximally margins the input space's separation. This is how the ideal hyperplane is determined.

$$w\,.\,x_i + b \geq +1, \text{if } y_i = +1 \quad (7)$$

$$w.\,x_i + b \leq +1, \text{if } y_i = -1 \quad (8)$$

where yi is the class label of the ith input (y ∈ {-1, +1}), xi is the ith input vector (x ∈ RN), w is the weight vector that is normal to the hyperplane, and b is the bias. Two margins that run parallel to the ideal hyperplane determine the optimal hyperplane. Eq. 9 finds the margins.

$$w.\,x_i + b \leq +1 \quad (9)$$

Support vectors are the input vectors that are used to calculate the margins. In the event that the problem is not linearly separable, the input vectors should be subjected to a kernel function in order to transform the problem into a transformed space.

$$k(x_i x_j) = \varphi(x)\ \varphi(x_j) \quad (10)$$

The following is the solution to a linearly non-separable problem with two classes:

$$f(x) = \text{sign}(\sum \alpha_i y_j \varphi(x)\ \varphi(x_j) + b) \quad (11)$$

Convolutional Neural Network

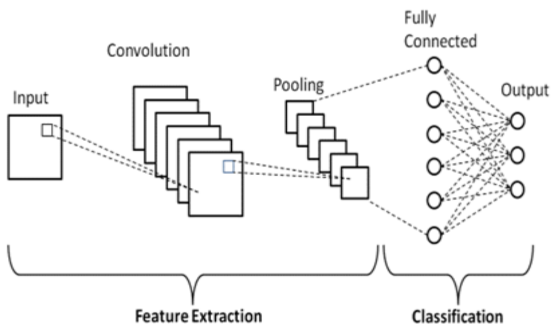

Figure 3. CNN model for EEG signal

- Max pooling layer of size: 2
- Convolution layer and filters: 32
- Kernel size: 3
- Activation function: ReLu
- No. of hidden layers: 16

Recurrent Neural Network

The RNN model is much simpler than the majority of models currently in use. In order to improve a model's performance, the LSTM autoencoder was also included [11].

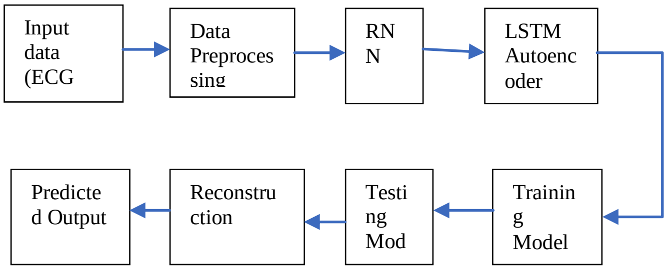

Figure 4. Block diagram of detection of depression using LSTM.

In Figure 4. shows the system's architecture, which is where the system gets its data from. After that, we did data preprocessing to change the names of some of the dataset's columns, and we did data exploration to look around the dataset. After that, this data is learned by the RNN and sent to an LSTM autoencoder for training model. A test portion is performed on training data to classify and predict normal values unsafe heartbeats after the training process is finished. The predicted output of this model is obtained in this manner. It has two parts to the typical construction of an autoencoder. A signal is compressed by encoders; decoders attempt to reproduce it. Yield expectations are then obtained from these reproduced input values.
TheRNNthenlearnsthisdataandsendsittotheLSTMautoencodertotrainthemodel.Afterthetrainingiscomplete ,atestisrunonthetrainingdatatoclassifyandpredictnormalanddepressedheartrhythms.ItturnsoutthatanSVM classifiercanbeselectivelydevelopedtoachieveveryhighaccuracy.Astandardautoencoderstructurecontainsoftwo parts.Encoderscompresstheirinput;decoderstrytorecreateit.Outputpredictionsarethenobtainedfromthesereconstructedinputvalues. extracted from ECG signals. To classify the depressed or normal person by using RNN and Autoencoder techniques.

RESULT AND DISCUSSION

Data Collection

The data acquisition process, EEG collection sites that have been shown to be closely associated with depression. Surface electrodesFp1,Fp2,F3,F4,C3,C4,T3,T4,T5,P3,andP4areplacedonthescalpaccordingtotheInternationalElectrodeSystem 10-20 to record multi-channel EEG data.
For that channel per frame: 32, sampling rate: 128 Hz, and the information about EEG signal by electrode Fp1 with eyes closed , eyes opened and in task condition, from that observed information of EEG signal shown in Figure 5.
The feature extraction of EEG signals done. Total eight features are analyzed from that are 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 is most suitable for EEG signals.

Table 2. Features extracted from EEG Signals.

EEG Signal	Hjorth Activity	Hjorth Mobility	Hjorth Complexity	Band Power Alpha
HS1EC	310	0.180	4.30	6
HS1EO	360	0.180	4.40	9
HS1TASK	360	0.340	3.1	140
HS2EC	960	0.130	4.7	6.8
HS2EO	900	0.086	6.6	37
HS2TASK	360	0.340	3.1	140
DS1EC	60	0.300	1.9	4.2
DS1EO	130	0.170	3.1	12
DS1TASK	370	0.140	3.6	40
DS2EC	130	0.250	1.8	9.4
DS2EO	480	0.130	3.4	87
DS2TASK	1900	0.630	2.6	20

Performance Analysis

Accuracy is used to assess the type overall performance of 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 in efficiently catching the worst samples. Recognition accuracy refers to the bare potential of the classifier to efficiently find distinctly labelled samples. All these figures are calculated using the following formulas:

$$\text{Accuracy} = \frac{\text{tp} + \text{tn}}{\text{tp} + \text{tn} + \text{fn} + \text{fp}} \quad (12)$$

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

$$\text{Sensitivity} = \frac{\text{tp}}{\text{tp} + \text{fn}} \quad (13)$$

$$\text{Selectivity} = \frac{\text{tp}}{\text{tp} + \text{fp}} \quad (14)$$

$$\text{Specificity} = \frac{\text{tn}}{\text{tn} + \text{fp}} \quad (15)$$

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

The preprocessed ECG signal applied for the classification requires more time and accuracy is less in rage of 50% to 60%. If ECG signal extracted prominent features and sent for the classification then training time requires less and accuracy is improved up to 98%. During training process number of iteration improves the accuracy and reduces the loss function.

For training, to set the maximum number of epochs to allow the network to make number of passes through the training data. the 10 epochs are taken and vary the maximum batch size from 30 to 100. above 100 the memory issue is occurred so we can set maximum batch size is 100 and observed training and testing accuracy

The maximum batch size 100 performance better as compared to other batch size. After that maximum batch size kept 100 and epochs are considered as 10,20 and 30.

If batch size and no. of epoch are larger value got high accuracy. That can vary as per system memory. In this experiment we have taken batch size is 100 and epochs are 30.

Extensive experimentation and empirical is done and it shows that performance parameters such as accuracy, sensitivity, selectivity and specificity of two-dimensional sequence input are higher than that of one-dimensional sequence input to the network for ECG signals that is shown in Figure 5.

Table (3) shows that accuracy using SVM and CNN for EEG signals.

Table 3. Accuracy of SVM and CNN

Sr. No.	Model	Accuracy
1.	CNN	97.69%
2.	SVM	76%

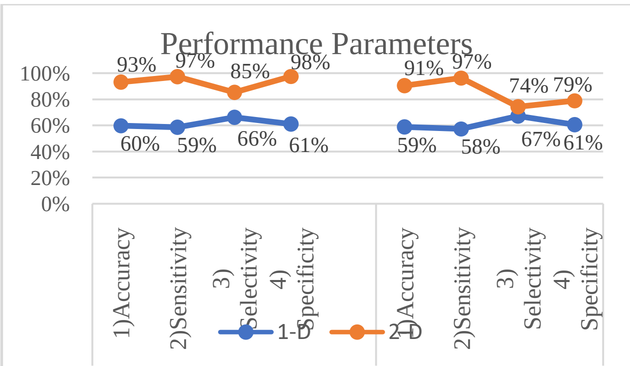

Figure 5. The performance parameters of depression system using ECG signals.

CONCLUSION

In the present system Wavelet transform and FFT's are used for feature extraction of EEG and ECG signals. The prominent features like Hjorth activity (HA), standard deviation, entropy and band power alpha are most vital for EEG signals and arithmetic mean is significant for ECG signals.

LSTM autoencoder and RNN with two-dimensional sequence input is employed as classifier and attains higher accuracy, sensitivity, selectivity, and specificity. The present system attains 93% accuracy for ECG signals. For EEG signals CNN gives better accuracy (97.69%) than SVM.

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