

Depression Analysis and Diagnosis using Machine Learning

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Abstract:

The century's most famous event is the COVID-19 pandemic. Many people experience stress throughout the pandemic. Physical and mental health issues can be brought on by prolonged stress. It takes time, care, and experience to manually mark depression. The present method detects and diagnoses depression using EEG and ECG measurements. The goal of this work is to create a machine learning-based framework that uses EEG and ECG signals to assess and identify depression. System design calculations and tactics include extraction and selection methods for classification, including hybrid methods. The EEG and ECG functions are then submitted for categorization following retrieval. The ST segment, P wave, QRS wave, and ECG data are extracted as functions. The most significant characteristics examined from EEG signals were alpha band power, entropy, standard deviation, and Hjorth activity (HA). ECG data were analyzed using the Long Short-Term Memory (LSTM) Autoencoders and the RNN deep learning model methodology, while EEG signals were classified using the Support Vector Machine (SVM) and Convolutional Neural Network (CNN) techniques. Higher accuracy, sensitivity, selectivity, and specificity are achieved when using an RNN and an LSTM Autoencoders with two-dimensional sequence input as classifiers. For ECG signals, the current system achieves 93% accuracy. CNN outperforms SVM in terms of accuracy (97.69%) for EEG signals.

Keywords: LSTM Autoencoders, Machine Learning, EEG and ECG Signals, Feature Extraction, and Depression Diagnosis.

1. OVERVIEW

Electroencephalography (EEG) is the most widely used and effective method of recording brain activity. Neurological conditions such schizophrenia, Parkinson's disease, depression, epilepsy, OCD, seizure prediction, Alzheimer's disease, stroke, Creutzfeldt-Jakob disease, sleep analysis, and mood state analysis are now commonly diagnosed with it. Depression is predicted to afflict 3.8% of individuals globally, 5.7% of people over 60, and 5% of all adults (4% of men and 6% of women). Depression is a significant concern since it affected 280 million people globally. Depression affects 10% of expectant and future mothers globally. Nearly 7 lakh people die by suicide each year [23]. Depression research and analysis often aid physicians in detecting and treating depression. Depression research and analysis often aid physicians in detecting and treating depression. The literature study indicates that EEG has a bright future and can be used to track and monitor people's

health. Medical, psychological, and physical approaches have traditionally been the cornerstones of depression treatment. A novel, inexpensive, and relatively safe treatment for depression is acupuncture. Electroencephalography (EEG) is the most widely used and effective technique for capturing brain activity. Neurological conditions such as schizophrenia, Parkinson's disease, depression, epilepsy, OCD, Alzheimer's disease, stroke, Creutzfeldt-Jakob disease, sleep evaluation, and heart disease are currently diagnosed with it on a large scale. 3.8% of people worldwide suffer from depression, which affects 5.7% of people over 60 and 5% of all adults, with 4% of males and 6% of women affected. Depression affects 280 million people globally, making it a serious problem. Depression affects 10% of pregnant and new moms worldwide. Suicide claims the lives of almost 7 million people year [23]. Researching and diagnosing depression helps the physician identify and treat depression.

According to the literature study, EEG is a useful tool for monitoring and tracking human health, and the future seems bright. Historically, medical, psychological, and physical approaches have been the main focus of depression treatment. An innovative, reasonably priced, and low-risk treatment for depression that doesn't involve the possibility of drug dependence is acupuncture.

Currently, clinical practice uses psychological measures, particularly qualitative ones, to evaluate the treatment impact of depression. There is a strong association between the patient's present mental state and the results of the Self-Assessed Depression Scale (SDS), which is a time-consuming and intricate tool. The current approach analyzes depression by taking into account both EEG and ECG signals. Choosing the best course of action depends on the suggested system's ability to withstand noise by using Multi-scale Principal Component Analysis (MSPCA) to eliminate noise from EEG readings. Instead of using each main element separately, To achieve the maximum possible classification accuracy, the MSPCA picks components based on the Kaiser rule and blends wavelets with PCA. Other techniques are assessed by the preprocessing module. In the current study, MSPCA, temporal filtering, and spatial filtering were the most effective methods. While spectrum entropy and instantaneous frequency features are retrieved from ECG data, the primary features extracted from EEG signals following the Hjorth activity (HA) are standard deviation, entropy, and band power alpha. The LSTM auto encoder with RNN classifier also processes these features. As part of the system performance evaluation, the classifiers and accuracy utilized for depression recognition with PhysioNet datasets are assessed.

A REVIEW OF LITERATURE

The experts provide a thorough analysis and evaluation of the studies conducted in the field of depression detection. Papers from the last nine years are examined in this presentation to honor work. According to Yibo Zhu et al., major depressive disorder (MDD) can have a detrimental effect on actual recovery in a number of clinical situations, including strokes and spinal cord injuries. The review's suggested assessment method employs useful fNIRS technology and concentrates on crisis preparedness. This can be quickly implemented by incorporating it into already-existing recovery projects. The XG Boost classifier produced 92% precision, 85% recall, and 93% accuracy for the top 5 normal elements. The average oxygen-hemodynamic was determined by this investigation.

Oleksii Komarov et al. [2] developed the Daily Sampling System (DSS), a smartphone app that uses a comprehensive academic questionnaire to measure changes in excitement and sleep quality by integrating several levels of self-assessment. After the report is finished, it also examines the daily scores of individuals who regularly input their depression data and took part in the relaxation-induced EEG data collection. The study collected 1835 daily evaluations, 94 combined EEG records, and an 80% participation rate from 18 college students (ages 23–27) in order to present the daily data over the course of a semester.

Marcel Trozsek et al. [3] showed that they could identify sorrow in social media messages and used machine learning algorithms to identify sadness early. Semantic metadata supplied by users is used to analyze and classify an artificial neural network (ANN). In an ongoing current location task, it is demonstrated that a combination of both approaches yields excellent results. Furthermore, a thorough analysis of the well-known Early Risk Detection Error (ERDE) score as a metric for early detection systems is currently in progress. To find a more effective method of coordinating the metadata, more experiments are required.

The RM-6280C multifunctional physiology experiment device from Chengdu Instrument Factory in Sichuan, China, was used by Zang Xiaohan and associates [4] to collect the participants' ECG data at a sample rate of 1 kHz. Throughout 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 dataset used in the study was split up into 5 second (or varying duration) segments, and each segment was given a category. A one-dimensional CNN was utilized to identify and extract features from ECG segments.

Bueno-Notivol Juan et al.'s study [5] was deemed protected if it provided unambiguous cross-sectional data on the prevalence of depression during the COVID-19 pandemic, highlighted societal factors with extensive samples, described a method for diagnosing or evaluating depression, and made sure the full text was accessible. According to the most recent meta-analysis, which included 12 more studies, comorbid depression was present in 25% of COVID-19 patients in poor nations. The different measures employed in the research that made up this meta-analysis are the reason for the disparity in depression rates. For evaluation, use the SDS scale and PHQ-9.

Purude et al. [6] talked about a way to detect depression by gathering information by sending questionnaires to people on several platforms. In this context, classifiers such as logistic regression, decision trees, support vector machines (SVM), and k-nearest neighbor (KNN) are used. The accuracy level attained by the system is 90%. One drawback of the system is its limited database. By looking at posts on social media platforms like Twitter, a machine learning algorithm is used to identify depression. Tweets are stripped of their keywords. The Bayes classifier and Python were used to determine whether the person was depressed.

A model for detecting sorrow based on local circumstances was presented by Bryan G. Dadiz et al. A video recording's facial image is extracted and cropped. On every boundary, LBP is conspicuous due to its formal attire. The impacts are grouped and analyzed using the eigenvalues from the first highlights during Principal Component Analysis (PCA). The SVM classifier attains an 81% accuracy rate in the system while using a radial basis function as the kernel. In addition to capturing particular

background elements, the Viola and Jones method was utilized to extract facial features from video images.

The goal of the study by Mandar Deshpande et al. [9] is to identify sentiment associated with depression by examining Twitter feeds. The tweet is categorized as either accurate or inaccurate based on the use of a carefully selected set of terms to identify symptoms of depression. Both SVM and the Naive-Bayes classifier were used for classification tasks. The confusion matrix, precision, and F1 score are crucial categorical characteristics that are utilized to illustrate the results. More than 10,000 tweets were gathered for the training and test databases using the Twitter API. 20% of the data was used for testing, while the remaining 80% was used for training. Naive Bayes is a popular text classification method that works well with multinomial data. It also makes use of the SVM classifier.

Shen Jian et al. [12] used a three-electrode invasive EEG acquisition device to record EEG data while the subjects' eyes were closed at rest. Using ubiquitous EEG, a novel technique for detecting and diagnosing depression was presented by examining scalp electrodes at the emotions-related Fp1, Fpz, and Fp2. All 170 patients (81 with depression and 89 without) had their peripartetic Pervasive EEG recorded while they were sleeping with their eyes closed during the trial.

To predict heart difficulties, Noor, Sumaiya Tarannum, and their collaborators [13] used a feature extraction method in this model. The extracted ST segment and QRS wave from ECG data can be used by a web application to identify whether a user is under acute, chronic, or hyper acute stress. This configuration forecasts PVC, aberrant, and normal heartbeats using an LSTM auto encoder and an RNN. An RNN model that distinguishes between PVC, irregular, and normal heart beats is based on deep learning. The model forecasts PVC and irregular heartbeats using a collection of heart rate data. For the dataset, 5000 ECG samples were used.

He Lang together with his associates [15]. Speech talents offer useful information for depression analysis. During the Depression, a number of depressing marketing strategies were implemented. recognition of the image using the AVEC2013, AVEC2014, AVEC2016, and AVEC2017 datasets that shows innovation and rebellion. Based on the AVEC2013 and AVEC2014 datasets, three regression techniques were developed, taking into account the AVEC2016 and AVEC2017 data for the type methodology. It makes use of AVEC2013 and AVEC2014 data. Through an analysis of overall performance, depression is predicted using mean absolute error (MAE) and root mean square error (RMSE).

Muhammad Tariq Sadiq and colleagues [16] proposed a simple and dependable automated multivariate empirical wavelet transform (MEWT) approach for decoding different motor imagery (MI) tasks. There have been four significant contributions made. First, preprocessing is done using the multi-scale principal component analysis technique. Subsequently, a novel automatic channel selection method is introduced and assessed by closely analyzing three different approaches to channel matching. Thirdly, a technique combining MEWT with sub-band alignment is being used for the first time to give concurrent amplitude and frequency components in MI applications. Additionally, a strong emphasis is placed on correlation-based feature selection methods to reduce computational load and system complexity.

Following computations, the sample's classification accuracy, sensitivity, and specificity were found to be 91.4%, 92.1%, and 93%, respectively. Text Altered was developed by Shamla Mantri and associates [17] using a sample of individuals ages 16 to 60. They were recommended for usage by both those with and without depression. The traditional 10-20 Electrode Placement System is used to collect brain impulses from electrode placements while the subject is immobile for five minutes. To eliminate power supply interference, samples are taken at 256 Hz after the signal has been filtered at 50 Hz. Several EEG signal frequency bands were obtained using the Butterworth band pass filter: δ up to 4 Hz, θ up to 8 Hz, α up to 13 Hz, and Beta β up to 30 Hz. DFT and FFT are used to extract features. ANN and SVM were used to classify EEG signals. The accuracy, specificity, and term sensitivity of this approach are used to assess its performance.

TABLE 1 IN CONTRAST WITH PREVIOUS STUDIES

Methodology of the Author Precision (%) The percentage of sensitivity Specificity (percent)

Author	Methodology	Sensitivity (%)	Specificity (%)	Accuracy (%)
Proposed system	LSTM Encoder (ECG Signals)	97	98	93
	CNN (204 Samples) (EEG Signals)	-	-	97.69
Xiaohan Zang et. al. [4]	CNN (74 patients) (ECG Signals)	89.43	98.49	93.96
Muhammad Tariq Sadiq et. al. [22]	MSPCA, cascade forward neural network CFNN (EEG Signals)	95.2	96	95.3
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

On a national and worldwide scale, research indicates that ECG signals have an accuracy of 93.96% and EEG signals have an accuracy of 95.3%. This is compared with current systems in Table 1.

2. METHODS AND MATERIAL

The purpose of the current method is to use EEG and ECG measures to diagnose depression. The Butterworth filter was used to preprocess the raw EEG and ECG signals. The ST segment, P wave, and QRS wave of the ECG signal are extracted independently, as are the characteristics from the

EEG's theta, delta, alpha, and beta waves. The most notable features are forwarded for additional processing in order to analyze depression. For classification, the LSTM auto encoder with RNN is employed. The EEG and ECG readings are used in the methodical procedure of connecting the depression analysis technique depicted in Figure 1.

Step 1: Database

The current system uses 204 EEG signals in ". edf" format from the PhysioNet database. 102 of the 204 EEG signals are from healthy people, and the remaining 102 are from patients who are sad. These 102 examples include 34 with their eyes open, 34 with their eyes closed, and 34 while performing a task. The ".mat" formats of the ECG datasets. In the current investigation, 8500 ECG signals in total are employed. Of those, 700 are from people who are depressed, 5050 are from people who are normal, and the remaining signals are from various illnesses.

Step 2: Preparation

EEG is a painless way to detect the physiological indication of a brain movement wave. Every recorded EEG signal contains noise, or artifacts, which can occasionally make it difficult to make a precise diagnosis. To separate noise from the raw EEG data, the MSPCA technique is first used. Multi-scale principal component analysis (MSPCA) is a hybrid signal denoising approach that combines the advantages of PCA with wavelet transform.

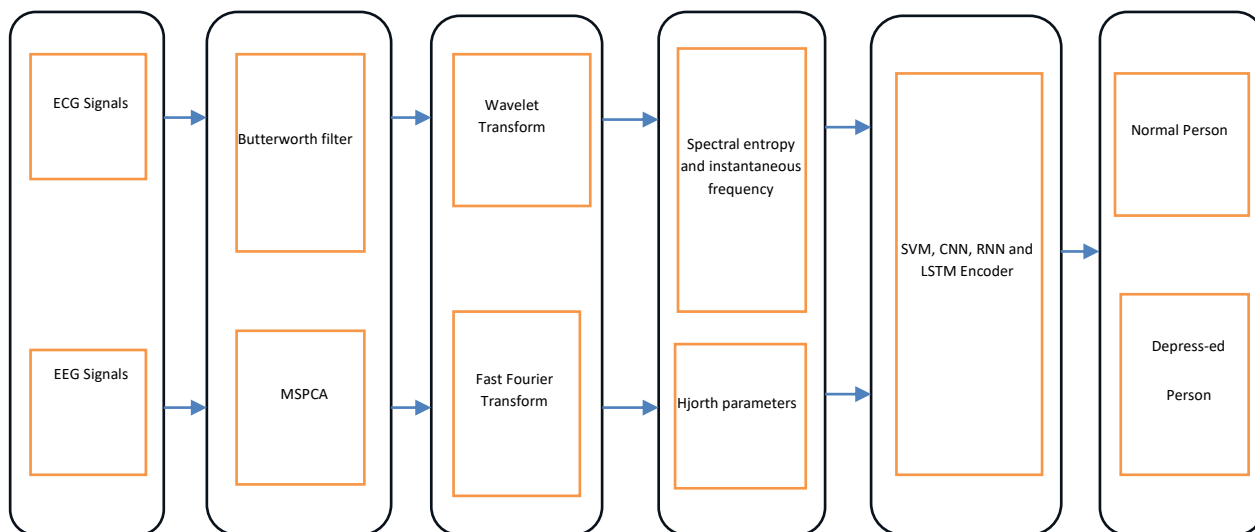


Figure 1: EEG and ECG signals are used to diagnose depression.

The Butterworth filter is used to eliminate ECG signal artifacts.

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

Step 3: Extraction of Features

Both with and without the eyes, signals from the left and right sides of the brain are recorded.

Average statistical features are extracted from the 30 time-domain-analyzed EEG signal recordings. The sample mean values of the EEG signal are obtained by moving window segmentation.

The following features are used to analyze EEG data:

- a) Linear features: Band power, DFT, and FFT
- b) Features that is not linear: Discrete Wavelet Transform
- c) Statistical characteristics: Hjorth parameters, skewness and kurtosis, variance, standard deviation, mean, and median.

Activity, Mobility, and Complexity are the parameters. and band power alpha are frequently employed in the feature selection process of EEG data processing.

Where the signal is denoted by $y(t)$.

Activity in Hjorth

The signal power, or variance of a time function, is represented by the activity parameter. This can show the frequency domain power spectrum surface. The following equation serves as a representation of this:

$$Activity = var(y(t)) \quad (2)$$

Mobility of Hjorth

The power spectrums mean frequency or percentage of standard deviation is represented by the mobility parameter.

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

COMPLEXITY OF HJORTH

The frequency change is represented by the Complexity parameter. The parameter evaluates how similar the signal is to a pure sine wave; if the signal is more similar, the value converges to 1.

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

The ECG signal is composed of the P-QRS-T waves in a single cardiac cycle. We can extract the properties of the ECG signal using the wavelet transform. The amplitudes and intervals define the

characteristics of the ECG signal. The depression is visible in the ST segments of the ECG signal. The main difference between a normal and depressed person is the ST segment in Figure 2.

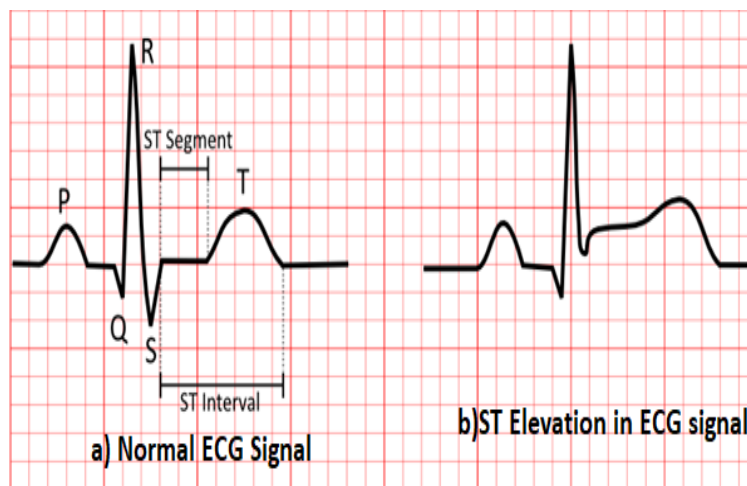


Figure: 2 ECG signal, a) Normal b) Depressed

Features such as spectrum entropy, instantaneous frequency, and its arithmetic mean were chosen for ECG signals. Given a time-frequency power spectrogram $S(t,f)$, the probability distribution at time t can be used to calculate the instantaneous spectral entropy.

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

At time t , the spectral entropy is then:

$$H(t) = - \sum_{m=1}^N P(t, m) \log_2 P(t, m) \quad (6)$$

Step 4: Categorization

The order is finished using CNN, KNN, and SVM classifiers. Most ECG signal analysis techniques make extensive use of them. The basic LSTM technique provides the lowest RMSE value when compared to other models. Thus, sorrow may be predicted from ECG measurements using the LSTM model. EEG readings are analyzed using CNN and SVM algorithms.

Assist Vector Machine:

Support vector machines (SVMs), which are frequently utilized in the diagnosis of neurological conditions like epilepsy and sleep disorders, are used to classify electroencephalogram (EEG) signals. SVM does well in generalizing to high dimensional data because of its convex optimization problem.

The support vector machine (SVM) is a classification method that is grounded in statistical learning theory. Support vector machines, or SVMs, look for a hyper plane that maximally bounds the separation of the input space in a given two-class linearly separable classification issue. Equations 7

and δ determine the ideal hyper plane in this manner.

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

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

where x_i is the i th input vector ($x \in \mathbb{R}^N$), w is the weight vector normal to the hyper plane, b is the bias, and y_i is the class label of the i th input ($y \in \{-1, +1\}$). The ideal hyper plane is determined by two margins that run parallel to it. The margins are found via Equation 9.

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

The input vectors used to determine the margins are called support vectors. If the problem is not linearly separable, the problem should be transformed into a transformed space by applying a kernel function to the input vectors.

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

Equation 11 computes the following solution to a linearly non-separable problem with two classes.

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

Neural Network Convolution:

Figure 3 depicts the CNN model, which consists of input, output, pooling, and convolution layers.

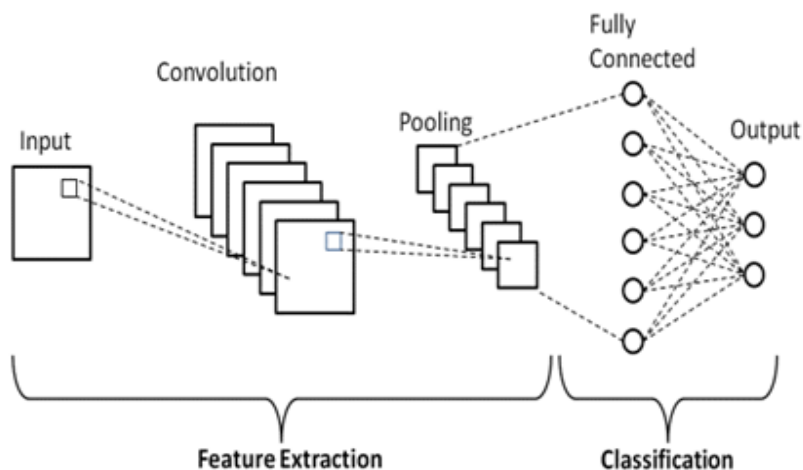


Figure 3: CNN EEG signal model

- The maximum pooling layer size is two.
- Filters and convolution layer: 32
- Size of kernel: 3.
- ReLU is the activation function.
- There are sixteen secret layers.

Neural Network Recurrence

Compared to most existing models, the RNN model is far more straightforward. The LSTM auto encoder was also incorporated to enhance a model's performance.

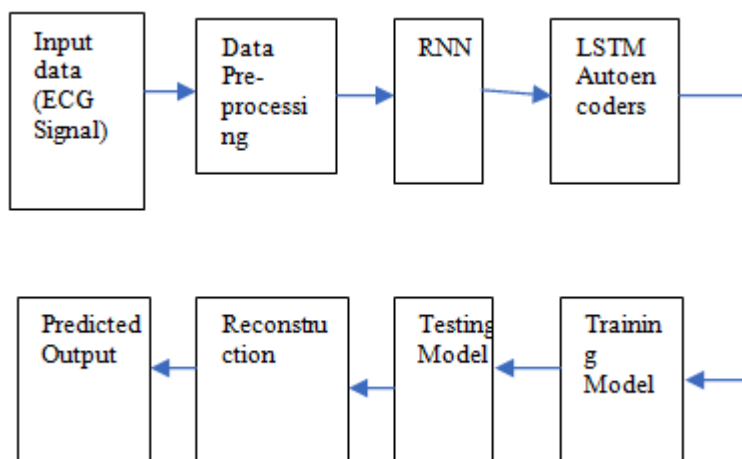


Figure 4: Block diagram for LSTM-based depression diagnosis.

Figure 4 shows the system architecture, which is the source of the data. After that, we conducted data preparation to rename some of the dataset's columns and data exploration to look over the dataset. This data is subsequently learned by the RNN and sent to an LSTM auto encoder for model training. Following training, the training data is subjected to a test portion that classifies and predicts safe heartbeats. This yields the expected result of the model. There are two parts to the typical auto encoder construction. A signal is compressed by encoders and then attempted to be replicated by decoders. The yield expectations are then calculated using these repeated input values. The RNN uses the LSTM auto encoder to train the model after learning this data. Tests to classify and predict both normal and depressed cardiac rhythms are conducted on the training data after training. It turns out that selectively constructing an SVM classifier can lead to very high accuracy. A common auto encoder structure consists of two parts. Encoders compress their input while decoders try to reconstruct it. Predictions for the output are then produced using these restored input values, extracted from the ECG data in order to classify a person as either normal or depressed using RNN and auto encoder techniques.

3. RESULTS

Information Gathering EEG collecting sites and the data capture procedure has been found to be closely linked to depression. In accordance with the International Electrode System 10-20, surface electrodes Fp1, Fp2, F3, F4, C3, C4, T3, T4, T5, P3, and P4 are positioned on the scalp to record multi-channel EEG data.

Information regarding the EEG signal by electrode Fp1 with eyes closed, eyes open, and under task state was obtained from that observed information of the EEG signal for that channel per frame: 32, sampling rate: 128 Hz. EEG signal feature extraction was completed. Hjorth activity (HA), complexity (HC), and mobility (HM) are the eight features that are examined in total. The parameters that are used include standard

deviation, entropy, mean, variance, and band power alpha. EEG signals are best suited for the Hjorth activity (HA), standard deviation, entropy, and band power alpha.

4. TALK

Accuracy is used to evaluate the system's overall performance. Sensitivity is a parameter associated with a classifier's upper potential to efficiently identify good patterns. The term "specificity" describes the classifier's higher likelihood of effectively capturing the worst samples. Recognition accuracy is the classifier's bare potential to effectively locate clearly labeled samples. The following formulas are used to calculate each of these figures:

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_N + F_P} \quad (12)$$

$$Selectivity = \frac{T_P}{T_P + F_P} \quad (14)$$

$$Specificity = \frac{T_N}{T_N + F_N} \quad (15)$$

FP is falsely positive, FN is falsely negative, TP is true positive, and TN is true negative.

Features taken from EEG signals are shown in Table 2.

EEG Signal	Hjorth Activity	Hjorth Complexity	Hjorth Mobility	Band Power Alpha
HS1EC	310	4.3	0.18	6
HS1EO	360	4.4	0.18	9
HS1TASK	360	3.1	0.34	140
HS2EC	960	4.7	0.13	6.8
HS2EO	900	6.6	0.086	37
HS2TASK	360	3.1	0.34	140
DS1EC	60	1.9	0.3	4.2
DS1EO	130	3.1	0.17	12
DS1TASK	370	3.6	0.14	40
DS2EC	130	1.8	0.25	9.4
DS2EO	480	3.4	0.13	87
DS2TASK	1900	2.6	0.63	20

The preprocessed ECG data used for categorization takes longer and has a 50% to 60% lower accuracy rate. As seen in figure 5, training time is reduced and accuracy is increased by up to 93% if the ECG signal's salient features are extracted and transmitted for classification. Numerous iterations throughout the training procedure increase accuracy and decrease the loss function. Setting the maximum number of epochs during training will enable the network to run through the training data a certain number of times. The maximum batch size is varied from 30 to 100 throughout the course

of 10 epochs. We can set a maximum batch size of 100 and observe training and testing accuracy since above 100, a memory problem occurs.

When compared to other batch sizes, the maximum batch size of 100 performs better. Following that, epochs are regarded as 10, 20, and 30, and the maximum batch size is maintained at 100.

High accuracy is obtained if the batch size and epoch number are greater. Depending on system RAM, that may change. We used a batch size of 100 and epochs of 30 in this experiment.

Numerous experiments and practical studies demonstrate that, for ECG signals, as depicted in Figure 5, the performance metrics of two-dimensional sequence input to the network, such as accuracy, sensitivity, selectivity, and specificity, are higher than those of one-dimensional sequence input.

The accuracy of SVM and CNN for EEG signals is displayed in Table (3).

TABLE 3: SVM AND CNN ACCURACY

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

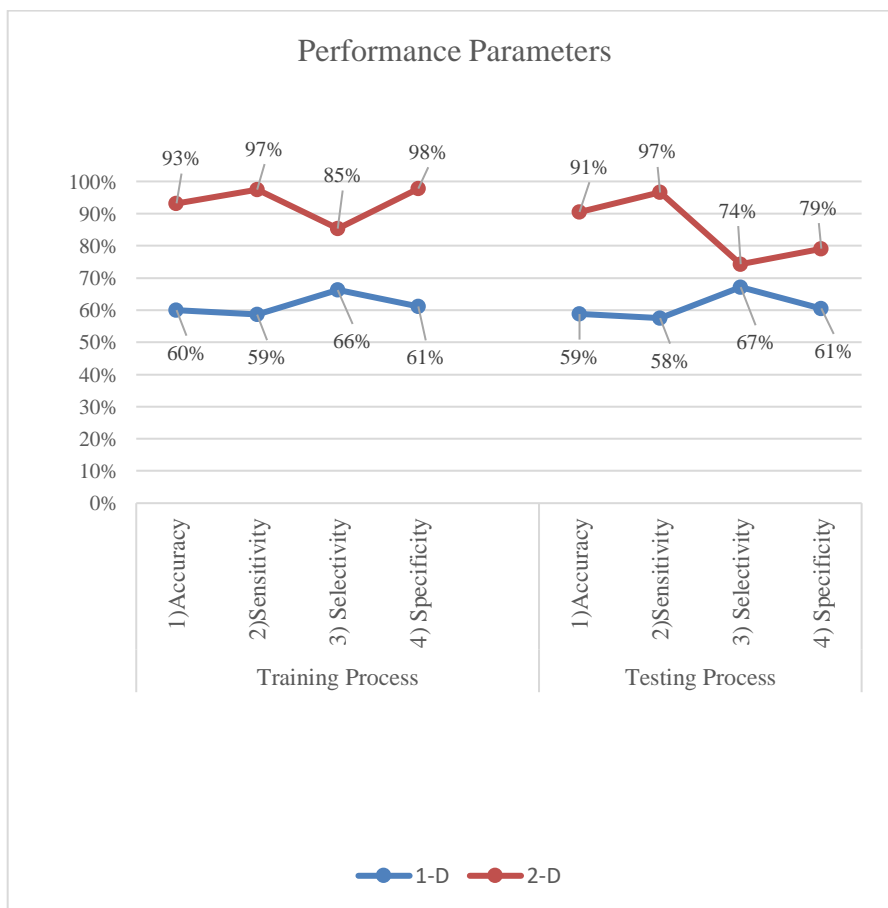


Figure 5 shows the depression system's performance metrics using ECG data.

5. FINAL COMMENT

The current approach uses FFTs and wavelet transforms to extract features from EEG and ECG signals. For EEG signals, the most important characteristics are Hjorth activity (HA), standard deviation, entropy, and band power alpha; for ECG signals, the arithmetic mean is important. Higher accuracy, sensitivity, selectivity, and specificity are achieved when using an RNN and an LSTM auto encoder with two-dimensional sequence input as classifiers. For ECG signals, the current system achieves 93% accuracy. CNN outperforms SVM in terms of accuracy (97.69%) for EEG signals.

ASSERTIVE

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