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Machine Learning Based Framework for Depression Diagnosis Using EEG and ECG Signals

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ABSTRACT

Diagnosing depression manually requires patience, attention to detail, and significant expertise. The current approach leverages electroencephalogram (EEG) and electrocardiogram (ECG) signals to identify and diagnose depression. The proposed work aims to develop a machine learning-based system that uses EEG and ECG data for the effective detection of depression. Feature extraction and selection strategies, separate approaches, are employed in the design of classification methodologies. Key segments of the ECG signal P, QRS, and ST are extracted as functional features. From EEG signals, the most significant features include alpha band power, entropy, standard deviation, and Hjorth activity (HA). EEG data are classified using Support Vector Machine (SVM) and Convolutional Neural Network (CNN) models, while ECG signals are analyzed using Long Short-Term Memory (LSTM) Autoencoders and Recurrent Neural Network (RNN) architectures. The performance of these classifiers in terms of accuracy, sensitivity, selectivity, and specificity is enhanced when two-dimensional sequence inputs are utilized in RNNs and LSTM Autoencoders. The current approach achieves a 93% accuracy rate for ECG signal classification, while CNN outperforms SVM in EEG signal classification with an accuracy of 97.69%.

1. INTRODUCTION

The most popular and efficient way to measure brain activity is electroencephalography (EEG). It is currently frequently used to identify neurological disorders such schizophrenia, Parkinson's disease, depression, epilepsy, OCD, seizure prediction, Alzheimer's disease, stroke, Creutzfeldt-Jakob disease, sleep analysis, and mood state analysis. 3.8% of people worldwide, 5.7% of persons over 60, and 5% of all adults (4% of men and 6% of women) are expected to suffer from depression. Since depression impacted 280 million people worldwide, it is a serious issue. 10% of expecting and potential moms worldwide suffer from depression. Every year, suicide claims the lives of around 7 lakh people. Research and analysis on depression frequently help doctors identify and treat depression. Research and analysis on depression frequently help doctors identify and treat depression. EEG has a promising future and can be used to track and monitor people's health, according to the literature review. The mainstays of depression treatment have historically been medical, psychological, and physical methods. Acupuncture is a new, affordable, and reasonably safe treatment for depression. The most popular and efficient method for recording brain activity is electroencephalography (EEG).

EEG is a valuable tool for tracking and monitoring human health, and the future appears bright, according to the literature review. Traditionally, the primary focus of depression treatment has been on physical, psychological, and medicinal methods. Acupuncture is a novel, affordable, and low-risk treatment for depression that eliminates the risk of drug dependence. 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. The preprocessing module evaluates other methods. The most successful techniques in the current investigation were spatial filtering, temporal filtering, and MSPCA. Standard deviation, entropy, and band power alpha are the main features that are derived from EEG signals after the Hjorth activity (HA), even though spectrum entropy and instantaneous frequency features are also obtained from ECG data. These features are also processed by the LSTM auto encoder with RNN classifier. The classifiers and accuracy used for depression recognition with PhysioNet datasets are evaluated as part of the system performance evaluation.

2. LITERATURE SURVEY

Researchers had done a comprehensive review and analysis of the research done in the area of depression identification. This lecture honors work by reviewing papers over the past nine years.

Recent research has introduced a functional near-infrared spectroscopy (fNIRS)-based evaluation system to monitor hemodynamic responses in patients with neurological impairments, achieving over 90% accuracy with an XGBoost classifier [1]. The findings suggest that such neuroimaging modalities, combined with machine learning, could significantly enhance crisis readiness in rehabilitation contexts.

Beyond static signal analysis, continuous and longitudinal monitoring has also gained traction. Studies leveraging daily smartphone-based assessments and EEG data have captured temporal variations in mood and behavior, with a particular focus on young adults [2]. This approach emphasizes the importance of long-term data collection in identifying individual patterns of depressive symptoms, aligning with a more personalized understanding of mental health.

Parallel efforts have explored social media and digital behavior as proxies for mental states. A hybrid model combining artificial neural networks with semantic metadata has been developed to analyze social media posts, reporting notable improvements in early depression detection using the ERDE metric [3].

Large-scale meta-analyses have revealed that nearly one in four patients in developing countries experienced depression during the pandemic, while also exposing inconsistencies in assessment instruments such as the SDS and PHQ-9 [4]. These findings underscore the need for standardized measurement frameworks that can adapt across cultural and socioeconomic contexts.

Further studies have validated the potential of using classifiers like SVM and Naive Bayes for sentiment-based detection of depressive tendencies in user-generated content [5]. These works highlight the richness of linguistic and emotional cues embedded in digital communication, though limitations in dataset size and the risk of bias remain critical concerns.

In contrast to text-based approaches, vision-based systems have utilized facial expression analysis from video data to classify emotional states indicative of depression. By employing Local Binary Patterns (LBP), Principal Component Analysis (PCA), and SVM with a radial basis function kernel, recent work achieved an 81% accuracy rate [6]. This approach provides an alternative modality for affective computing, particularly where verbal communication is restricted.

Sentiment analysis of social media content has also been explored, with studies focusing on distinguishing depression-related tweets using SVM and Naive Bayes techniques. One such study assembled a dataset of over 10,000 tweets and employed standard classification metrics to assess model performance, highlighting the value of real-time, user-generated content for mental health monitoring [7, 8].

While some research has pursued broader applications in neural signal analysis, such as EEG preprocessing using the Multivariate Empirical Wavelet Transform (MEWT) for motor imagery classification [9], these innovations indirectly benefit mental health research by improving the granularity and interpretability of neural data—techniques transferable to depression detection.

Advances in deep learning have enabled the development of models for Major Depressive Disorder (MDD) detection using single-channel ECG signals. One such model incorporates R-R intervals and visibility graph-derived features, achieving a 7% accuracy improvement over traditional HRV-based methods while using 20-second overlapping segments for efficient prediction [10].

Resting-state EEG analysis has also been applied to depression detection, though with more modest performance (69.21% balanced accuracy) when using 1D-CNN models [11], underscoring the challenges in extracting reliable depressive markers from neural signals alone. Similarly, autonomic nervous system features derived from ECG have been analyzed, with SVM models achieving 67% accuracy, reinforcing the link between cardiovascular biomarkers and affective disorders [12].

Recent research has demonstrated the superiority of multi-modal and hybrid models in depression detection. One study combined EEG-based spectrogram features (via 3D-CNN), raw signal analysis (via 1D-CNN), and classical spectral features, achieving 96% accuracy [13]. Such composite frameworks reflect a growing trend toward integrating multiple data perspectives to better capture depression's complex manifestations.

The percentage of sensitivity Specificity (percent) 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.

Table 1. Comparison with previous studies

Ref.	Methodology	Sensitivity (%)	Specificity (%)	Accuracy (%)
Proposed system	LSTM Encoder (ECG Signals)	97	98	93
	CNN (204 Samples) (EEG Signals)	-	-	97.69
[14]	CNN (74 patients) (ECG Signals)	89.43	98.49	93.96
[15]	Support Vector Machine (SVM) (EEG Signals)	-	-	83.07
[16]	FFT and ANN (EEG Signals)	-	-	84.00
[17]	KNN (EEG Signals)	-	-	83.96
[18]	MSPCA, cascade forward neural network CFNN (EEG Signals)	95.2	96	95.3

3. TECHNIQUES AND SUPPLIES

The current approach aims to identify depression using EEG and ECG measurements. The raw EEG and ECG signals were preprocessed using the Butterworth filter. The features of the EEG's theta, delta, alpha, and beta waves are extracted separately, as are the ST segment, P wave, and QRS wave. To analyze depression, the most noteworthy features are sent for further processing. The LSTM auto encoder with RNN is used for categorization. The methodical process of connecting the depression analysis technique shown in Figure 1 uses the EEG and ECG readings.

Step 1: Database

The PhysioNet database contains 204 EEG signals in ". edf" format that are used by the current system. Of the 204 EEG signals, 102 come from healthy individuals and the other 102 are from depressed patients. Of these 102 instances, 34 show them completing a task, 34 show them with their eyes closed, and 34 show them with their eyes open. The ECG dataset's ". mat" formats. A total of 8500 ECG signals are used in the current study. Of those, 700 come from sad individuals, 5050 from healthy individuals, and the remaining signals come from a variety of disorders. Individuals suffering from heart disease often experience depression, The ECG signals related to depression are fewer in comparison to those from other illnesses. Due to that the less no. of sample used for analyzing ECG signals.

Step 2: Getting ready

EEG is a non-invasive technique [19] for determining a brain movement wave's physiological indication. Sometimes noise, or artifacts, in all recorded EEG signals can interfere with a proper diagnosis. First, the MSPCA method is used to remove noise from the raw EEG data. Multi-scale principal component analysis (MSPCA) is a hybrid signal denoising technique that combines the advantages of principal component analysis and wavelet transform [20].

The Butterworth filter is used to eliminate ECG signal artifacts.

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

Step 3: Features extraction

EEG signals are recorded from both the left and right sides of the brain, under conditions with eyes open and closed. A total of thirty time-domain EEG signal recordings are analyzed to extract their average statistical characteristics. To compute sample mean values of the EEG signals, a moving window segmentation technique is applied.

The EEG data [21] are analyzed using the following types of features:

Linear features: Band power, Discrete Fourier Transform (DFT), and Fast Fourier Transform (FFT)

Non-linear features: Discrete Wavelet Transform (DWT)

Statistical features: Hjorth parameters (Activity, Mobility, and Complexity), skewness, kurtosis, variance, standard deviation, mean, and median.

Among these, Activity, Mobility, Complexity [22], and alpha band power are commonly used in the feature selection process during EEG data analysis.

Let the EEG signal be denoted by y(t).

Hjorth activity: The Activity parameter represents the signal power, which corresponds to the variance of the time-domain signal. It reflects the surface area under the power spectrum in the frequency domain. The Activity can be mathematically expressed as:

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

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

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

Hjorth complexity: 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 as shown in Figure 2 [23, 24].

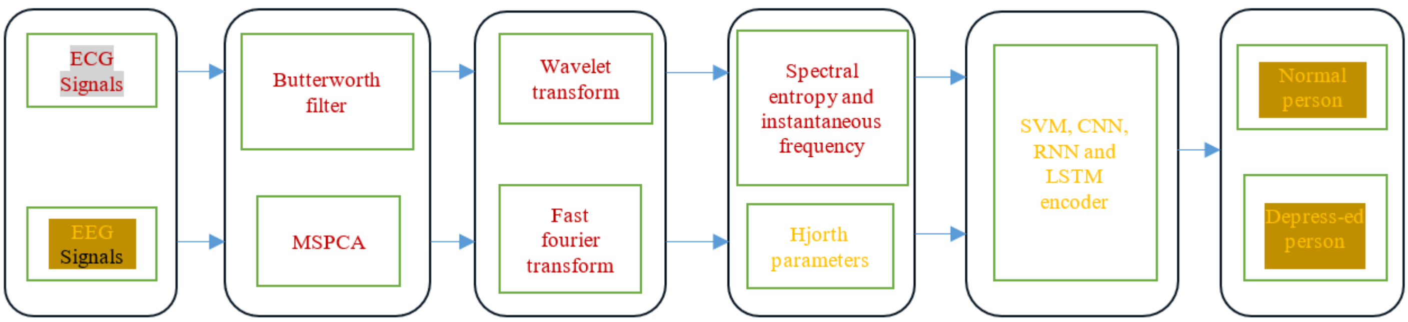

Figure 1. EEG and ECG signals are used to diagnose depression

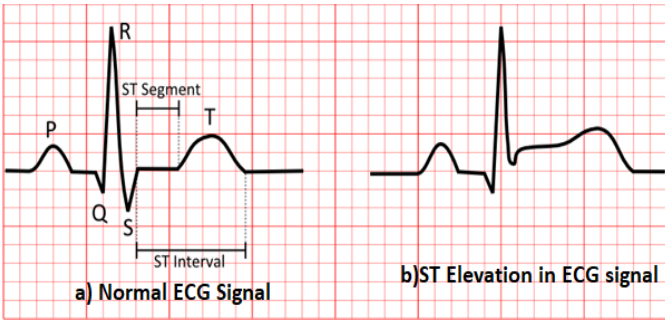

Figure 2. ECG signal, (a) normal (b) depressed

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.

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

At time t, the spectral entropy is then:

$$H(t) = -\sum_{m=1}^{N} P(t,m)log2P(t,m) \tag{6}$$

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 [25] 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.

Support vector machine: Electroencephalogram (EEG) signals [26] are classified using support vector machines (SVMs), which are widely employed in the diagnosis of neurological illnesses such as epilepsy and sleep disorders. SVM's convex optimization problem helps it generalize well to large 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, or SVMs, search for a hyper plane that maximally bounds the separation of the input space. In this way, the ideal hyper plane is found using Eqs. (7) and (8).

$$w.x_i + b \geq +1, if\ y_i = +1 \tag{7}$$

$$w.x_i + b \leq +1, if\ y_i = -1 \tag{8}$$

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

$$w.x_i + b \leq +1 \tag{9}$$

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.

$$k(x_i x_j) = \varphi(x)\,\varphi(x_j) \tag{10}$$

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

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

Figure 3 depicts the CNN model [27], which consists of input, output, pooling, and convolution layers.

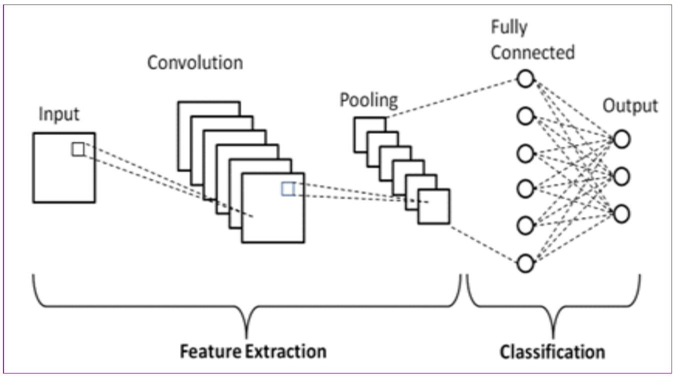

Figure 3. CNN EEG signal model

•Two is the maximum size for the pooling layer.
•Convolution layer and filters: 32.
•Kernel size: 3.
•The activation function is ReLU.
•Sixteen mysterious layers are included.

The RNN model is far simpler than the majority of current models. To improve a model's performance, the LSTM auto encoder [28] was also included.

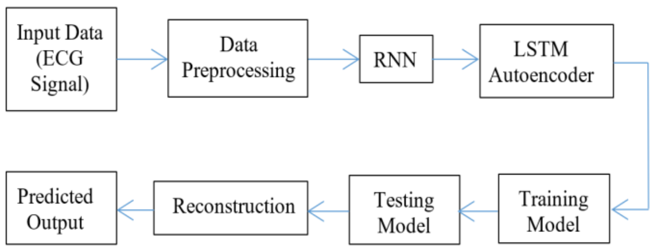

Figure 4. LSTM-based depression diagnosis block diagram

The system architecture, the data source, is depicted in Figure 4. Following that, we performed data exploration to examine the dataset and data preparation to rename a few of its columns. The RNN then learns this data, which is then passed to an LSTM auto encoder for model training. After training, a test section that categorizes and forecasts safe heartbeats is applied to the training data. This produces the model's anticipated outcome. The usual auto encoder construction consists of two pieces. After encoders have compressed a signal, decoders try to reproduce it. These repeated input values are then used to compute the yield expectations. After learning this data, the RNN trains the model using the LSTM auto encoder. Following training, tests are performed on the training data to categorize and forecast both normal and depressed heart rhythms. It turns out that extremely high accuracy can be achieved by building an SVM classifier [29] selectively. Two components make up a typical auto encoder structure. While decoders attempt to recreate their input, encoders compress it. These repaired input values are then used to generate output predictions derived from the ECG data using RNN and auto encoder approaches to determine if a person is sad or normal.

4. RESULT

Information Gathering Depression has been found to be closely associated with EEG collection sites and the data capture process. To record multi-channel EEG data, surface electrodes Fp1, Fp2, F3, F4, C3, C4, T3, T4, T5, P3, and P4 are placed on the scalp in compliance with the International Electrode System 10-20.

From the observed information of the EEG signal for that channel per frame: 32, sampling rate: 128 Hz, information on the EEG signal by electrode Fp1 with eyes closed, eyes open, and under task state was gathered.

The extraction of EEG signal features was finished. In total, eight features are analyzed: mobility (HM), complexity (HC), and Hjorth activity (HA). 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). EEG signals are characterized by high dimensions and noise interference is always observed in the signal. Hjorth parameters can be directly calculated in the time domain, eliminating the need for complicated transformations such as FFT or wavelets, which makes them suitable for real-time uses like Brain-Computer Interfaces (BCI), standard deviation, entropy, and band power alpha [30].

5. DISCUSSION

The system's overall performance is assessed using accuracy. One measure of a classifier's maximum capacity to effectively spot quality patterns is called sensitivity. "Specificity" refers to the classifier's increased capacity to successfully capture the worst samples. The ability of the classifier to efficiently find samples with clear labels is known as recognition accuracy. Each of these numbers is computed using the following formulas:

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_N + F_P} \tag{12}$$

$$Selectivity = \frac{T_P}{T_P + F_P} \tag{13}$$

$$Specificity = \frac{T_N}{T_N + F_N} \tag{14}$$

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.

Table 2. Feature extraction for EEG signals

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

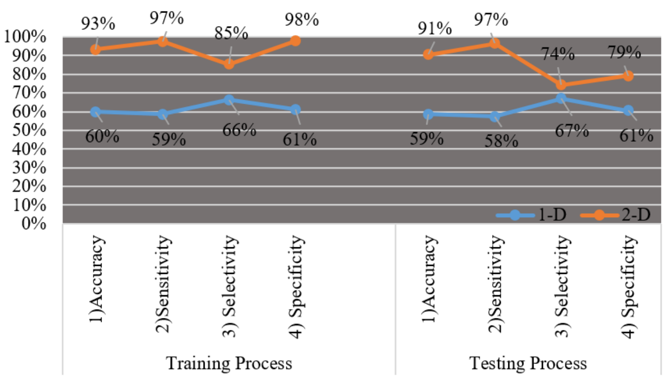

Figure 5. Depression system's performance metrics using ECG data

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. The 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.

Accuracy is higher if the batch size and epochs are greater. The present system configuration is Intel Core i5 speed, RAM. A batch size of 100 and 30 epochs are optimized for the present research work.

Empirical analysis demonstrates that, for ECG signals, the performance metrics (for two-dimensional sequence input to the system) such as accuracy, sensitivity, selectivity, and specificity, are higher than those of one-dimensional sequence input.

Confidence Intervals (CI) for accuracy for 700 ECG samples got 93%.

$$CI = p \pm Z\sqrt{\frac{p(1-p)}{n}} \tag{15}$$

p = observed accuracy
n = number of test samples
Z = 1.96 for 95% confidence

$$CI = 0.93 \pm 0.0189 \tag{16}$$

CI: 91.1% to 94.9%.

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%

6. CONCLUSION

The proposed system demonstrates the effectiveness of EEG and ECG signal analysis using advanced machine learning techniques for the diagnosis of depression. Feature extraction using wavelet transformations and FFTs, along with the selection of critical features such as Hjorth Activity, entropy, and alpha band power for EEG, and arithmetic mean for ECG, contributes significantly to classification performance. The use of RNN and LSTM Autoencoders with two-dimensional sequence input enhances the accuracy, sensitivity, selectivity, and specificity of the system. The proposed approach performs better over previous models, improving overall classification accuracy from 95.3% to 97.69%. Additionally, CNN proves superior to SVM for EEG classification, achieving the highest accuracy of 97.69%, while the ECG classification model attains accuracy of 93%. These results highlight the potential of the proposed system as a reliable and efficient for automated depression detection.

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