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Research Article

Development of Sophisticated System for Identifying Emotional Stress Concentration Recognition of Child Utilising EEG and Psychophysiological Inputs

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ABSTRACT

Using multi-modal biosignals, this study suggests a novel method for identifying emotional stress. The primary signal is the electroencephalogram (EEG), which is utilized in clinical diagnosis and biological research since it is a mirror of brain activity. We used the cognitive model of the brain under emotional stress to choose the appropriate child's EEG channels. We developed a successful protocol for recording participants' EEG and psychophysiological signals in a calm-neutral, negative-excited picture-induction environment. Appropriate EEG signal segments have been selected using both qualitative and quantitative analyses of psychophysiological signals in an attempt to improve the efficacy and performance of the emotional stress detection system. After the data were preprocessed, both linear and nonlinear characteristics were employed to extract the EEG parameters. The features of the EEG signal were extracted using wavelet coefficients and chaotic invariants, such as correlation dimension and fractal dimension by Higuchi's method. The outcomes showed that in two emotional states, the Elman classifier had an 82.7% classification accuracy. These results demonstrate a significant improvement over earlier equivalent published studies.

Keywords: Emotional stress, EEG signal, SVM, Dwt, wavelet coefficients; nonlinear features; genetic algorithm; classification

INTRODUCTION

Over the past few years, a great deal of study has been done on stress evaluation. The primary cause of this is the reality that sentiments are present in the majority of human interactions. The body's response to perceived mental, emotional, or physical suffering is commonly used to characterize stress. Despite the fact that this definition seems circular, it contains important notions [1]. Evaluating the definition of emotions is a significant issue in the study of emotion.

As a matter of fact, there is disagreement among psychologists themselves over the definition of an emotion and the range of emotional kinds. Arousal, which ranges from calm to excited, and valence, which ranges from negative to positive (or unpleasant to pleasant), combine to form the most widely recognized theory of emotions, which depicts emotions in two or three dimensional spaces and is based on cognitive theories [2]. Emotions in humans can be divided into a limited number of examples, according to psychologists. Consider Ekman and colleagues. [3] discovered that utilizing a standardized stimulus set, people from diverse cultures could categorically distinguish six different facial expressions: afraid, angry, sad, disgusted, joyful, and astonished. An important factor in emotion identification is brain activity. Motivation, perception, cognition, creativity, attention, learning, and decision-making are all significantly influenced by emotion [3, 4]. Few studies have, meanwhile, employed it to evaluate the emotional states. The chaotic character of the human electroencephalogram (EEG) was discovered through recent research. We use the fact that the brain exhibits chaotic behavior and that the EEG signal represents the interplay of millions of neurons to find novel features. It makes sense, then, to avoid applying traditional techniques that presuppose that emotion can be quantified using linear models [5].

Prior research has examined the application of both brain and psychophysiological data independently [3, 6, 7], but

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the connections between the two signals have received less attention to date. It is challenging to analyze the findings of earlier research because, in order to compare the outcomes of studies that try to apply emotion recognition systems as a classification problem, it is crucial to take into account the number of participants and the manner in which emotions are elicited—the latter being particularly crucial when introducing a user-independent system.
Chanel [6] asked participants in one study to recall past emotional experiences. For three categories, the greatest results were obtained with 79% EEG and 53% peripheral signals, and for two categories, 76% EEG and 73% peripheral signals. In a follow-up study, Hosseini [7] stimulated subjects with two distinct emotions using EEG and psychophysiological data, and he was able to identify 70% of the correctly identified patterns. Kim [8] created a system that doesn't need a user by using music and stories together as stimuli with fifty participants. The results were 61% and 78.4% for the third and fourth categories, respectively.
Additionally, Takahashi [9] employed movie scenes to elicit five distinct emotions from his students; consequently, 42% of the patterns were accurately identified.

PROPOSED SYSTEM ARCHITECTURE

Three steps make up the labeling process for EEG data: self-assessment, qualitative analysis, and quantitative study of psychophysiological signals. Figure 2 depicts the many phases of the procedure. Emotions are known to be highly subjective and reliant on prior experience, therefore knowing the subject's "level" of emotional stimulation can be gained from the self-assessment phase that followed the experiment [3]. We will be able to determine the overall quality of the data—that is, whether the data are good or bad—through this study.
Respiration is one category of this data. For instance, breathing slowly is associated with calm, whereas breathing quickly, irregularly, or completely correlates with more intense emotions such as fear or rage [6]. Skin conductance is an additional one that gauges the skin's conductivity. Sweating is associated with an increase in SC, which can occur when experiencing stress or other emotions. Lang found a correlation between the level of arousal and the mean value of the SC [6, 17]. Furthermore, protective responses, how pleasant a stimulus is, and fundamental emotions are all correlated with blood pressure and heart rate variability [6].
We used the PPG signal to extract HRV because HRV analysis provides a valuable way to investigate the many functions of the autonomic nervous system [18]. We must first pre-process the psychophysiological data by using filters to remove background noise before we can perform a quantitative analysis on them. We used the same set of feature values for the signals. The aspects of respiration are described by time and frequency domains; the features of skin conductance and photoplethysmograph are described by time, frequency domains, and fractal dimension; and the features of heart rate variability are described by time domains (Table 1).

Table I. Features Extracted From Psychophysiological Signals

Signal	Extracted features
Respiration	The variables that are calculated are mean, variance, standard deviation, kurtosis, skewness, maximum minus minimum value, mean of derivative, and power 5 frequency band, which ranges from 0.25 to 2.75 Hz.
Skin Conductance	The variables under consideration are mean, variance, standard deviation, kurtosis, skewness, maximum response, mean of derivative, energy response, and the ratio of negative samples to all samples in the derivative.

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Photo plethysmo graph	Variance, mean, and the standard deviation Kurtosis skewness Average of the trough's variability, Variability of the trough Peak variability mean, variation in peak variability Average of variability in amplitude, amplitude variability variation, average value fluctuation fluctuation in mean value variance, Standard deviation and average of the baseline variability
Heart Rate Variabilit y	Variance, mean, and Maximum value, Minimum value, Standard deviation, Low power frequency of 0.05–0.15 Hz, Higuchi's algorithm for the fractal dimension, and the ratio of low power frequency to total power frequency

Figure 1 depicts the suggested system design. Pre-processing is.

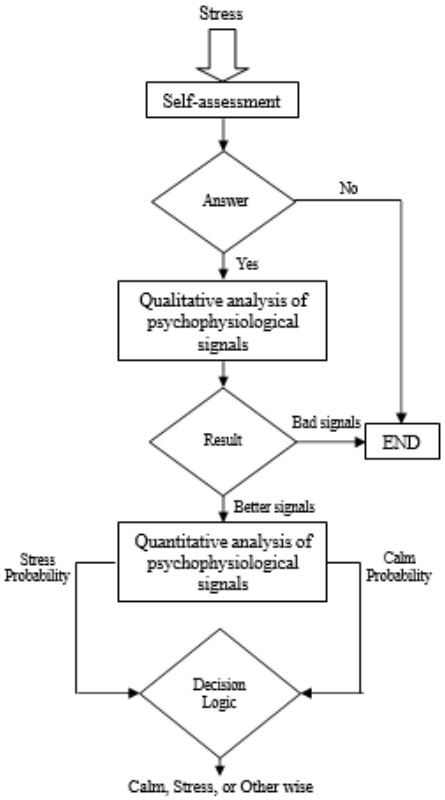


Fig. 1. Flow Diagram of the proposed work

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ANALYSIS OF EEG SIGNALS

A. ***Pre-processing***

The electrical activity in the brain is measured in microvolts. These transmissions are typically quite weak and contain a lot of noise. EEG signals must be pre-processed in order to eliminate drifts and background noise. A 0.5–35 Hz band pass filter is used for this purpose. The δ (1-4Hz), θ (4-8Hz), α (8-13Hz), and β (13-30Hz) bands are the frequency intervals of importance in EEG, which is why this band was chosen. The majority of the artifacts and all high frequency noise will be eliminated by this filter. Prior to analysis, we use an electrooculogram (EOG) to eliminate the data segment that clearly shows eye blinking.

B. ***Feature extraction***

Feature extraction is the process of extracting useful information from the signal. The characteristics of a signal are what enable it to distinguish between distinct emotions. We make use of our common feature values for brain signals. Nonlinear measures have attracted the most attention among the measurements previously mentioned, such as time domain, frequency domain, and other linear features. Among the nonlinear collection of features used are signals from the correlation and fractal dimensions. The characteristics of each electrode are obtained from the EEG readings. ***Fractal dimension*** In chaotic process analysis, one often used measure is the correlation dimension (D2). The Grassberger and Procaccia approach (GPA) [21] was used in our work to estimate D2 (see [21] for a review in equation). The choice of a suitable time delay (r) and embedding dimension (d) is critical to the attractor reconstruction process using finite data. We calculated D2 for each person using dE values between 2 and 10. It is evident that D2 saturates above the embedding dimension of seven. Consequently, dE=8 has been used for the invariant estimate and embedding space creation..

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Wavelet coefficients: Applications for physiological pattern identification have successfully used feature extraction based on discrete wavelet transform (DWT) with encouraging outcomes [22]. Selecting an appropriate wavelet and determining the number of decomposition levels are crucial when analyzing data with DWT. In this work, the statistical feature from the EEG signal was extracted using the Daubechies wavelet function of order db4 [22].

Table II. Frequencies With A 256 Hz Sampling Frequency Corresponding To Various Levels Of Decomposition For A "Db4" Wavelet

Decomposition levels	Frequency Bandwidth (Hz)	Frequency bands
D1	64-128	Noises
D2	32-64	Noises (Gama)
D3	16-32	Beta
D4	8-16	Alpha
D5	4-8	Theta
A5	0-4	Delta

The derived wavelet coefficients offer a condensed depiction of the EEG signal's energy distribution in terms of both frequency and time. With a sample frequency of 256 Hz, Table 2 displays frequencies that correspond to various stages of decomposition for db4 wavelets. Table 2 shows that the components D5 are in the theta (4–8 Hz), D4 are

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in the alpha (8–13 Hz), D3 are in the beta (13–30 Hz), and A5 are in the delta (0–4 Hz). In a typical EEG, lower level decompositions associated with higher frequencies have very small magnitudes.
Using statistics over the set of wavelet coefficients, the derived feature vectors' dimensionality was further reduced..

- The average of each sub-band's wavelet coefficients' absolute values
- The wavelet coefficients' average power in each sub-band
- The wavelet coefficients' standard deviation for each sub-band

Feature selection

The problem of having too many characteristics is resolved by the Genetic Algorithm (GA), a feature selection technique [23]. To get near-optimal results faster and with less computing strain on the training system, the genetic algorithm is used for feature selection. Every population in the GA has a unique genome that is generated at random and split into 100 sizes. 0.4 was chosen as the crossover probability and 0.01 as the mutation probability. Together with the trained network's classification performance using the complete dataset, the value of the fitness function was returned to the GA. We attempted to determine the feature sets linked to a calm or negative mood reaction using EEG signals.

Classification

Finding the emotion is a necessary step after extracting the desired features. A classifier will handle this procedure. A classifier is a system that can identify the correlation between the attributes and the emotional state after classifying the data into distinct groups. An Elman network [24, 25], a two-layer back-propagation neural network with an additional feedback connection from the hidden layer's output to its input, is one really helpful classifier. The Elman network may learn to identify and produce both spatial and temporal patterns thanks to this feedback loop. Tansig neurons are found in the Elman network's hidden (recurrent) layer, while purelin neurons are found in the output layer.

This combination is unique in that any function (with a finite number of discontinuities) can be approximated with arbitrary precision by two-layer networks using these transfer functions. For training, the Levenberg-Marquardt back-propagation method is employed. When compared to alternative training functions, the Levenberg-Marquardt algorithm will have the fastest convergence [25]. For stop training, the error ratio was regarded as 0.001. This combination is special because these transfer functions allow two-layer networks to approximate any function (with a finite number of discontinuities) with arbitrary precision.

For training, the Levenberg-Marquardt/back-propagation method is employed. When compared to alternative training functions, the Levenberg-Marquardt algorithm will have the fastest convergence [25]. It was assumed that the error ratio for stop training would be 0.001.

In this work the dataset which is used from these data 75% data from set A and 75% data from set E is used for Training. For testing purpose 25% data is used. This selected data is used as input to the MLPNN Classifier which is used in this work. The number of neurons in the input layer symbolizes the number of features presented to the network, followed by hidden layer with neurons which transforms the input into nonlinear combinations and passes the signals to the output layer [19].

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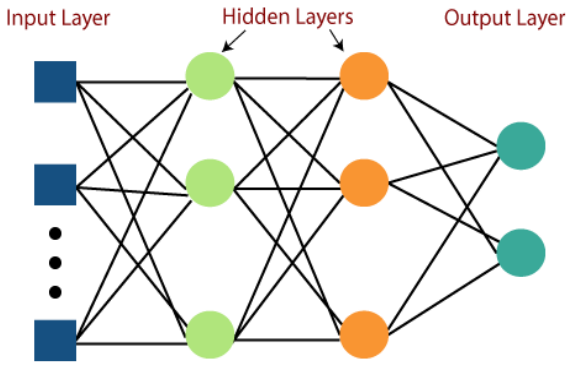


Figure Multilayer perception

In this proposed framework, the number of neurons in the input layer is ten corresponding to CFI and the number of neurons in the output layer is three to classify three different classes. The most challenging task is to select the number of neurons in hidden layer. In our work we varied the numbers of hidden nodes from 6 to 3 to find out the architecture giving the better performance with high accuracy. We have adapted our method by systematically enumerating all combinations of feature vectors and the combination of and checking all different size CFIs for the optimality of the features. Different features combination set has been obtained, and performance is evaluated from MLPNN.

Wavelet Transform for Signal Analysis:

We used Wavelet transform technique to decompose the signals and reconstruct the data accurately. rippling remodel technique could be a appropriate analytical tool for the Non Stationary signals analysis like encephalogram and it had been projected by Jean Morlet a French geologist in 1982[12]. It involves the breaking down of the brain signals into numerous shorter reads of bands as per demand. In distinct wavelet analysis, a multi-resolution description is employed to decompose a given signal f(t) into progressively finer details supported 2 sets of basic functions [13] the wavelets and the scaling functions, as follows:

$$f(t) = \sum_{i=z} 2^{\frac{j}{2}} C_j(k)\varphi(2^j t - k) \sum_{j=0}^{j-1} \sum_{k=0}^{\infty} 2^j d_j \psi(2^j t - k)$$

---------- (1)

where functions. Φ(t) and ψ(t) are the basic scaling and mother wavelet respectively. Five sub-bands are obtained, namely Delta (0-4.05 Hz), Theta (4.05-8.1Hz), Alpha (8.1- 12.15 Hz), Beta (12.15-32.5 Hz) and Gamma (>32.5 Hz) [14].

The number of decomposition levels is chosen supported the dominant frequency parts of the signal. The amount Decomposition of Non-epileptic and Epileptic EEG signal with delta, theta, alpha, beta and gamma subband decomposition is shown in Figure 3 and 4 with decomposition frequency of each subband. According to the Nyquist Theorem, the maximum useful sampling frequency is half of the sampling frequency.

RESULTS

MATLAB software was used to implement the simulations. We divided the data using a rectangular frame that did not overlap for two seconds. Our program was educated on the nuances of identifying mood from the EEG and psychophysiological signals using the collected data. Roughly 65% of the data were utilized for training, 10% were used for data validation, and 25% were used to assess the validity of the theory connecting an EEG signal to emotion.

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Our greatest performance was an accuracy of 82.7% using the EEG signals for the two categories (negative exited vs. relaxed)..

Through the use of fivefold cross-validation, the system was tested. The training data are split into five sections in this manner. The classifier is trained on the remaining four pieces after testing on one. Five times through the process, a distinct set of data was used. By ensuring that the system is evaluated with samples that differ from those it has seen during training, this technique reduces the likelihood that variations in the findings could be caused by a different distribution of training and test data.

Using the EEG data, we were able to obtain an accuracy of 79.2% for the two categories of emotional stress by using a 5-fold cross validation approach for both training and testing. The steps taken and the results of the suggested work are displayed in Figures 2 through 7.



Figure 2. GUI of the proposed model

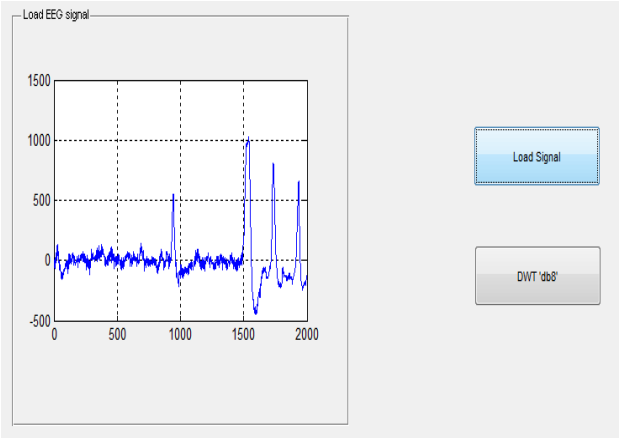


Figure 3. Loading of the EEG signal

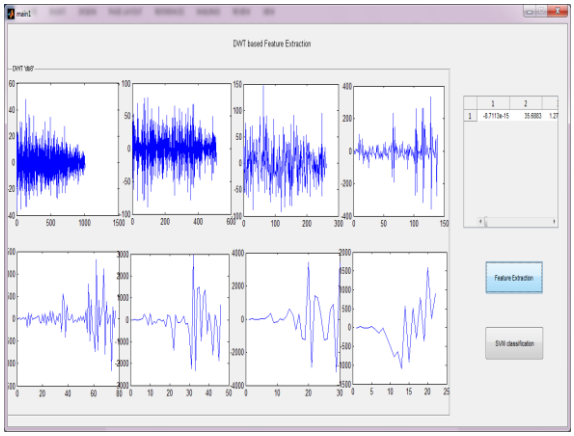


Figure 4. DWT based feature extraction

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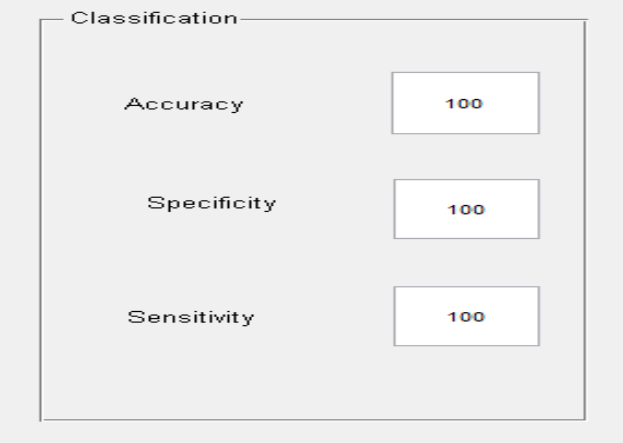


Figure 4. Classification Results

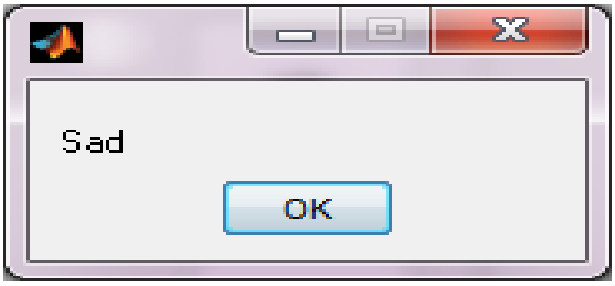


Figure 5. Sad emotion output

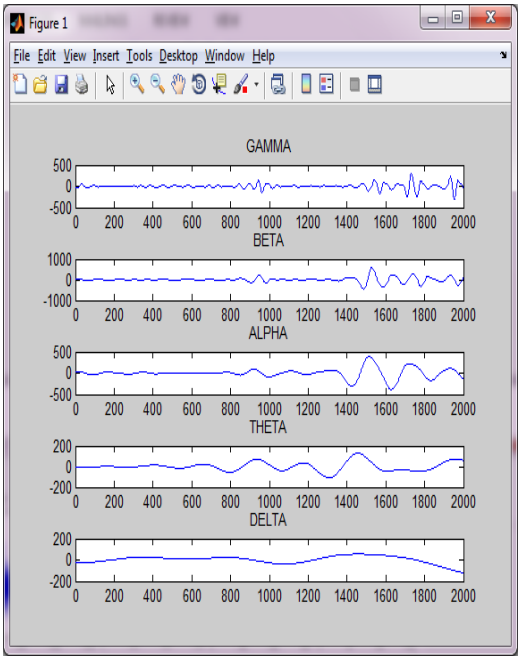


Figure 6. EEG Analysis and its various results

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$$Sensitivity = TPR = \frac{TN}{TP + FN} \times 100\%$$

$$Specificity = TNR = \frac{TP}{TN + FP} \times 100\%$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100\%$$

For SAD emotion frequency obtained result:

Gamma: Maximum occurs at 34.00 Hz.

Beta: Maximum occurs at 25.00 Hz.

Alpha: Maximum occurs at 15.000000 Hz.

Theta: Maximum occurs at 5.000000 Hz.

Delta: Maximum occurs at 3.000000 Hz.

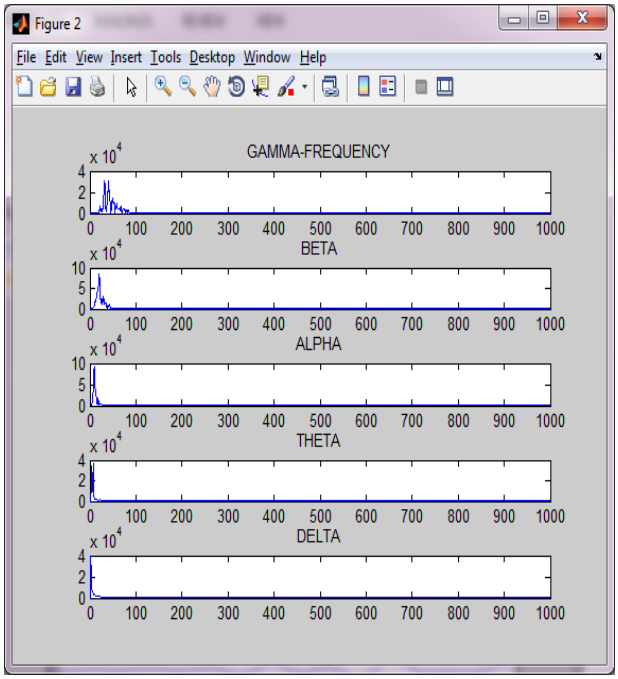


Figure 7. EEG Analysis and its various results

In this process classification is done for ictal state (E) and other healthy state (A) and in order to measure the performance of the classifier, Sensitivity (True Positive Ratio - TPR) and Specificity (True Negative Ratio - TNR) were calculated.

Sensitivity (TPR): Sensitivity is the strength of the capacity to detect and discriminate stimuli. It is how strong the perception of a stimulus is in an individual. A person who has higher sensitivity will perceive a stimulus more strongly at a lower level than someone who is less sensitive to the stimulus.

Specificity (TNR): Specificity relates to the test's ability to correctly detect patients without a condition. Consider the example of a medical test for diagnosing a disease. Specificity of a test is the proportion of healthy patients known not to have the disease, who will test negative for it.

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Accuracy: Accuracy is the degree of closeness of a measured or calculated quantity to its actual (true) value. A measurement system or computational method is called valid if it is both accurate and precise. Equation given below describe the formula used for calculating Sensitivity and Specificity using True Positive (TP), True negative (TN), False Positive (FP) and False Negative (FN).

CONCLUSION

Because of its superior temporal resolution, the electroencephalogram has historically been the most widely used signal to evaluate brain function. In this study, we propose a method that uses physiological cues to identify emotion in the two primary valance-arousal spaces. Over the past ten years, numerous analyses have approaches have been used to EEG recordings in both healthy and pathological circumstances on several occasions, and it has been demonstrated that they provide fresh insights into intricate brain dynamics [21, 26, 27]. Fractal dimension and correlation dimension are two examples of the nonlinear measures. The problem with all of them is that the defined dimension for the phase space is not constant for all channels of recorded EEG signals or for different subjects, and the chosen dimension may vary depending on the circumstances. For the majority of measures, a dimension should be defined in order to visualize the attractor in phase space.

Our study's findings indicate that as compared to calm activity, negative emotional activity has a lower D2. Additionally, it is evident that Higuchi's method shows a comparable pattern of FD value reduction for negative emotional EEG in comparison to calm EEG. For participants in a negative emotional state, the fall in FD values and D2 is indicative of a loss in brain system complexity [21]. Therefore, using nonlinear time series analysis on EEG recordings provides insight into the variety and dynamic nature of brain signals.

The EEG signals associated with negative and normal emotions are clearly characterized by chaotic measurements. According to the results, new EEG and psychophysiological signal fusions are more reliable than the signals taken individually [3, 6, 7]. Because EEG signals have a greater time response than psychophysiological signals, our results demonstrate the significance of EEG signals for emotion assessment via categorization. In order to recognize emotional stress, we employed two-second time intervals for brain signal analysis, yielding a two-second temporal resolution.

A higher but virtual time resolution, which would be helpful in biofeedback applications, could have been obtained if we had used shorter time periods with overlap. EEG signals were used with an 82.7% categorization accuracy in two emotional states. Owing to variations in the experimental setup, our findings cannot be compared to those of previous studies that have tried to include emotion recognition systems as a classification challenge. However, we obtained a about 11% improvement in our results when compared to similar works [6, 7].

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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