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Research Article

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Enhancing Anxiety Diagnosis through ADA BOOST-Assisted Decision-Level Fusion

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Abstract

Background: *Humans naturally respond with anxiety to mental stress caused by a variety of circumstances. Anxiety impairs memory function and makes it difficult to learn and retain information. Additionally, sustaining high productivity while balancing life's stresses can be achieved through good anxiety and stress management.*

New Method: *This paper presents an effective technique for automatically classifying two anxiety levels: normal and anxious, using an analysis of EEG data. The EEG signals found in the DASPS database were utilized. This database includes 14-channel EEG recordings taken under normal and anxious settings from 23 individuals (10 male and 13 female, average age 30 years). Brain sub bands were extracted from EEG signals using wavelet transform. Different features such as Hjorth coefficients, entropy, autoregressive, and energy were extracted. The feature vector was reduced by the PCA method, and the classification was carried out by the Ada boost classification method.*

Results: *The results demonstrate the effectiveness and efficiency of the proposed model in diagnosing anxiety, with an accuracy of 80.58%.*

Comparison with Existing Methods: *Our study highlights the superior performance of the Ada boost method compared to other methods, showcasing its potential for accurate anxiety classification using EEG data.*

Conclusions: *In conclusion, the proposed method shows promise for automatic classification of anxiety levels using EEG data. By leveraging machine learning techniques and EEG analysis, our approach could contribute to improved anxiety diagnosis and stress management strategies.*

Keywords: Ada Boost, Anxiety, Decision Tree, EEG, Stress

1. Introduction

Many people feel emotional pressure states like stress and anxiety, particularly in recent years due to the contemporary lifestyle. This condition has impacts on the neurological, psychological, and physiological levels. The body's reaction to a need for change is called stress. This degrades quality of life and impacts the main facets of everyday activity. Stress-reduction strategies are crucial for maintaining one's health as well as the welfare of society [1]. scalp electrical activity generated by brain structures. Alternating electrical activity that is recorded from the scalp's surface using metal electrodes and conductive material is known as an electroencephalogram, or EEG [2]. Most people experience stress from time to time in their daily life. Complex reasons can cause stress [3].

This is a typical physically response that people have when they feel frightened or challenged by their surroundings [4]. The body's reaction to physical, mental, or emotional pain is known as stress. In addition to causing erratic behavior, stressful situations might worsen blood pressure or coronary artery disease if they persist [5]. Diseases like depression and irritable bowel syndrome are also linked to stress. Blood circulation and respiration are further effects of stress. Heart rate and respiration both increase under stressful circumstances [6]. Since anxiety is essentially a prolonged state of stress, it causes our bodies to release huge amounts of the stress hormone, which is linked to a decrease in bodily performance. Performance in the classroom may also be impacted by this unseen handicap. Anxiety impairs memory function and makes it difficult to learn and retain information. Furthermore, you can retain high productivity and a positive quality of life while managing your anxiety and stress effectively [7]. Finding balance between job, relationships, and self-awareness is the aim, as is learning coping mechanisms for anxious situations so that obstacles can be overcome. However, there is no one-size-fits-all approach to managing anxiety, so we must learn to identify when worry arises, how it manifests physically, and how our nervous system responds to different circumstances. Emotion diagnosis requires the diagnosis of anxiety [8].

2. Material and Methods

In this paper, at the beginning, the database for anxious states based on a psychological stimulus (DASPS) is investigated and since these data are noise-free, there is no need for any noise removal method [9, 10]. Therefore, the results of this database the data is the main basis of the next experiments. In this work, we intend to consider the best extracted features that have been reported in previous works.

Extract the best features from the relevant data. Finally, if necessary, we use the feature reduction algorithm, and at the decision-making level, we use the structure of ethics in order to achieve the best result.

In this paper, an automatic method for anxiety detection using EEG signal and Ada boost algorithm is proposed [11].

The proposed method includes four steps:
- Data acquisition
- Pre-processing
- Feature extraction
- Classification.

Figure 1 shows the outline of the proposed method.

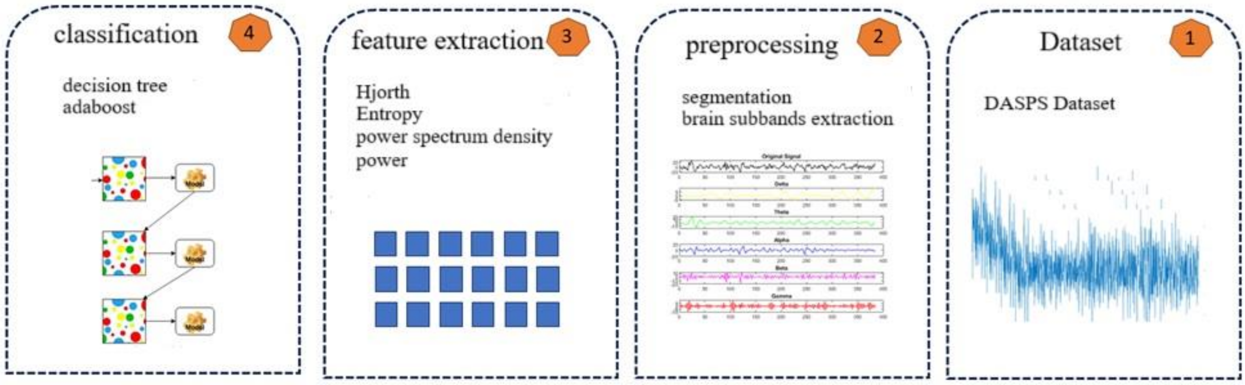

Figure 1: Overview of the Proposed Method.

According to Figure 1, at the beginning, the DASPS free access dataset includes the EEG signal of different people in anxiety conditions. Then, in the pre-processing stage, segmentation of the signal and extraction of brain sub-bands was done. In the next step, different features are extracted from the signals and then the dimensions of these features are reduced by the PCA method [7]. Finally, the feature vectors were classified into anxious and normal states by the etiquette model and decision tree. The details of each step are described below.

2.1. Dataset

One of the most time-consuming stages of research is recording and collecting data related to research. The data used in this thesis was used from the " Database for Anxious States based on a Psychological Stimulus (DASPS)" database [9, 10]. This database consists of EEG signals of 23 people, 13 women and 10 men, with an average age of 30 years. Before the test, the level of anxiety was evaluated by Hamilton's test. At the beginning of the experiment, in the first 15 seconds, the psychotherapist reads the anxiety situation to the participant, and in the second 15 seconds, the participant remembers the situation, and after each situation, the participant gives a score to his feeling during the stimulation with the SAM test.

6 anxiety situations are implemented for each participant in the following order:
- Loss
- Family Issues
- Financial Issues
- Deadline
- Witness a Fatal Accident
- Abuse.

After finishing the situations, the participant's anxiety is measured once again with the Hamilton test. Figure 2 shows how to record the EEG signal. According to Figure 2, 30 seconds of EEG signal was recorded for each anxiety situation (6 situations). Then every 30 seconds of signal recording is divided into two parts of 15 seconds. Therefore, the EEG signals for each participant are 12 pieces with a length of 15 seconds [13].

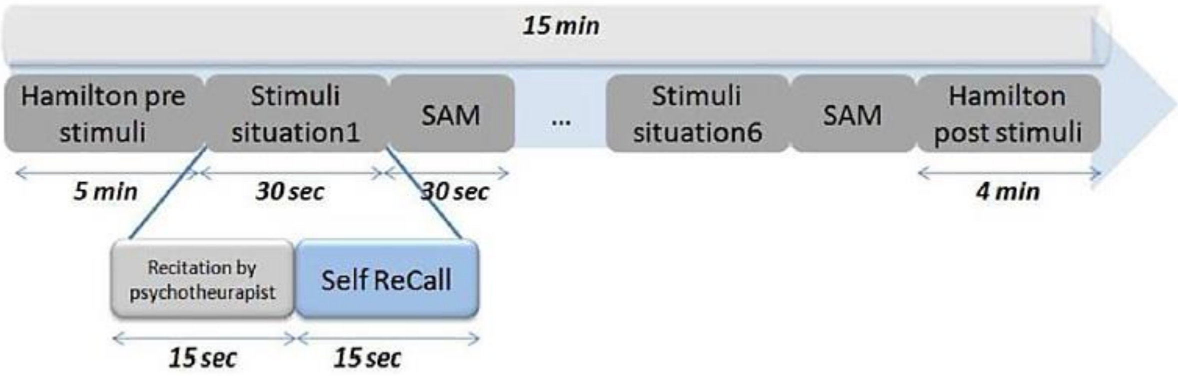

Figure 2: Method of Recording EEG Signal in DASPS Database.

These signals were recorded with a sampling frequency of 128 Hz and by 14 electrodes named AF3, AF4, F7, F8, F3, F4, P7, P8, T7, T8, O1, O2, FC5, FC6. Figures 3 and 4 show examples of database signals for two classes, anxiety and normal, respectively.

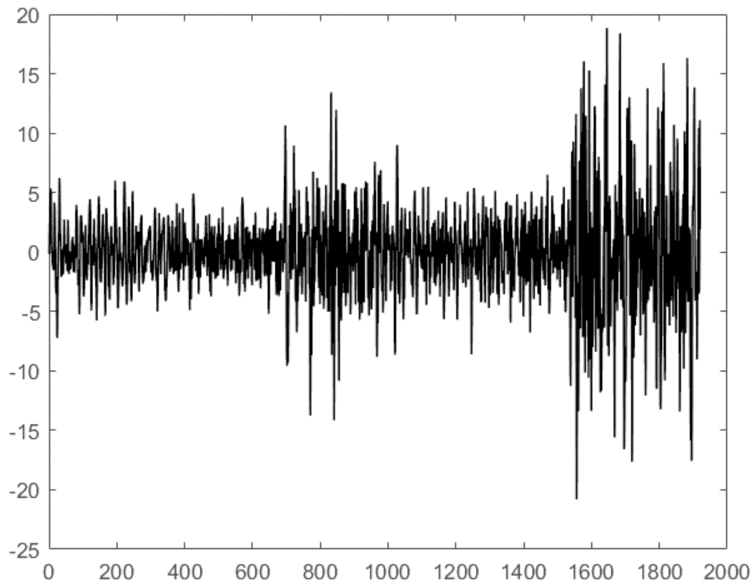

Figure 3: Example of Database EEG Signal in Anxiety Class.

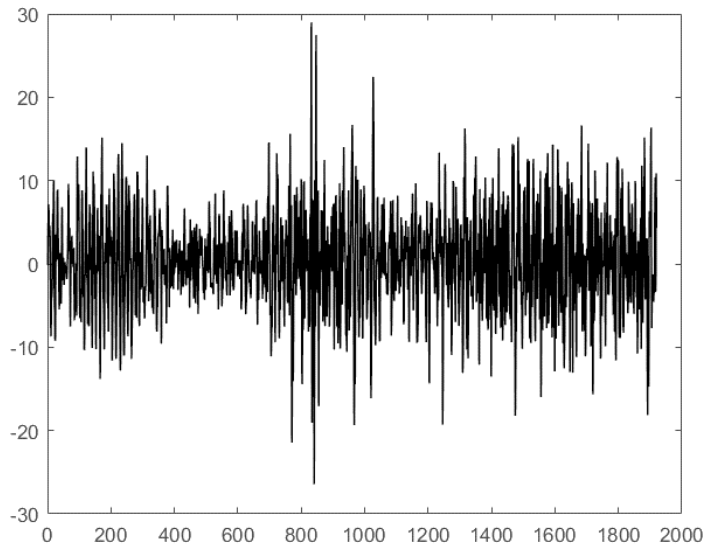

Figure 4: Example of Database EEG Signal in Normal Class.

2.2. Mathematical Backgrounds

2.2.1 Pre-Processing

Since the data is usually obtained from sources that have produced or maintained the data regardless of data mining processes, it is necessary to prepare the data according to the conditions and the problem in question so that it can be correctly and as the appropriate input for the main algorithm. be used to prepare the data, the following steps can be taken:

2.2.1.1. Noise Reduction

In this step, noises in the data such as interfering signals or unwanted items are removed. This can be done using filters, error correction methods, or data preprocessing techniques. Therefore, since the data in the DASPS database are noise-free, there is no need to use noise removal methods [9, 10].

2.2.1.2. Signal Segmentation

Signal segmentation is a process in signal processing where the input signal is divided into smaller and manageable parts. This process is based on time, frequency or other conditions. These segments can be defined consecutively in time (time segmentation) or defined in different frequency bands (frequency segmentation). Time segmentation means dividing the signal into smaller time intervals. These intervals are commonly known as frames or windows. Frames may be contiguous and overlapping or defined individually and non-overlapping. This method allows us to examine the signal over time and extract its different characteristics. Therefore, in this dissertation, segmentation without overlapping and with a window length of 3 seconds (384 samples) has been done. After segmentation, the number of signals has increased to 1380.

2.2.2. Extraction of Brain Sub Bands

Extraction of brain sub bands is a process in brain signal processing, the purpose of which is to decompose the brain signal into different frequency sub bands. This process is based on brain signal processing techniques and algorithms. A brain signal consists of the brain's electrical activity. These activities can be detected in different frequency bands and each frequency band usually shows certain characteristics [14]. In this paper, wavelet transform is used to extract brain sub bands. Wavelet transform is a mathematical process that allows signal decomposition in the time and frequency domain. In wavelet transform, a mother wavelet function is combined with the brain signal. This mother wavelet is applied to the signal as a moving window over time and calculates how well it matches the signal at each point. By moving this window over time, the frequency information of the signal is extracted at different times. Therefore, in order to extract brain sub bands, wavelet transform in 4 levels and Daubechies's mother wavelet have been used. Figure 5 shows how to decompose the signal and extract brain sub bands by wavelet transform. After analyzing the signal, according to the frequency content of the analyzed components, parts D1, D2, D3, D4 and A4 were extracted as brain sub bands.

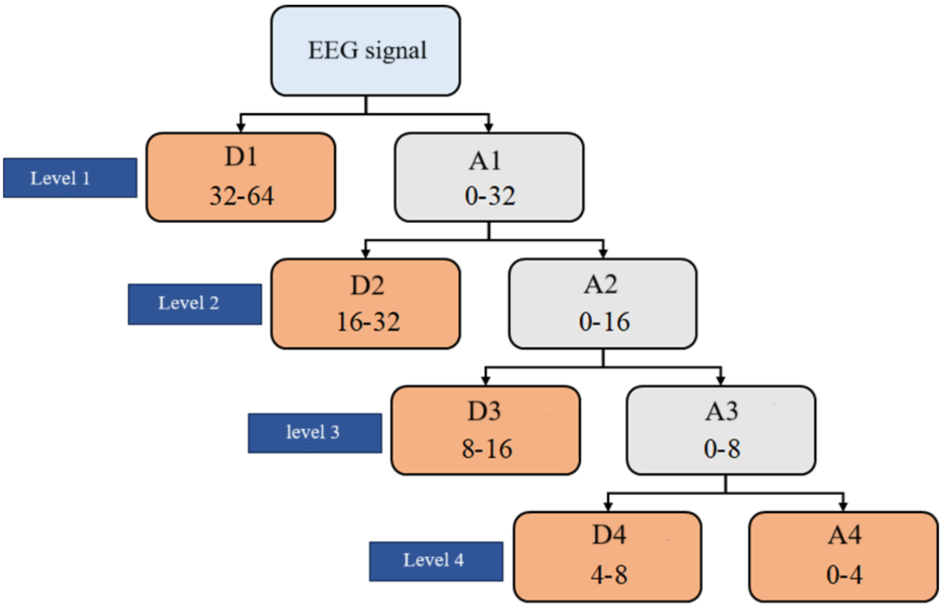

Figure 5: The Method of Signal Analysis and Extraction of Brain Sub bands (Orange Areas: Brain Sub bands)

2.2.3. EEG Feature Extraction

EEG features that are commonly used in time, space and frequency domains. In the following, the common methods of feature extraction are described. Feature extraction is an important process in data analysis and signal processing. In this process, meaningful and useful features are extracted from the primary data so that important and usable information can be extracted from the data and used in subsequent analyzes and algorithms. Feature extraction can be done manually or using automated methods and complex algorithms. In any case, the main goal of feature extraction is to extract important and discriminating features from the data and remove or reduce other unnecessary information [15]. In this thesis, Hjorth coefficients (activity, mobility and complexity), autoregressive coefficients, Shannon entropy and power spectrum density have been used to extract features. These features (6 features) have been extracted from EEG signals and different sub bands as well as 14 available channels. Therefore, the features of the total number of features acquired from each signal are 504 features. The feature extraction process is shown in Figure6.

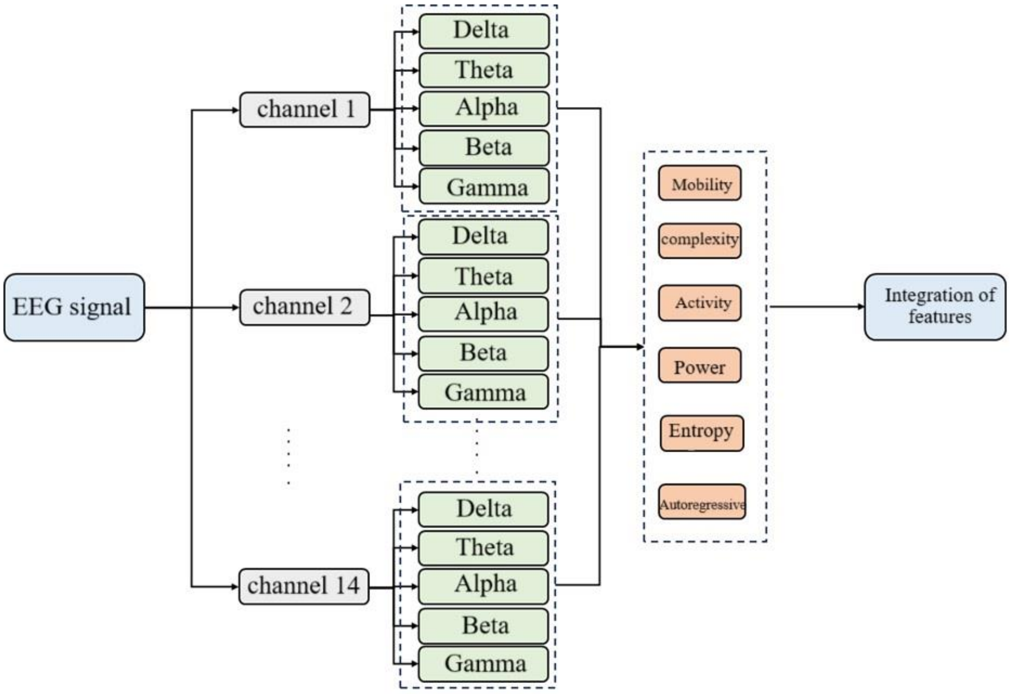

Figure 6: Feature Extraction Process

In the following, in order to reduce the dimensions of the feature and reduce the calculations, the PCA method is used. After applying PCA, 130 features of the best features with high intra-class correlation have been selected and used to train the classification models [16].

2.2.3.1. Hjorth's Features

Hjorth is a continuous probability distribution that is widely used in data analysis and statistics. This distribution is described as a soft and continuous infinite curve and is defined based on two parameters, mean (μ) and variance (σ). The use of Hjorth distribution in statistical calculations can help to estimate parameters, calculate confidence intervals, test hypotheses and model data. These coefficients are used for various calculations and analyzes using Hjorth distribution [17].

Hjorth features are a set of features used in temporal signal analysis. These features are determined based on the wavelet transform and time derivatives of the signal and can be useful in identifying patterns and characteristics of time signals. Hjorth 's feature set includes three main parameters:
Activity: This parameter indicates the amount of oscillatory changes and energy in the signal. A value higher than the average indicates more activity and a lower value indicates less activity.

Mobility: This parameter shows how much the signal changes or to what extent it can be moved. A higher value of variance indicates more movement and a lower value indicates less movement.
Complexity: This parameter shows how complex and structured the signal is. A higher value of complexity indicates a signal with a more complex structure and a lower value indicates a signal with a simpler structure.

These features are commonly used in the analysis of temporal signals such as electroencephalogram (EEG) signals and can be useful in identifying patterns and changes in signals.

2.2.3.2. Linear Features

Important linear features include mean, variance, standard deviation, power, skewness, and kurtosis. How to calculate these features is given in the relations 1 to 6 [18].

$$Variance = \frac{1}{N}\sum_t (x[\mathrm{n}] - \mu)^2 \tag{1}$$

$$\sigma = \sqrt{Variance} \tag{2}$$

$$S_{kmc} = \frac{\sum_{t=1}^{N} \frac{x[\mathrm{n}]-\mu)}{N}^{3}}{[\sum_{t=1}^{N} \frac{(x[\mathrm{n}]-\mu)}{N}^{2}]^{\frac{3}{2}}} \tag{3}$$

$$\mathrm{E} = \sum_{n=-\infty}^{\infty} |x[n]|^2 \tag{4}$$

$$K_{mc} = \frac{\sum_{t=1}^{N} \frac{(x[\mathrm{n}]-\mu\,)}{N}^{4}}{[\sum_{t=1}^{N} \frac{(x[\mathrm{n}]-\mu)}{N}^{2}]^{2}} - 3 \tag{5}$$

$$\mu = \frac{1}{N}\sum_{t=1}^{N} x[\mathrm{n}] \tag{6}$$

2.2.3.3. Non-Linear Features

Dynamic nonlinear characteristics can be helpful in representing the nonlinear nature of the EEG signal. By examining the hidden patterns and mechanisms in the EEG signal, these features aid in the acquisition of additional information on the structure and temporal properties of the signal. [19].

Some commonly used nonlinear features are:
Autoregressive: which measures the correlation of the signal with itself over time.

Approximate entropy: which measures the complexity and incompleteness of the signal and makes it possible to understand dynamic and complex systems.

Sample entropy: which calculates the complexity and anisotropy of the signal.
Permutation entropy: which measures the complexity based on the order of different patterns in the signal.

Wavelet entropy: which analyzes the complexity of the signal at different scales and has the ability to detect different time patterns [20].

Spectral features: include criteria such as power spectrum, abundance criteria, and abundance correlation criteria that consider the signal's spectral information.

The use of these nonlinear features can help to better understand the dynamics and temporal characteristics of the EEG signal and be useful in the analysis and interpretation of brain information.

2.2.3.3.1. Autoregressive

Autoregressive (AR) is a statistical concept that measures the degree of correlation or relationship between a signal and itself over time. This concept is very important in the analysis of signals and time systems. In autoregressive, the original signal is time-delayed with itself and the correlation between different time points of the signal is calculated. This concept gives us information about patterns, repetitions and temporal relationships in the signal.

The leaf method is one of the parametric methods for estimating the power spectrum (PSD) of signals based on the autoregressive model [21]. Autoregressive can be calculated by the relation 7:

$$x(n) = \sum_{k=1}^{p} a_k * x(n-k) + e(n) \tag{7}$$

where e(n) is the input data, x(n) is the output of the system, and ak is the autoregressive coefficients. The advantages of the leaf method include high frequency resolution, relative stability, and low computational load, and the disadvantages of this method are frequency displacement from the actual frequency [4].

2.2.3.3.2. Approximate Entropy (APEN)

Approximate entropy is a nonlinear measure used to measure the complexity and anisotropy of signals. This criterion is based on the analysis of signal patterns and provides us with information about the predictability and predictability of the signal and is calculated in the form of equation 8 [18].

$$ApEn(m, r, N) = \psi^{m}(r) - \psi^{m+1}(r) \tag{8}$$

where N is the data length, r is the threshold and m are the desired dimension.

2.2.3.3.3. Permutation Entropy

Permutation entropy is a nonlinear measure used to measure the complexity and anisotropy of signals. This measure is based on the analysis of signal permutation patterns and provides us with information about the predictability of the signal. The permutation entropy calculation algorithm for each time series $\{x(i)\ ,\ i = 1,2,..N\}$ with length N is expressed by equation (9) [22].

$$H_P(m) = -\sum_{g=1}^{k} P_g \ln P_g \tag{9}$$

where P is the probability distribution as $(P_1, P_2, \ldots, P_k)$, g = 1, 2..., k and m are the dimension.

2.2.4. Reducing Feature Dimensions

Feature dimensionality reduction is a process in which the number of features of a system or data is directly reduced, so as to preserve important and usable information. By reducing the dimensions, the data can be represented in a new space with less dimensions, it can also be used to simplify calculations and algorithms, remove duplicate data and noise, and also improve the interpretability of the data. In general, feature dimensionality reduction is an important process in data processing that enables the optimal use of data and can be used in many fields, including pattern recognition, classification, image analysis, and speech processing [23].

2.2.5. Classification

Data can be categorized using an analytical technique called classification, which groups data according to certain attributes. The aim of classification is to effectively and precisely separate the data into distinct groups according to the characteristics included in the data. The data should first be categorized using validation techniques into two groups: training and testing, before beginning the classification process. Models are trained in the training category, and their assessment and training are assessed in the test category. The data in this research are classified using the k-fold method with k=10. Stated differently, a total of 1242 data points were utilized for training the model, and an additional 138 data points were used for testing the model ten times. Following the data classification process, 100 decision trees and decision tree models were utilized to train and evaluate the data. [24].

3. Results

The features of activity, mobility, complexity, autoregressive coefficients, Shannon entropy, and power spectrum density are extracted using it in this work. The average of the data in two anxiety and normal groups has been computed after PCA in order to examine these aspects. [25]. The average value of the acquired traits in the two anxiety and normal classes is displayed in Figure 7. It is evident from the graphic that the traits in the two classes have different average values.

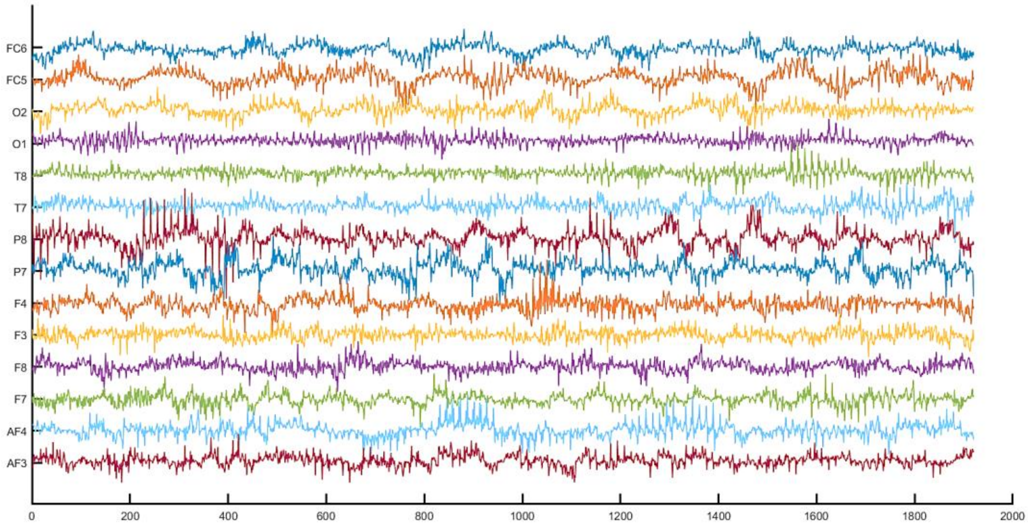

Figure 7: View of the EEG Signal of a Participant in the DASPS Database.

In this article, 100 decision trees and the k-fold validation approach with k=10 are used to classify the data. The confusion matrix for the decision tree and Ada boost method models, each with 100 decision trees, is displayed in Figures 8 and 9, respectively.

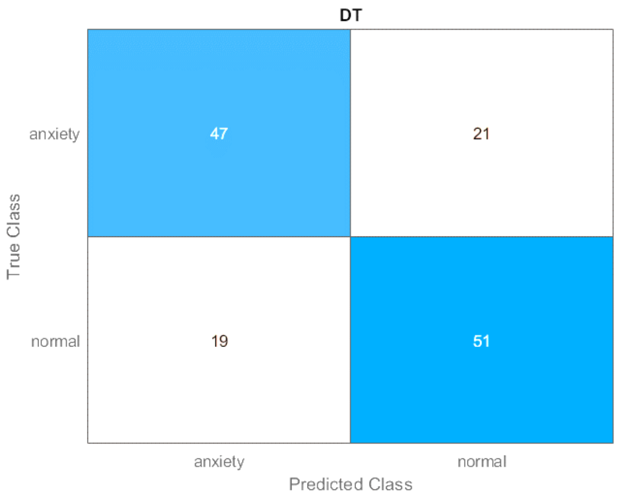

Figure 8: Confusion Matrix for Test Data in Decision Tree Model.

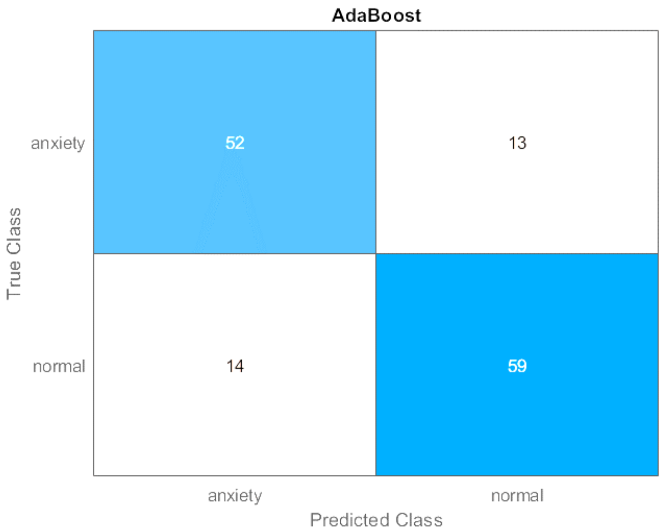

Figure 9: Confusion Matrix for Test Data in Ada Boost Model.

Fold	Accuracy	Sensitivity	Specificity
1	21/65	60/60	44/69
2	66/66	63/63	44/63
3	71/79	78/78	55/80
4	73/71	72/72	83/70
5	66/66	69/69	88/63
6	36/75	69/69	55/80
7	84/68	18/68	44/69
8	29/70	24/72	66/66
9	84/68	72/72	27/65
10	81/76	78/78	75
Mean	83/4 ± 01/71	88/5 ± 90/70	84/5 ± 11/71

Table 1: Classification Results for Test Data in Decision Tree Model.

Fold	Accuracy	Sensitivity	specificity
1	15/81	27/77	72/84
2	08/76	69/69	94/81
3	05/84	27/77	27/90
4	05/84	27/77	27/90
5	43/80	84/84	38/76
6	71/79	81/81	77/77
7	88/81	30/80	33/83
8	26/78	75/75	55/80
9	36/75	27/77	61/73
10	78/84	84/84	72/84
Mean	29/3 ± 58/80	54/4 ± 63/78	51/5 ± 36/82

Table 2: Classification Results for Test Data in Ada Boost Model.

According to Table 1 and Table 2, it can be seen that the Adaboost method has a much higher performance compared to the decision tree. Diagram 1 compares the average accuracy in both models and for different k. According to the diagram 1, it can be seen that the Adaboost method has a higher performance compared to the decision tree for all k.

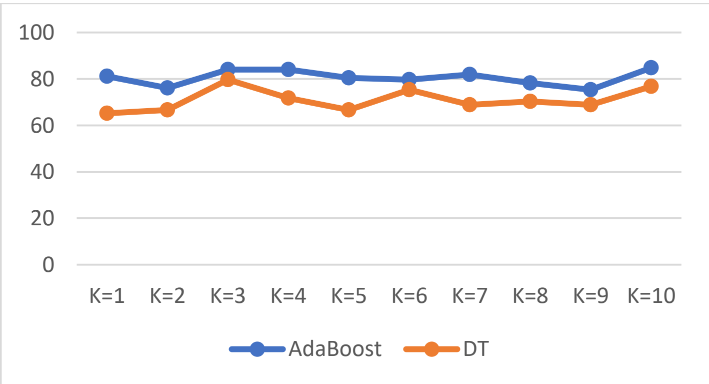

Diagram 1: Comparison of Accuracy for Different N in Two Methods of Decision Tree and Ada Boost.

4. Discussion

Ada boost method has the best performance in forecasting with an average accuracy of 80.58%. Table 3 shows the comparison of the proposed method with other researches.

Accuracy	classification	Number of classes	features	Year of publication	Method
15/76	ESN	2 class	Subband power	2018	Felman et al[26]
49/62	SVM	2 class	Power spectrum density	2018	Fourati et al[27]
00/72	ANN,kNN, LDA	2 class	Cosine transform	2015	Lim et al[22]
58/80	AdaBoost	2 class	Various feature	2023	Proposed method

Table 3: Comparison of the Proposed Method with Other Studies.

The analysis of the approach's outcomes shows that, in comparison to the decision tree method, the accuracy attained by the method has improved. Consequently, it would seem that a larger data set should be used to reevaluate the suggested strategy because anxiety is influenced by a variety of circumstances. Nonetheless, it can be said that the suggested approach worked admirably in general based on the outcomes that were produced [12, 26, 27].

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