Predicting Anxiety Among Young Adults Using Machine Learning Algorithms

Pralhad R Yadawad
School of Electronics and Communication Engineering
KLE Technological University
Hubballi, India
0009-0002-0627-0661

Lokesh Pandey
School of Electronics and Communication Engineering
KLE Technological University
Hubballi, India
0009-0008-3752-3223

Kaushik Mallibhat
School of Electronics and Communication Engineering
KLE Technological University
Hubballi, India
0000-0002-3610-0332

Uma Mudenagudi
School of Electronics and Communication Engineering
KLE Technological University
Hubballi, India
0000-0003-1111-7522

***Abstract*— This study describes the process, procedure, and analysis used to quantify the amount of anxiety experienced by engineering students during the set of activities. The paper presents a comprehensive literature review, collection methods for anxiety detection, and emphasizes the advantages of portable EEG devices. The core methodology involves inducing specific anxiety types through structured activities, coupled with EEG data analysis followed by use of a machine learning algorithm towards classification of anxiety. The experimentation included data from nine participants aged 18-21 years. EMOTIV EPOC+ portable EEG machine was used to record the EEG from the participants during anxiety-triggering activities. The authors used statistical methods such as the Wilcoxon signed-rank test and Mann-Whitney U test to identify significant changes in EEG signals during anxiety-triggering activities compared to the relaxed state. The Self-Assessment Manikin (SAM) method is employed to categorize data into light, moderate, severe anxiety, and normal states. Machine learning algorithms, including Random Forest and XGBoost, demonstrate notable efficacy, achieving an accuracy of 72.27%. This research contributes valuable insights to mental health research and treatment, emphasizing the potential for personalized interventions based on neural and behavioral markers.**

Keywords*— *EEG signals, Behavioral Markers, Anxiety Detection, Machine Learning, Mental health research.

I. Introduction

Anxiety is a multifaceted emotional state and psychological process, typically triggered by perceived threats. Research indicates that while a certain level of anxiety can enhance performance and help tackle challenges, excessive anxiety can negatively affect sleep, attention bias, and the ability to think abstractly. At present, identifying anxiety disorders is primarily dependent on clinical methods or through a variety of surveys, including the Beck Anxiety Inventory, State-Trait Anxiety Inventory, Manifest Anxiety Scale, Self-Rating Anxiety Scale[1], and the Hamilton Anxiety Scale[2]. Nonetheless, this diagnostic approach may not be fully unbiased and presents a potential for subjective prejudice, which could affect the accuracy of the assessment. On the other hand, neuro-imaging technologies like Magnetic Resonance Imaging (MRI)[3] and Electroencephalography (EEG)[4], known for their high accuracy and relative objectivity, are extensively used in emotion assessment. Specifically, EEG has a clear lead over other techniques due to its high temporal resolution and immediate nature of emotion generation. Presently, numerous anxiety studies are EEG-based. These researches suggest that anxiety primarily manifests as alterations in neurobehavioral function, which in turn affect EEG patterns [4].

Anxiety disorders pose a considerable mental health obstacle, impacting a reasonable segment of the young adult demographic. Effective counseling and treatment depend on the early detection and classification of diverse anxiety types, which include long-term illnesses like Generalized Anxiety Disorder (GAD)[5] as well as transitory episodes brought on by specific circumstances.

This study embarks on a multifaceted journey, leveraging province tools for psychological testing and predicting anxiety in young individuals. Specifically, we integrate electroencephalogram (EEG) signals, widely recognized for their potential to capture neural responses and validated psychological questionnaires, including the Generalized Anxiety Disorder 7-item scale (GAD-7)[6] and the Depression, Anxiety, and Stress Scale (DASS-21)[7]. By combining objective and subjective measures, the current research endeavors to achieve a comprehensive understanding of the anxiety spectrum.

Accordingly, the authors organized a range of activities carefully designed to induce distinct temporary anxiety types, from specific phobias to panic disorder, separation anxiety, social anxiety, and performance anxieties like stage fear and exam fear. EEG data is recorded and analyzed during these activities to capture dynamic changes in beta wave activity, a well-established marker of anxiety. For the personal questionnaire, the authors took the reference from GAD-7 and DASS-21[4][7].

The machine learning framework, encompassing various machine learning algorithms such as random forest (RF) and XGBoost (XGB), is employed to process EEG data, extract essential features, and predict the presence and intensity of anxiety. The amalgamation of EEG signals, questionnaire responses, and activity-induced alpha, beta, gamma, and theta wave analysis forms the cornerstone of the proposed research. The significance of these endeavors extends to the potential identification of distinctive neural and behavioral markers for various anxiety types, informing the development of tailored interventions and support strategies. By harnessing the power of machine learning and neuroscience, the authors aim to improve the overall well-being of young adults grappling with the multifaceted challenges of anxiety.

The techniques, findings, and discussions supporting our effort to identify and categorize different types of anxiety in young people are presented in the following parts, which will contribute significantly to the larger field of mental health research and treatment.

A. *Objectives of the study*

1. Conduct a review of the literature to understand the state of the art in detecting and evaluating anxiety.
2. Classify the intensity of anxiety from EEG signals using machine learning algorithms.

The organization of the paper is as follows. The required taxonomy followed with the state of art towards detection of anxiety, the pros and cons of each of the methods are described in section II while the data collection methods and proposed pipeline are explained in section III followed by data analysis methods and results in the subsequent sections.

II. LITERATURE SURVEY

A crucial component of mental health research is understanding and predicting anxiety among young adults, as anxiety disorders constitute a significant mental health challenge that affects an essential percentage of the young adult population.

Anxiety, a nuanced emotional state with profound psychological implications, spans a spectrum from fleeting, short-term episodes to persistent, long-term conditions. Long-term anxiety poses a significant mental health challenge, with Generalized Anxiety Disorder (GAD) and chronic stress emerging prominently. GAD, marked by excessive, uncontrollable worry, represents a prolonged pattern of anxiety, while chronic stress stems from extended exposure to stressors.

In contrast, short-term anxiety reveals its intricacy through diverse, transient episodes. This study explores the landscape of short-term anxiety, including Specific Phobias, Panic Disorder, Separation Anxiety, Social Anxiety, Stage Fear, and Exam Fear. These episodic anxieties surface in specific circumstances, spanning performance-induced fears to situational triggers. Our research navigates the complexities of these anxiety types, unveiling the neural and behavioral markers that differentiate them. Employing advanced techniques such as EEG signals and machine learning, our paper aims to elevate our comprehension and intervention capabilities.

Numerous studies on anxiety monitoring in young adults have already been published, but they mainly concentrate on identifying whether a student has anxiety permanently. Different research papers identified anxiety in individuals using different techniques. Researchers employed skin temperature (ST) [8], photoplethysmogram (PPG)[9], electroencephalography (EEG)[10], electrocardiogram (ECG)[11], heart rate (HR)[12], oximetry(Ox)[13], respiration (RSP)[14], and electrodermal activity (EDA)[15], alongside a questionnaire, in a comprehensive study to collect and analyze the relationship between various physiological parameters [16] and anxiety.

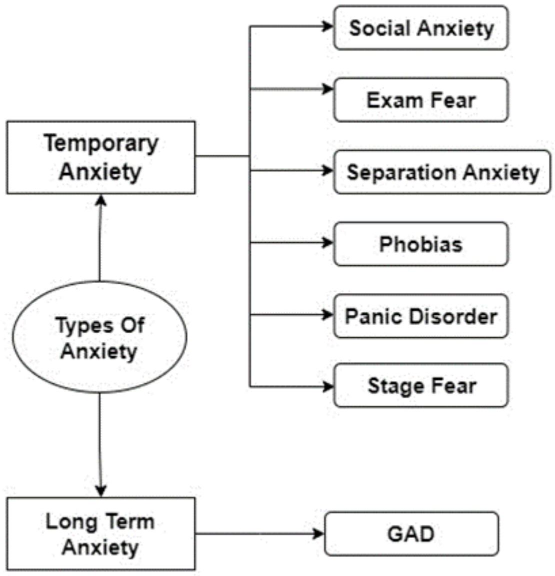

Fig. 1. Types of Anxiety

Various papers show the experimentation with different parameters and combinations of these parameters to get maximum accuracy in predicting anxiety. A typical gap that authors found in most of the papers was that these people were oriented on identifying whether the given test subject (human being) had temporary anxiety or not but the type of anxiety was not classified and limited research is available in this direction.

EEG signals have been widely utilized in the study of anxiety. The presence of specific patterns, particularly increased beta wave activity, is indicative of increased anxiety levels [18]. EEG signals have been employed to investigate real-time anxiety responses during anxiety-inducing activities. Psychological questionnaires, such as Generalized Anxiety Disorder 7 (GAD-7)[5] and Depression, Anxiety, and Stress Scale (DASS-21)[7], provide valuable self-reported data regarding chronic anxiety symptoms [1]. These questionnaires help assess long-term anxiety conditions and offer a complementary perspective to the neural data obtained from EEG signals [5][7]. This research has embraced a holistic approach that integrates EEG signals, questionnaire responses, and the utilization of activity-induced beta wave changes [7][18]. By engaging participants in anxiety-inducing activities specific to certain anxiety types, such as specific phobias, panic disorder, or social anxiety, researchers can effectively trigger and identify patterns in EEG data that correspond to these conditions [16]. The existing literature underscores the potential of EEG signals, machine learning, and psychological questionnaires in advancing our ability to predict and address anxiety among young adults. As the field continues to evolve, it holds great promise for more accurate and personalized mental health interventions.

Table 1 summarizes various anxiety assessment methods, including psychological questionnaires (e.g., HAM-A, STAI, BAI, DASS-21, GAD-7) and physiological measurements (e.g., EDA, ECG, EEG, RSP, ST, PPG, Ox, HR). Each method is briefly described with its advantages, disadvantages, and references. Psychological questionnaires offer detailed assessments but require interpretation by trained clinicians. Physiological measures provide valuable insights into anxiety-related changes, each with specific strengths and limitations.

Table 1 Classical Anxiety Assessment Methods

Method	Advantages	Disadvantages	References
Hamilton Anxiety Rating Scale (HAM-A)	Provides a comprehensive assessment of anxiety symptoms. It is widely used in both clinical and research settings.	Requires a trained clinician for administration and interpretation.	[2]
State-Trait Anxiety Inventory (STAI)	Distinguishes between the temporary condition of "state anxiety" and the more general and long-standing quality of "trait anxiety."	It is self-reported, so it may be influenced by the individual's current state or willingness to report their feelings accurately.	[1]
Beck Anxiety Inventory (BAI)	Quick and easy to administer. It focuses on somatic symptoms of anxiety, which can help differentiate anxiety from depression.	It may not be as effective in individuals who do not experience somatic symptoms. It may also be influenced by the individual's willingness to accurately report their feelings.	[1]
DASS-21 (Depression Anxiety Stress Scale-21)	Has good internal reliability (Cronbach's alpha), and its ordinal alpha demonstrated good internal reliability for all its sub-scales.	Information not found	[7]
General Anxiety Disorder (GAD-7)	It's free to use, available in several languages, relatively brief, and easy to score, and it correlates with other psychiatric instruments to support its reliability and validity.	The GAD-7 provides only probable diagnoses that should be confirmed by further evaluation.	[6]
Electrodermal Activity (EDA)	Electrodermal Activity (EDA) is an output of various processes in the central nervous system. It's a biomarker for emotional responses. EDA biofeedback is studied for treating anxiety and stress-related disorders.	The main disadvantage of EDA recording is poor spatial resolution. The EEG signal does not help pinpoint the exact source of activity.	[15]
Electrocardiogram (ECG)	ECG helps measure three basic parameters of clinical interest; ECG represents data in the topographic form, which provides higher diagnostic information.	ECG monitoring should document symptoms such as syncope and palpitations, but 24 hours is often too short a period. Therefore, other devices have been introduced.	[11]
Electroencephalography (EEG)	EEG is a functionally fast, relatively cheap, and safe way of checking the functioning of different brain areas. High-precision time measurements can be achieved.	The main disadvantage of EEG recording is poor spatial resolution.	[4]
Respiration (RSP)	RSP can provide continuous monitoring.	Information not found.	[14]
Skin Temperature (ST)	a non-invasive, objective evaluation of human sensations, allows personalized monitoring and aids in early detection of anxiety disorders.	Information not found.	[9]
Photoplethysmogram (PPG)	PPG is simple, reliable, and inexpensive. It can easily be integrated into wearable healthcare devices for various health-related measurements such as pulse rate (or heart rate), blood flow, Heart Rate Variability (HRV), etc.	PPG sensors lack accuracy. They can't show anomalies in the heart because these detectors are not fixed in that area and work on a different principle.	[10]
Oximetry (Ox)	Oximetry is a safe, comfortable, and inexpensive method with no need for end-user calibration. It can be self-applied and does not require a medical specialist.	For people with health anxiety or whose doctors have not helped them understand the role of an oximeter, this can cause unnecessary worry.	[13]
Heart Rate (HR)	HR monitoring techniques that rely on PPG sensors have several advantages over traditional ECG-based systems. For instance, PPG sensors use simpler hardware implementation and have lower costs, and for operation, only a single sensor is required to be placed on the body.	Information not found.	[12]

Based on the ease of use, flexibility, and the ability to seamlessly integrate the use of devices into the existing systems, the EEG method of capture was selected as the device for experimentation.

III. Methodology

The proposed method for detecting and classifying temporary anxiety utilizes a multi-stage pipeline towards a diverse range of temporary anxiety types, encompassing social anxiety, exam fear, separation anxiety, phobias, panic disorder, and stage fear. This comprehensive approach aims to provide an objective and efficient way to detect and classify diverse forms of temporary anxiety. The following section focuses on the designing of anxiety-triggering activity, device description, participants, data capture setup, labeling methods followed by data analysis methods.

A. Design of Triggering activity

Structured activities were designed for inducing short-term anxiety covering a diverse range of anxiety-inducing situations like "Pick and Speak," "Scary Scene," and "Spell Bee" were crafted to replicate real-world triggers like public speaking, exposure to fear-inducing stimuli, and cognitive challenges. The thoughtful curation of these scenarios aimed to evoke genuine short-term anxiety responses, fostering a nuanced comprehension of distinct anxiety types and their associated neural and behavioral markers.

B. Data capture and participants

The current data set includes nine individuals (nine participants). All of the participants are between the ages of 18 and 21 and are pursuing a bachelor's degree. All of the participants have finished primary school at an English board school. The subjects declared that they had not ingested alcohol or any form of neural drugs before the dataset collection, which could have affected the study, and proper consent was obtained. Study participation was entirely voluntary, and consent was acquired through a Google form. Prior permissions to conduct the study were obtained from the University's Institutional Review Board (IRB). Fig. 2 shows the snaps taken during data capture.

Fig. 2. Data capture setup

C. Devices and Technology

The project was funded by the University under a Research Grant. The authors used Neurosky device and Emotiv device for initial experiments and later EMOTIV EPOC+, a precise and portable equipment, was chosen to capture the brain signals because of the advantages.

The EMOTIV EPOC+ is a 14-channel EEG system with high resolution. It was created to be quick and simple to fit and measure in real-world research applications. The 10-20 system is a widely used technique in EEG to position electrodes on the scalp. It divides the scalp into regions like frontal (F), parietal (P), temporal (T), occipital (O), and central, based on the relationship between electrode location and underlying brain areas. The electrodes were positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4.

The EMOTIV headband can record the EEG data at a sampling rate of 128 SPS / 256 SPS (2048 Hz internal). The EEG device has a resolution of 14 bits 1 LSB = 0.51V (16-bit ADC, 2 bits instrumental noise floor is discarded), but the settings can be changed to 16 bits and a bandwidth of 0.2 - 45Hz, with digital notch filters at 50Hz and 60Hz [19][20]. To hydrate all of the electrodes and connect the sensors, a saline solution containing 0.7% - 4% w-w sodium chloride was used. The Emotiv Launcher, EmotivPRO, and EmotivLABS software were used to connect the device to the PC via a Bluetooth dongle (for a better connection) and store the captured EEG data during triggering activities.

D. Experimental Procedure

Each participant completed five activities. There were five structured anxiety-triggering activities of 30 seconds each, and the EEG data was recorded simultaneously. The study comprised five distinct sessions designed to explore various facets of participants' experiences and responses. In the first session, individuals were instructed to put on earphones and listen to relaxing music, with the primary objective being to induce relaxation. The second session, "Pick and Speak," involved participants selecting a topic from a spinning wheel and delivering a spontaneous 30-second speech on the chosen subject. The third session focused on a "questionnaire" tailored to each participant, aiming to uncover individual anxiety levels through specific inquiries. The fourth session, titled "Scary Scene," exposed participants to a brief, 30-second video clip from a horror film, serving as a stimulus to gauge fear responses. The fifth session, "Spell Bee," required participants to spell out seemingly simple yet intricately challenging words. Each session provided unique insights into participants' emotional and cognitive reactions across a spectrum of scenarios.

E. Labeling of Data

The labeling of the data acquired was according to the Self-Assessment Manikin (SAM) method [20]; for each session, the valence (denotes the positive or negative nature of emotion, extending from pleasant to unpleasant) and arousal (relates to the level of activation or energy associated with an emotion, ranging from low to high) of every test subject were recorded, and the labeled the CSV file with the labels light anxiety, moderate anxiety, severe anxiety, and normal. According to the SAM rating-based labeling, any experimental trials with a valance score below five and an arousal score above five are deemed ‘normal’. Trials that have valance scores from 0 to 2 and arousal scores from 7 to 9 are designated as Severe. Subjects falling within the valance score range of 2 to 4 and arousal scores between 6 and 7 are recognized as having Moderate anxiety. Finally, subjects who have valance scores from 4 to 5 and arousal scores between 5 and 6 are classified as experiencing Light Anxiety [20]. The data distribution of the collected data set is shown in Fig. 3.

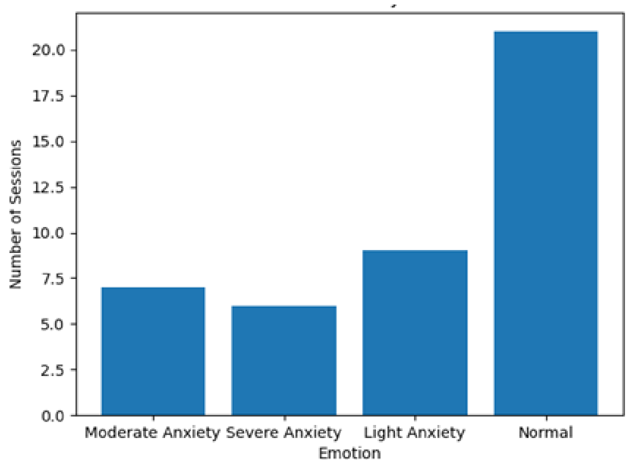

Fig. 3. Data Distribution

F. Proposed pipeline towards anxiety detection

Fig. 4 shows the proposed pipeline towards anxiety detection. The EEG signals recorded from participants were acquired and subjected to feature selection in the conducted study. Specifically, the band power feature of the EEG data was chosen, focusing on the frequency information power within the theta (4-8Hz), alpha (8-12Hz), low beta (12-16Hz), high beta (16-25Hz), and gamma (25-45Hz) frequency bands across channels[20]. In Electroencephalography data analysis, band power denotes the mean power or strength of the signal within a designated frequency range. Typically, the EEG signal is decomposed into functionally distinct frequency bands. In this study, band power is a crucial element for predicting and classifying anxiety states. The computation of band power provides a singular metric that encapsulates the influence of specific frequency bands on overall signal power, contributing significantly to our objective [21].

For example, during deep sleep, the prevalence of slow waves in the delta band (0.5 to 4 Hz) aligns with our approach, reflecting synchronized brain activity. Conversely, the reduced delta activity and increased higher-frequency activity during wakefulness support our focus on using band power to differentiate anxiety states. The choice aligns with the inherent characteristics of EEG wave bands, where lower-frequency bands (delta and theta) exhibit significantly larger values than higher-frequency bands (alpha and beta). This selection enables effective tracking of temporal changes and facilitates comparing band strengths, enhancing the precision of our anxiety state predictions. Utilizing the EPOX PRO software from Emotive, band power values for each sensor and across all EEG frequency bands, i.e., alpha, gamma, high beta, low beta, and theta, were directly obtained, resulting in a feature vector with a length of 70.

Data packets serve as discrete units transmitted between devices or systems across a network. In the EmotivPRO context, these packets encapsulate information acquired from the headset's sensors and transmitted to a computer. The recurring one-second cycle of headset data, operating at either 128 Hz or 256 Hz, is illustrated by grey sawtooth lines. The utilization of a USB extender to connect the headset's dongle to the computer ensured no data packet loss, preserving information integrity. All 70 features within the feature vector were utilized for classification using various models, including Support Vector Machine, Random Forest, XGBoost, Decision Trees, K-nearest Neighbour, Naïve Bayes, Logistic Regression, Voting Classifiers (combinations of RF, DT, SVC), Simple Neural Network, and Complex Neural Network. The highest accuracy, at 72.27%, was achieved with the Random Forest model.

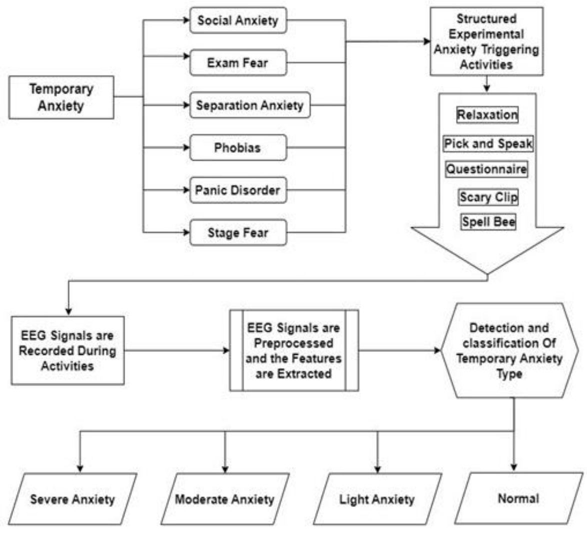

Fig. 4. Proposed pipeline towards anxiety detection

G. Algorithm for EEG Feature Selection

Input: 1) Extracted feature group FV = Band Power.
2) Class Labels = Normal, Light anxiety, Moderate anxiety
3) Classifier =RF, DT, LR, SVM, KNN, NB, XGb, Voting Classifier, Neural networks
4) EEG frequency bands = α, β, δ, γ, θ.
5) Number of EEG bands = N.

Output: Process EEG Data for Emotion Classification

If the EEG data DataFrame is not empty:

- Set parameters for segmenting EEG signals.
- Define target frequency bands: Alpha, Theta, BetaL, BetaH, Gamma.
- Initialize an empty dictionary to store values for each frequency band.

For each frequency band in each segment:

For each target frequency band:

- Initialize an empty Series for the current frequency band.
- Iterate over EEG data segments:

For each segment:

- Process frequency values for the current segment and frequency band.
- Concatenate processed values to the overall frequency values.
- Calculate and print the average value for the current frequency band.

End

End

End

Prepare data for machine learning:

- Create a DataFrame 'X' with columns for each frequency band.
- Drop rows with missing values (NaN) from 'X.'

Assign emotion labels based on the file path:

- Use a function (e.g., determine_emotion_label) to determine the emotion label.
- Update the counter for emotional occurrences.

Print the assigned emotion label for verification.

Else,

if the EEG data DataFrame is empty:

Print a message: "The DataFrame is empty. Please check the file contents."

End

End

End

IV. Data Analysis

This section focuses on the use of statistical analysis methods, namely the Wilcoxon signed-rank test and the Mann-Whitney U test. The methods were employed to scrutinize variations in EEG signals across distinct anxiety-inducing activities in comparison to the baseline relaxed state[22]. The selection of these statistical methods was based on their suitability in handling non-normally distributed data, such as EEG signals, providing robustness and reliability in detecting significant differences.

The Wilcoxon signed-rank test, a non-parametric statistical method for paired samples, was particularly relevant for comparing EEG signals within the same participant across various sessions. This test is well-suited for scenarios where normal distribution assumptions may not hold. For each participant, this test was used to assess the significance of differences between the relaxed state and each of the four anxiety-triggering sessions. The resulting p-values represented the probability of obtaining results as extreme as the ones observed, allowing for the identification of statistically significant alterations in EEG signal amplitudes.

The Mann-Whitney U test, another non-parametric test for comparing two independent groups, was applied to assess variations in EEG signals between the relaxed state and each anxiety-triggering session. This test is advantageous when dealing with small sample sizes and is robust against outliers. Similar to the Wilcoxon test, the Mann-Whitney U test provided p-values indicating the significance of differences in EEG signals. In examining the results, EEG signals (alpha, beta L, beta H, gamma, and theta waves) from 14 electrodes were compared for each participant during the relaxed state against the four anxiety-triggering sessions. The Wilcoxon test revealed statistically significant changes of 5% and above in EEG signal amplitudes during anxiety-inducing activities, signifying the impact of structured anxiety-triggering sessions on neural activity.

The significance of these findings is rooted in the precise identification of EEG signal changes associated with induced anxiety states. Employing both the Wilcoxon signed-rank test and the Mann-Whitney U test facilitated a comprehensive evaluation, covering both paired and independent comparisons. The acquired p-values indicate the probability of observing such differences due to random chance, with lower p-values suggesting greater confidence in rejecting the null hypothesis and indicating substantial alterations in EEG signals during anxiety-triggering sessions compared to the relaxed state. Notably, variations exceeding 5% were identified in alpha, beta L, beta H, gamma, and theta waves across all 14 electrodes during anxiety-triggering activities. These observed changes underscore the signals' sensitivity to anxiety-inducing scenarios. The resulting p-values provide substantial evidence, confirming the accuracy of SAM-based data labelling and emphasizing the statistical significance of the observed alterations. The rigorous statistical analysis strengthens the neurological impact of structured activities, affirming the reliability of the assigned labels and highlighting the effectiveness of statistical methods in precisely evaluating neural responses to anxiety triggers.

V. Results

The experimental study presented in this paper aims to determine the most effective EEG recording phase for categorizing anxiety into different groups. Features extracted from various EEG bands were analyzed using band power during activity phases in an open-eye condition. The pipeline includes data pre-processing and feature extraction steps, followed by the performance evaluation of various classifiers on the extracted features. The authors compared the obtained results with existing studies and discussed the implications and limitations of the proposed approach.

The proposed pipeline shown in Fig. 4 begins with the capture of raw EEG signals from the participants. The raw EEG signals recorded from the participants were pre-processed using the EmotivPRO software, which performed band-pass filtering, artifact removal, and data segmentation. The pre-processed signals were then exported as CSV files for further analysis. For each participant, we obtained five CSV files corresponding to the five activities they performed: relaxing music, pick and speak, questionnaire, scary scene, and spell bee. Each file contained 14 columns for the 14 EEG channels and one column for the timestamp. The sampling rate was 128 Hz, and the duration of each activity was 30 seconds, resulting in 3840 samples per file. To extract features from the EEG signals, we used the band power method, which computes the average power of the signal within a specified frequency range. We focused on the five EEG frequency bands: theta (4-8 Hz), alpha (8-12 Hz), low beta (12-16 Hz), high beta (16-25 Hz), and gamma (25-45 Hz). For each channel and each frequency band, we calculated the band power using the EmotivPRO software, which resulted in a feature vector of length 70 (14 channels x 5 bands) for each activity. We then concatenated the feature vectors of the five activities for each participant, forming a total feature vector of length 350. We also assigned a class label to each feature vector based on the SAM ratings of the participants, as described in Section III. The class labels were normal, light anxiety, moderate anxiety, and severe anxiety.

The feature vectors were categorized into the four anxiety levels using a variety of machine learning techniques. 90% of the data was used for training, and 10% was used for testing after the data was divided into training and testing sets. On the training set, we used 10-fold cross-validation to adjust the classifiers' hyperparameters and assess their effectiveness. The performance was evaluated using the following metrics: F1-score, recall, accuracy, and precision. To see the classification outcomes, we also plotted the confusion matrices.

The classifiers we used were Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes (NB), XGBoost (XGB), Voting Classifier (VC), Simple Neural Network (SNN), and Complex Neural Network (CNN). The VC was a combination of RF, DT, and SVM, using hard voting. A simple Neural network Model Was also implemented, which resulted in an accuracy of about 51%. During this process, we also found out that including all band power spectra, i.e. (α, β, δ, γ, θ) results in a better accuracy score, as the study using SAM, which might also be reasons for low accuracy, the study employed fourteen classification algorithms, with the Random Forest classifier yielding the best results achieving the highest accuracy of 72.27% and 73.79% (10-fold cross-validation) [19].

Fig. 5 shows the accuracy graph of the classifiers on the testing and training set. The RF classifier achieved the highest accuracy of 72.27%, followed by the VC(SVC+RF+DT+XGB) with 68.40%. The RF classifier

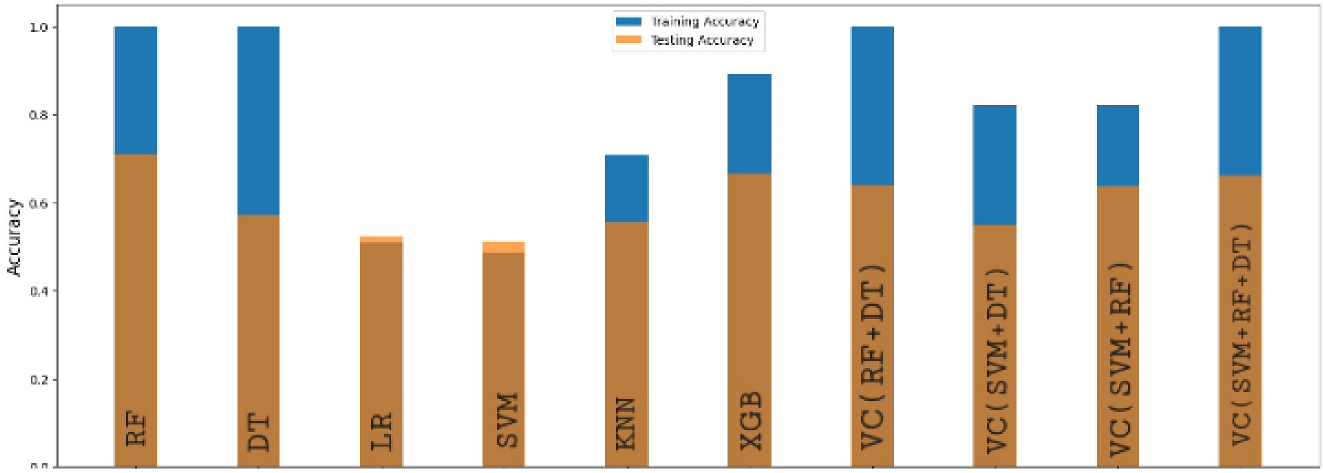

Fig. 5. Comparison of training accuracies and testing accuracies of various machine learning algorithms

also had the highest precision, recall, and F1 scores. The NB had the lowest accuracy of 19.17%, followed by the SVM with 50.94%. The NB and SVM also had the lowest precision, recall, and F1 scores for all classes. Fig. 6 shows the confusion matrices of the random forest classifiers on the testing set. The RF and the VC had the most balanced confusion matrices, with relatively high true positive rates and low false positive rates for all classes. The VC and the NB had the most skewed confusion matrices.

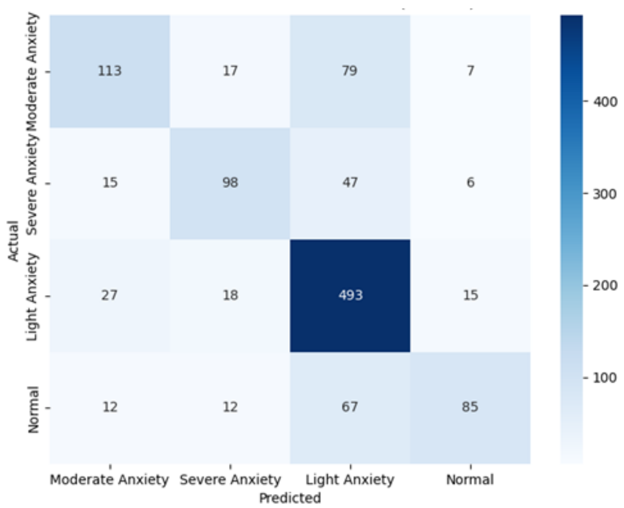

Fig. 6. Confusion Matrix

VI. Conclusion

This research presents a pilot study towards predicting and classifying anxiety levels as well as provides a methodology for recorded EEG data. From the alpha, gamma, low beta, high beta, and theta bands of EEG data collected during the experimentally designed tasks, which trigger multiple kinds of anxiety, band power was considered as a feature during the study. Wilcoxon signed-rank test, Mann-Whitney U test were used to strengthen the neurological impact of structured activities and affirm the reliability of the assigned labels and highlighting the effectiveness of statistical methods in precisely evaluating neural responses to anxiety triggers. Further various machine learning algorithms were used and random forest outperformed with an accuracy of 72.27%

Acknowledgment

We express our heartfelt gratitude to our university for the research grant towards procuring the hardware and software required to conduct the study.

References

[1] Virgil Zeigler-Hill, Todd K. Shackelford, Encyclopedia of Personality and Individual Differences, Springer Nature Switzerland AG 2020

[2] Beck, A. T., & Steer, R. A. (1991). Relationship between the Beck Anxiety Inventory and the Hamilton Anxiety Rating Scale with anxious outpatients. Journal of Anxiety Disorders, 5, 213–223

[3] P. Brambilla, F. Barale, E. Caverzasi, and J. C. Soares, "Anatomical MRI findings in mood and anxiety disorders," Epidemiologia e Psichiatria Sociale, vol. 11, no. 2, pp. 88–99, Apr. 2002.

[4] R. K. Nath and H. Thapliyal, "Machine Learning-Based Anxiety Detection in Older Adults Using Wristband Sensors and Context Feature," SN Computer Science, vol. 2, article number 359, June 2021.

[5] D. Ibrahim, R. M. Ahmed, A. Z. Mohammad, B. Ibrahim, T. Mohammed, M. E. Mohamed, T. Abdelgadir, B. Mohammed, M. Ibrahim, and K. M. A. Shaaban, "Prevalence and correlates of generalized anxiety disorder and perceived stress among Sudanese medical students," BMC Psychiatry, vol. 24, Article number: 68, Jan. 2024.

[6] M. A. Rahman, M. A. Hossain, and M. A. Rahman, "Validity and reliability of the Generalized Anxiety Disorder-7 (GAD-7) in the context of university students in Bangladesh," PLoS ONE, vol. 16, no. 12, Dec. 2021

[7] J. Lee, E. Lee, and S. H. Moon, "Systematic review of the measurement properties of the Depression Anxiety Stress Scales–21 by applying updated COSMIN methodology," Quality of Life Research, vol. 28, pp. 2325–2339, Apr. 2019

[8] P. Jefferies and M. Ungar, "Social anxiety in young people: A prevalence study in seven countries," PLoS ONE, vol. 15, no. 9, e0239133, Sep. 2020.

[9] S. Morishima, Y. Xu, A. Urashima, and T. Toriyama, "Human body skin temperature prediction based on machine learning," Artificial Life and Robotics, vol. 26, pp. 103–108, 2021.

[10] Azwani Awang, Nazrul Anuar Nayan, Nik Ruzyanei Nik Jaafar, Mohd Zubir Suboh, Khairul Anuar A Rahman, Siti Nor Ashikin Ismail, "Machine Learning Approach on Photoplethysmogram," 2021

International Conference on Inventive Research in Computing Applications (ICIRCA), 15-17 July 2021.

[11] A. Arsalan, M. Majid, and S. M. Anwar, “Electroencephalography Based Machine Learning Framework for Anxiety Classification,” in Communications in Computer and Information Science, vol. 1198, pp.

[12] McDuff, D.; Gontarek, S.; Picard, R. Remote measurement of cognitive stress via heart rate variability. In Proceedings of the 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 26–30 August 2014; pp. 2957–2960.

[13] Florian Ritsert 1,2, Mohamed Elgendi 1, Valeria Galli 1 and Carlo Menon 1, Heart and Breathing Rate Variations as Biomarkers for Anxiety Detection,2022.

[14] Hyeon-Sang Hwang 1 and Eui-Chul Lee 2, Non-Contact Respiration Measurement Method Based on RGB Camera Using 1D Convolutional Neural Networks, published 2021.

[15] R. K. Nath and H. Thapliyal, “Machine Learning-Based Anxiety Detection in Older Adults Using Wristband Sensors and Context Feature,” SN Computer Science, vol. 2, article number 359, June 2021

[16] Jetli Chung and Jason Teo, Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges, Hindawi Applied Computational Intelligence and So Computing, Volume 2022,2022.

[17] K. M. Cooper, V. R. Downing, and S. E. Brownell, “The influence of active learning practices on student anxiety in large-enrollment college science classrooms,” International Journal of STEM Education, vol. 5, Article number: 23, Jun. 2018.

[18] S. Jones, C. Moore, et al., “New theory explains how beta waves arise in the brain,” Proceedings of the National Academy of Sciences, Jul. 2016.

[19] A. Arsalan, M. Majid, and S. M. Anwar, “Electroencephalography Based Machine Learning Framework for Anxiety Classification,” in Communications in Computer and Information Science, vol. 1198, pp

[20] F. Muhammad and S. Al-Ahmadi, “Human state anxiety classification framework using EEG signals in response to exposure therapy,” PLoS ONE, vol. 17, no. 3, e0265679, Mar. 2022.

[21] R. Vallat, “Bandpower of an EEG signal,” May 2018.

[22] H. Zhang, Q. Zhou, H. Chen, X. Hu, W. Li, Y. Bai, J. Han, Y. Wang, Z. Liang, D. Chen, F. Cong, and J. Yan, “The applied principles of EEG analysis methods in neuroscience and clinical neurology,” Military Medical Research, vol. 10, Article number: 67, Dec. 2023.