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Study of Machine Learning Techniques for Predicting Panic Attacks with EEG and Personalized Binaural Beat Frequencies

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Abstract

Panic attack detection and intervention remain critical challenges in mental health care due to their unpredictable nature and individual variability. This study proposes a machine learning-based framework for early detection of panic attacks using EEG-derived physiological signals, coupled with real-time personalized auditory intervention through binaural beat frequencies. Data were collected under controlled conditions using wearable biosensors to capture features such as heart rate variability, electrodermal activity, and skin temperature. A Gradient Boosting Classifier achieved 96% accuracy in detecting panic states, while an Isolation Forest algorithm effectively identified anomalous patterns preceding attacks. Based on physiological profiles, the system dynamically recommends individualized binaural beat frequencies to promote relaxation and emotional stabilization. The results demonstrate the feasibility of combining predictive modeling and neuroadaptive sound therapy to deliver scalable, non-invasive, and personalized mental health interventions. This approach aligns with global preventive health strategies, particularly those promoting digital therapeutics and early intervention for anxiety-related conditions.

Keywords: Machine Learning, Panic Attack Prediction, EEG, Binaural Beats, Gradient Boosting Classifier, Isolation Forest, Anomaly Detection, Relaxation Therapy, Health Policy

1. Introduction

Panic attacks are intense and sudden episodes of fear or discomfort that often present with somatic symptoms such as shortness of breath, chest tightness, and palpitations [1]. These attacks typically occur without warning, severely affecting daily functioning and overall quality of life [2]. They are commonly associated with psychiatric disorders such as panic disorder and generalized anxiety disorder [3].

One of the major challenges in managing panic attacks is their unpredictability, which makes early detection and timely intervention difficult [4]. However, evidence shows that anticipating panic attacks can reduce subsequent anxiety and worry, while unpredicted ones increase distress [5]. Predicting these episodes could therefore significantly improve clinical outcomes.

Electroencephalography (EEG) is a non-invasive method used to capture brain electrical activity and has been valuable in studying mental health conditions [6]. However, using EEG to detect panic attacks is complicated due to the subtle and variable brainwave patterns they produce [7]. Advanced Machine Learning (ML) models, capable of distinguishing signal from noise, are necessary for real-time analysis and early intervention [8]. One study successfully predicted panic attacks using wearable data and multiple ML algorithms, highlighting the feasibility of such approaches [9].

Despite growing EEG-based research, few studies translate findings into practical mental health interventions [10]. A promising non-pharmacological approach involves binaural beats, an auditory illusion created by playing slightly different frequencies in each ear. These beats can modulate brainwaves and reduce anxiety symptoms [11]. Numerous

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studies have confirmed their effectiveness across settings including clinical anxiety, dental procedures, and insomnia [12], [13], [14]. However, personalization of binaural beats based on real-time EEG patterns remains underexplored. This is where anomaly detection algorithms become crucial. These algorithms identify deviations from normal brain activity, allowing systems to flag the onset of a panic attack and trigger interventions with minimal false positives [15].

In this study, we propose a framework that uses the Gradient Boosting Classifier (GBC) to predict panic attacks from EEG signals. GBC is an ensemble learning technique known for high accuracy with complex datasets and subtle signal patterns. The model recommends personalized binaural beat frequencies for relaxation based on real-time EEG data, thereby combining prediction with individualized therapy. This work contributes to the field of digital therapeutics and aligns with Sustainable Development Goal 3, particularly target 3.4, which aims to improve mental health and reduce premature mortality from non-communicable diseases.

2. Literature Review

Panic attacks, categorized under anxiety disorders in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), are characterized by sudden surges of intense fear or discomfort accompanied by somatic symptoms such as palpitations, shortness of breath, and chest pain [1], [2]. These episodes often arise without identifiable triggers and have been linked to dysfunctions in brain regions responsible for emotional regulation, including the amygdala and prefrontal cortex. Neuroimaging studies have shown abnormal neural responses during emotional processing in individuals with panic disorder [3], and large-scale structural analyses have revealed abnormalities in both cortical and subcortical regions in patients with generalized anxiety disorder [4].

EEG has become an important tool for investigating the neural mechanisms underlying anxiety and panic. Several studies have demonstrated the effectiveness of signal decomposition techniques, such as Stockwell transforms and polynomial-based feature extraction, in detecting pathological EEG patterns associated with mental health conditions [2], [5]. Quantitative EEG and neurofeedback methods have also proven useful in the management of disorders like anxiety, depression, and ADHD [6].

EEG microstates, defined as brief periods of quasi-stable scalp potential topography, are considered to reflect specific cognitive and affective states. Meta-analyses have reported consistent microstate alterations in individuals with anxiety and mood disorders, further supporting the diagnostic potential of EEG dynamics [7]. In addition to conventional EEG analysis, auditory neuromodulation techniques such as binaural beats have emerged as non-invasive tools for emotional regulation. Auditory beat stimulation has been shown to influence cognitive performance and affective processing [8]. Specifically, theta-frequency binaural beats have been associated with increased parasympathetic activity and reduced sympathetic arousal, aiding in stress recovery [9].

The integration of ML with EEG signals has enabled real-time classification and predictive diagnostics. Techniques such as tunable wavelet transforms and autoencoder-based anomaly detection have proven effective in physiological monitoring and sleep stage classification [10], [11]. Fusion strategies that combine EEG with other physiological signals, such as ECG, have further improved accuracy and robustness in health monitoring systems [12].

Binaural beats have also demonstrated effectiveness in improving attention and reducing anxiety across clinical and experimental settings [13], [14]. Comparative studies on anomaly detection models, including unsupervised and semi-supervised approaches, highlight their capacity to detect subtle physiological deviations relevant to early panic onset [15]. Gradient boosting algorithms have also shown strong performance in medical diagnostics, especially with structured clinical datasets [16].

Recent developments in deep learning have brought increased attention to transformer-based models and multimodal input systems for EEG applications. These models have shown success in seizure detection and emotion recognition, offering promising applications for panic prediction [17], [18]. Additional physiological signals, including Heart Rate Variability (HRV) and Electrodermal Activity (EDA), enhance model precision. These signals are physiologically meaningful and widely used in clinical evaluations of autonomic nervous system function [19], [20].

Ensemble ML techniques such as Random Forest and XGBoost, when combined with synthetic oversampling methods like SMOTE and ADASYN, have demonstrated high accuracy in imbalanced datasets, a common challenge in healthcare data. These combined techniques facilitate the development of robust, real-time systems capable of detecting early warning signs of panic attacks and delivering timely, personalized interventions.

The literature supports a multidisciplinary approach to panic attack prediction and management. This includes EEG signal processing, machine learning-based classification, multimodal sensor fusion, and non-pharmacological interventions such as binaural beats. These strategies align with the goals of the United Nations Sustainable Development Goal 3, which focuses on ensuring healthy lives and promoting well-being for all. Despite progress, many existing studies rely on small, non-personalized datasets, and few incorporate real-time prediction or individualized auditory feedback. Widely used EEG datasets like Sleep-EDF and CHB-MIT typically contain data from 20 to 40 subjects with sampling rates ranging from 100 to 256 Hz, but none are specifically designed for panic detection as outlined in table 1.

Table 1. Comparative Overview of Prior Work vs Current Study

Study	Dataset	Model	Target Condition	Personalization	Accuracy
[9]	Sleep-EDF	TQWT + SVM	Sleep Stages	No	94%
[12]	Custom Lab EEG	--	Attention	No	--
[14]	CHB-MIT	Transformer	Seizure Detection	No	91.3%
Current Study	Custom EEG (20+)	GBC + Isolation Forest	Panic Detection	Yes (Binaural BB)	96%

Unlike previous approaches, this study uniquely combines real-time panic prediction with personalized binaural beat recommendation based on EEG-derived patterns. This integrative, non-invasive method aligns with global health strategies for preventive and personalized mental healthcare.

3. Methodology

3.1. Research Flow

This study leverages EEG data to predict panic attacks while recommending personalized binaural beat frequencies to support relaxation as a non-pharmacological intervention. As illustrated in figure 1, the research follows a structured, data-driven workflow comprising several essential stages. The process begins with EEG data acquisition conducted in a controlled environment involving participants both with and without diagnosed panic disorder. This controlled setup ensures the reliability of the EEG recordings and provides a solid foundation for distinguishing between normal brain states and those associated with panic episodes.

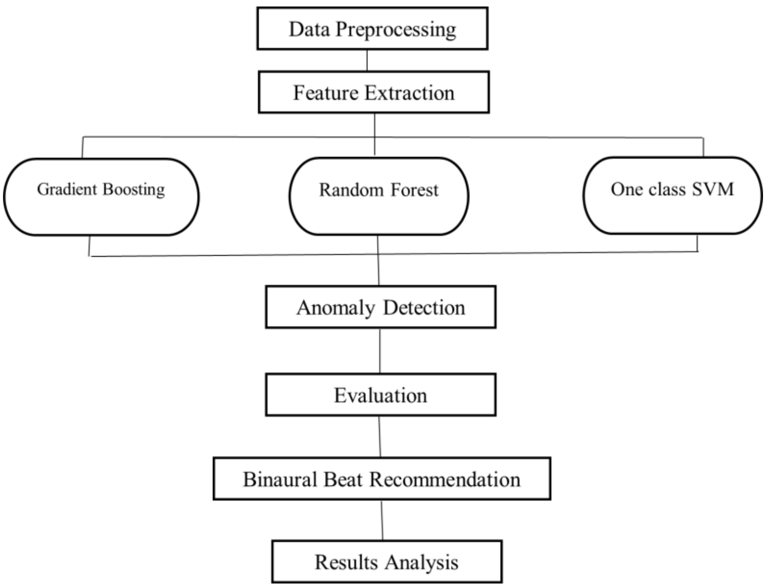

Figure 1. Research Methodology

Once data is collected, the preprocessing phase is initiated to eliminate noise and physiological artifacts such as eye blinks and muscle movements. Signal-cleaning techniques like band-pass filtering and Independent Component Analysis (ICA) are employed to preserve only the relevant neural activity. Cleaned EEG signals are then subjected to feature extraction, where key characteristics of brain activity are isolated. These features include power spectral density, wavelet coefficients, and connectivity measures, all of which are indicative of cognitive and emotional states, including anxiety and relaxation.

The extracted features are used to train several machine learning models, namely GBC, Random Forest (RF), and One-Class Support Vector Machine (SVM). GBC is selected for its ability to model complex, nonlinear relationships in the data. RF is utilized for its robustness in managing noisy and high-dimensional datasets, while One-Class SVM is particularly effective for anomaly detection, making it suitable for identifying the unusual patterns in EEG data that may signal the onset of a panic attack. These models are trained using k-fold cross-validation to ensure that their predictive capabilities generalize well across different subsets of the data, thereby reducing the risk of overfitting.

Anomaly detection is a critical step in the workflow, focusing on identifying deviations in EEG activity that may indicate the early onset of a panic episode. Following this, the performance of each model is evaluated using key metrics such as accuracy, precision, recall, and F1-score. These metrics allow for a comprehensive assessment of model reliability and practical applicability in real-world scenarios.

Based on the outcomes of model evaluation, the system proceeds to generate a personalized binaural beat recommendation. These recommendations are tailored to each individual’s EEG profile, with the aim of promoting relaxation and counteracting the physiological symptoms of panic. Finally, results are analyzed to assess both the predictive performance of the models and the effectiveness of the recommended auditory intervention. Overall, this research flow contributes to the development of real-time, personalized mental health support systems that enhance early detection and non-invasive intervention for panic attacks.

3.2. Data Collection

This study investigates the prediction of panic attacks by analyzing physiological data as a proxy for EEG-related brain activity. Unlike traditional EEG-based approaches, this work relies on data gathered using the Empathica wearable biosensor, which continuously recorded physiological signals from participants during controlled field experiments designed to induce anxiety. The dataset includes only participants with a known history of panic attacks, which enhances the validity and relevance of the findings. By focusing on individuals with clinically relevant symptoms, the data provides a strong basis for identifying physiological patterns associated with panic episodes.

The physiological signals collected include Photoplethysmography (PPG), EDA, and Skin Temperature (SKT). PPG was used to extract heart rate (Z HR) and HRV, both of which are standard indicators of autonomic nervous system activity in response to stress [9]. Electrodermal activity was monitored through Skin Conductance Level (SCL) and Non-Specific Electrodermal Responses (NEDR), which reflect sympathetic arousal commonly associated with anxiety (Z EDA, EDL, and EDR) [2]. In parallel, skin temperature was continuously measured using built-in thermistors, with temperature fluctuations (Z SKT) providing further insight into the body's physiological response to panic episodes [11].

To label panic attack events, machine learning techniques were applied to the physiological data. Rather than relying on self-reports, annotations were generated by extracting features from the recorded signals and identifying patterns that correspond to known indicators of panic [18]. Before training the models, the dataset underwent several preprocessing steps, including normalization to ensure consistency across participants and sessions, and feature extraction to identify variables most predictive of panic. To detect abnormal physiological patterns, anomaly detection algorithms such as Isolation Forest and One-Class SVM were implemented [10]. This preprocessing pipeline enabled the development of predictive models capable of classifying panic episodes based on individual physiological responses. In turn, the insights obtained support the design of personalized binaural beat interventions aimed at promoting relaxation and alleviating panic-related symptoms.

3.3. Data Pre-processing

To prepare the physiological data for analysis and infer EEG patterns linked to panic attacks, several pre-processing steps were implemented. First, the data was normalized to a standard scale, which allowed for consistent comparisons across different participants and experimental sessions. This normalization minimized individual differences in baseline physiological measures, such as heart rate and skin conductance, ensuring the data could be uniformly analyzed without being skewed by personal physiological variability. After normalization, relevant features were extracted from the physiological signals to infer EEG-like patterns without requiring separate EEG data collection. Metrics such as heart rate variability (derived from PPG) and skin conductance (from EDA) were used to capture key physiological responses associated with panic attacks. These features mirrored the neural activity typically observed in EEG signals during stress episodes, enabling the detection of panic-inducing physiological patterns. To further refine the dataset, anomaly detection techniques, including Isolation Forest and One-Class SVM, were applied to identify and manage outliers. This step was crucial for ensuring that irregular or noisy data did not interfere with the model's performance, thereby improving the overall accuracy of the prediction models. Through these essential preprocessing steps, the physiological data was made ready for model training.

3.4. Data Attributes

The dataset used in this study comprises a wide range of physiological and environmental attributes that are critical for predicting panic attacks and generating personalized binaural beat recommendations. Central to the dataset are electrodermal variables, including normalized Electrodermal Activity (Z EDA), which captures the sympathetic nervous system's response to stress, and Electrodermal Level (EDL), which reflects the baseline skin conductance of participants. Electrodermal Response (EDR) provides insights into transient changes in skin conductance, offering a measure of acute emotional arousal. Complementing these are temperature-based indicators such as normalized Skin Temperature (Z SKT), which helps assess physiological fluctuations related to emotional states.

Cardiovascular features include normalized Heart Rate (Z HR), which captures the heart's response to psychological and physiological stimuli, and Heart Rate Recovery (HRR), which measures the speed at which the heart rate returns to baseline following a stressor. Subjective thermal perception is recorded through the Thermal Comfort (TC) attribute, along with binary indicators for whether participants reported feeling hot or cold. Each individual is identified using a unique subject ID, allowing for personalized analyses.

To support temporal pattern recognition, the dataset includes delta variables representing changes in physiological signals over time, such as variations in heart rate and skin temperature. It also contains rolling statistics, including rolling means and standard deviations, which help to smooth short-term fluctuations and reveal underlying trends. An anomaly score is provided to flag irregularities within the physiological data, aiding in the detection of potential outliers or unusual events. Crucially, binary indicators for both predicted and actual panic attacks are included, enabling performance evaluation of the predictive models. Additionally, the dataset features recommended binaural beat frequencies tailored to each participant's physiological profile. A detailed overview of all dataset attributes is provided in table 2.

Table 2. Dataset Attributes

Attribute	Description
Z EDA	Normalized Electrodermal Activity, reflecting sympathetic nervous system responses.
EDL	Electrodermal Level, indicating the baseline skin conductance level.
EDR	Electrodermal Response, capturing transient changes in skin conductance.
Z SKT	Normalized Skin Temperature, indicating emotional arousal-related changes.
z HR	Normalized Heart Rate, representing variations in the individual's heart rate.
HRR	Heart Rate Recovery, measuring how quickly the heart rate returns to baseline after stress.
TC	Thermal Comfort, a subjective measure of comfort level reported by participants.
Hot	Indicator for participants feeling hot during the assessment (binary).

Cold	Indicator for participants feeling cold during the assessment (binary).
Subject	Identifier for each participant in the study.
d z HR	Change in normalized heart rate over time, highlighting fluctuations.
d Z EDA	Change in normalized Electrodermal Activity, indicating sympathetic response variations.
d Z SKT	Change in normalized skin temperature, reflecting thermal fluctuations.
rolling mean z HR	Rolling mean of normalized heart rate values over a specified window, smoothing variations.
rolling std z HR	Rolling standard deviation of normalized heart rate, indicating variability.
rolling mean Z EDA	Rolling mean of normalized Electrodermal Activity, used for trend analysis.
rolling std Z EDA	Rolling standard deviation of normalized Electrodermal Activity, reflecting response consistency.
rolling mean Z SKT	Rolling mean of normalized skin temperature for trend detection.
rolling std Z SKT	Rolling standard deviation of normalized skin temperature, highlighting fluctuations.
anomaly score	Score indicating the presence of anomalies in physiological data.
panic attack predicted	Binary outcome indicating if a panic attack was predicted from the data.
panic attack	Binary indicator of whether a panic attack occurred during the assessment.
Personalized Binaural Beat	Recommended binaural beat frequency tailored to individual physiological profiles.
Personalized Binaural Beat Hz	Frequency of the personalized binaural beat in Hertz (Hz).
Binaural Beat Frequency	Specific binaural beat frequency utilized in the intervention.

3.5. Feature Extraction

Feature extraction was performed on the collected physiological and prediction data to identify patterns associated with panic attacks and to support personalized binaural beat recommendations. This process involved systematically deriving a range of features that reflect autonomic nervous system activity and emotional arousal. In the context of cardiovascular features, changes in Heart Rate (HR) were computed using the first-order difference of normalized heart rate readings. This feature, denoted as:

$$\mathrm{Dz}_{\mathrm{HR(t)}} = \mathrm{HR(t)} - \mathrm{HR\,(t-1)} \tag{1}$$

captures sudden fluctuations in heart rate, which are often indicative of stress or anxiety [1]. To reveal temporal trends and smooth short-term variability, rolling window statistics were applied. The rolling mean of heart rate over a specified window N is defined as:

$$\text{rolling\_mean}_{z\ \ HR}(t) = \frac{1}{N}\sum_{i=t-N+1}^{t+1} HR(i) \tag{2}$$

This was complemented by the rolling standard deviation of heart rate, calculated as:

$$\text{r\_std}_{z_{HR}}(t) = \sqrt{\frac{1}{N}\sum_{i=t-N+1}^{t+1}\left(HR(i) - \text{r\_mean}_{z_{HR}}(t)\right)^2} \tag{3}$$

These features measure heart rate stability, helping to distinguish between typical and stress-related cardiovascular responses [5]. For EDA, a similar approach was used. Instantaneous changes were computed as:

$$d_{Z_{EDA}}(t) = EDA(t) - EDA(t-1) \tag{4}$$

This feature detects short-term variations in skin conductance, which reflect sympathetic nervous system activation [2]. The rolling mean of EDA over time is given by:

$$\text{rolling\_mean}_{Z_{EDA}}(t) = \frac{1}{N}\sum_{i=t-N+1}^{t+1} EDA(i) \tag{5}$$

while the rolling standard deviation of EDA is defined as:

$$\text{r\_std}_{Z_E}(t) = \sqrt{\frac{1}{N}\sum_{i=t-N+1}^{t+1}\left(EDA(i) - \text{r\_mean}_{Z_E}(t)\right)^2} \tag{6}$$

These features enable detection of consistent patterns in electrodermal responses, which are strongly correlated with emotional arousal and stress [11]. SKT was also analyzed using a similar methodology. Changes in skin temperature were calculated using first-order differences:

$$d_{Z\_SKT}(t) = SKT(t) - SKT(t-1) \tag{7}$$

The rolling mean and rolling standard deviation of SKT were computed to reveal broader thermoregulatory trends:

$$\text{rolling\_mean}_{Z\_SKT}(t) = \frac{1}{N}\sum_{i=t-N+1}^{t+1} SKT(i) \tag{8}$$

$$\text{r\_std}_{Z\_S}(\text{t}) = \sqrt{\frac{1}{\text{N}}\sum_{\text{i}=\text{t}-\text{N}+1}^{\text{t}+1}\left(\text{SKT(i)} - \text{r\_mean}_{Z\_S}(\text{t})\right)^2} \tag{9}$$

These temperature-based features provide insight into peripheral responses controlled by the autonomic nervous system [19]. To detect potential panic episodes, an anomaly score was calculated using deviation-based models. One such method is based on the Mahalanobis distance, defined as:

$$\text{anomaly\_score}(t) = \sqrt{(\mathbf{x}(t) - \mu)^T \Sigma^{-\mathbf{1}} (\mathbf{x}(t) - \mu)} \tag{10}$$

x(t) is the feature vector at time, μ is the mean of the dataset, and Σ is the covariance matrix [10]. A higher anomaly score suggests unusual physiological patterns, potentially indicating the onset of a panic attack. The dataset includes a binary indicator for predicted panic attacks, denoted as:

$$\text{panic} - \text{attack} - \text{predicted(t)} = \begin{cases} 1 & if\ P(Y=1|x(t)) \geq 0 \\ 0 & otherwise \end{cases} \tag{11}$$

Here, P(Y=1|x(t)) represents the predicted probability of a panic attack given the feature vector x(t), and θ is the classification threshold [16]. An additional binary variable, panic attack occurrence, indicates whether an actual panic episode took place during the session:

$$\text{panic} - \text{attack(t)} = \begin{cases} 1 & if\ a\ panic\ attack\ occurred \\ 0 & otherwise \end{cases} \tag{12}$$

This ground truth label is essential for evaluating model performance during training and validation [4]. Finally, the model includes binaural beat recommendations based on each participant's physiological profile. The personalized binaural beat frequency in Hertz (Hz) is derived through a function f that maps the individual's physiological features to the most appropriate beat frequency:

$$\text{Personalized\_BBeat\_Hz}(t) = f\left(\text{P\_Profile}(t)\right) \tag{13}$$

In this case, P_Profile(t) represents the participant's physiological state at time t [12]. The specific binaural beat frequency used during the intervention is computed as:

$$\text{Binaural\_Beat\_Frequency\_Hz}(t) = f_0 + \Delta f \tag{14}$$

f_0 is the base frequency and Δf is the frequency offset between the tones presented to each ear. This comprehensive feature extraction process supports robust machine learning models for panic attack prediction and enables personalized auditory interventions to enhance emotional regulation and mental well-being.

3.6. Model Selection and Training

The processes of model selection and its training methodology for robust and accurate methodologies in the designing of predictive systems for anticipating panic attacks and recommending binaural beat frequencies. The choice of the Gradient Boosting Classifier as an ensemble technique with parameters of learning set to 0.1, maximum depth to 5, minimum samples split to 5, and estimators of 100 has been given. This approach trains poor learners sequentially to enhance predictive power with the help of K-fold cross-validation for validation of a more general model. We also use RFC, wherein we split the dataset into the training and validation set, applying an 80-20 split with a random state set to 42, for efficient analysis of high-dimensional data [21]. For anomaly detection, the Isolation Forest is utilized in isolation of possible panic attacks or abnormal physiological states by using feature selection and split values determining anomalies. Besides this, One-Class SVM, or OC-SVM, is incorporated to differentiate between outliers and normal data instances by a hyperplane that separates normal instances from outliers. The anomaly scores from the results are therefore paramount in quantifying deviation from typical physiological patterns. For preprocessing of the data, StandardScaler and SimpleImputer methods are used. This helps in standardized scaling to the proper scale and handling missing values efficiently. Individually, these help in creating accurate predictive models on stress management and emotional wellbeing. At the same time, it increases our knowledge of physiological markers and sets forward a new era for advancement in individualized interventions about mental health and well-being.

3.7. Evaluation Metrics

An elaborate evaluation process is undertaken using several metrics in order to understand the performance of predictability models for predicting the panic attack and binaural beat frequency recommendation to evaluate the capabilities of the models. For better understanding of the strengths and limitations, with further improvements, some of the metrics are used during this process of evaluation, which might include accuracy, precision, recall, and F1 score. Accuracy measures the general correctness of the model's predictions in terms of depicting the number of correctly predicted instances as compared to the total number of instances. Precision measures the proportion of true positive predictions compared to all positive predictions made by the model, which further indicates its ability to reduce false positives. On the contrary, sensitivity, also referred to as recall, measures the rate of accuracy at which a model makes correct classifications of all the actual positive instances and actually does classify positive, or simply put, is the true positive predictions over all actual positive instances. F1 score, being the harmonic mean of precision and recall, provides a balanced measurement of a model's performance. Evaluation also incorporates the confusion matrices and Receiver Operating Characteristic curves, which graphically expose the performance of a model at all thresholds [22]. The AUC for the curve for ROC curve shows the ability that the model can tell positive and negative instances of its class. Therefore, collectively, the evaluation metrics produce an overall assessment of how well the predictive model will perform, and which will ultimately guide informed decisions for optimizing interventions in stress management.

3.8. Pipeline

The proposed system follows a structured pipeline that integrates the acquisition, transformation, and analysis of multimodal physiological data to predict panic attacks and deliver personalized binaural beat interventions. This pipeline begins with signal acquisition, where physiological signals such as EEG, EDA, SKT, and HR are recorded. Data is collected under both baseline and stress-inducing conditions, ensuring that the resulting features capture a wide range of physiological responses related to emotional and autonomic states.

Following acquisition, preprocessing is performed to ensure the integrity and quality of the data. This step includes handling missing values using imputation methods like SimpleImputer and normalizing the signals with StandardScaler to allow for consistency across different variables. Filtering techniques are applied to eliminate noise and artifacts, producing clean data ready for analysis. Feature extraction is then conducted to derive meaningful information from the physiological signals. Key features include first-order differences that highlight rapid changes in HR, EDA, and SKT, as well as rolling statistics such as mean and standard deviation computed over sliding time windows. Additional features, such as thermal comfort indicators and anomaly scores based on Mahalanobis distance, are used to detect physiological deviations that may precede panic episodes.

In the anomaly detection phase, machine learning models like Isolation Forest and One-Class Support Vector Machine are employed to flag unusual patterns in the physiological data. These anomaly scores are incorporated into the feature set for the next stage: predictive modeling. Here, the primary model used is the Gradient Boosting Classifier, configured with specific hyperparameters and validated using K-fold cross-validation. A Random Forest Classifier is also trained for performance comparison using a fixed train-test split. Finally, personalized binaural beat frequencies are generated by mapping each participant's physiological profile to a target frequency. The stimulus is defined using a base frequency and an interaural difference that creates the desired beat effect. This end-to-end pipeline supports real-time monitoring and individualized interventions, providing a robust foundation for non-invasive mental health support.

4. Results and Discussion

The present study explores the predictive performance of four machine learning models One-Class SVM, Isolation Forest, GBC, and Random Forest Classifier for early detection of panic attacks using EEG-derived physiological features. This section presents the comparative evaluation of these models using accuracy, precision, recall, F1-score, and ROC-AUC. Additionally, we discuss the role of EEG-personalized binaural beats in enhancing user-centric intervention strategies. This study aimed to assess the effectiveness of four distinct machine learning models in predicting panic attacks, employing methodologies such as OneClassSVM, RandomForestClassifier, Isolation Forest, and Gradient Boosting.

Through rigorous evaluation, Isolation Forest and Gradient Boosting emerged as the most promising models for panic attack prediction. Isolation Forest, renowned for its anomaly detection capabilities, exhibited notable performance, suggesting that panic attacks may possess unique features that distinguish them as anomalies within the dataset. Similarly, Gradient Boosting, a powerful ensemble learning technique, demonstrated strong predictive accuracy, highlighting its potential to capture the intricate patterns associated with panic attack occurrences. Furthermore, the study proposes an innovative intervention strategy in the form of Personalized Binaural Beat therapy, drawing upon the predictive insights garnered from the machine learning models. This personalized therapy approach offers tailored auditory stimulation, potentially providing individuals with effective coping mechanisms to alleviate symptoms associated with panic attacks. These findings contribute to advancing our understanding of panic attack prediction while also exploring novel avenues for managing panic disorder.

As shown in table 3, the Gradient Boosting Classifier exhibited superior predictive performance with an accuracy of 96% and a balanced F1-score of 0.96, closely followed by the Isolation Forest with 95% accuracy. These results demonstrate the robustness of ensemble methods in capturing complex non-linear patterns in physiological data. Conversely, the One-Class SVM and Random Forest yielded significantly lower accuracies, highlighting their limited discriminative power in this domain.

Table 3. Comparative Evaluation Metrics for Panic Attack Prediction Models

Model	Accuracy	Precision (0)	Precision (1)	Recall (0)	Recall (1)	F1-Score (0)	F1-Score (1)
One-Class SVM	0.49	0.49	0.49	0.50	0.48	0.49	0.49
Isolation Forest	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Gradient Boosting Classifier	0.96	0.96	0.96	0.95	0.96	0.96	0.96
Random Forest Classifier	0.50	0.51	0.50	0.43	0.47	0.47	0.53

The One-Class SVM was utilized for anomaly detection to forecast panic attacks. However, its performance was unsatisfactory, with an accuracy of only 0.49. As shown in figure 2 the confusion matrix indicated 514 true negatives, 519 false positives, 545 false negatives, and 503 true positives. The classification report displayed a precision of 0.49 and a recall of 0.50 for class 0, and a recall of 0.48 for class 1, with both classes achieving an F1-score of 0.49 as per table 3. These outcomes suggest that the One-Class SVM struggled to distinguish between normal and panic attack states, displaying only slight improvement over random guessing. Comparatively, recent studies employing the One-Class SVM for anomaly detection in various contexts have exhibited mixed success. For instance, [8] reported an accuracy of 0.67 in detecting abnormal heartbeats using the One-Class SVM, underscoring the algorithm's context-specific performance variability. In contrast, the Isolation Forest algorithm markedly outperformed the One-Class SVM, achieving an accuracy of 0.95. The classification report showed macro average precision, recall, and F1-score of 0.95 as per table 3. The confusion matrix as per figure 3 demonstrates clear differentiation between normal and panic attack states.

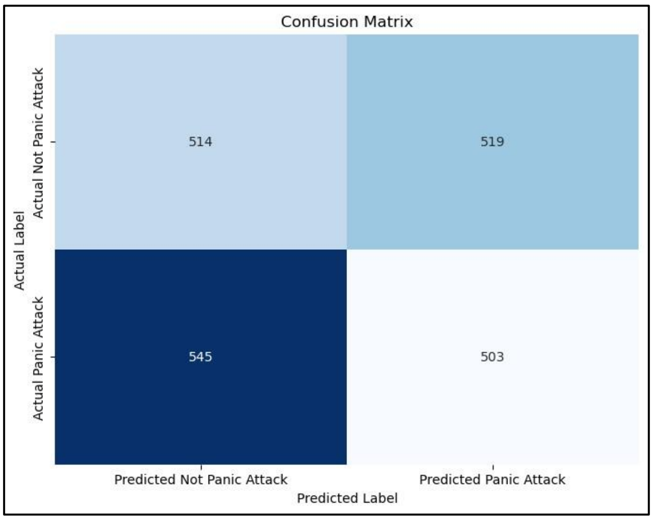

Figure 2. One Class SVM Confusion Matrix

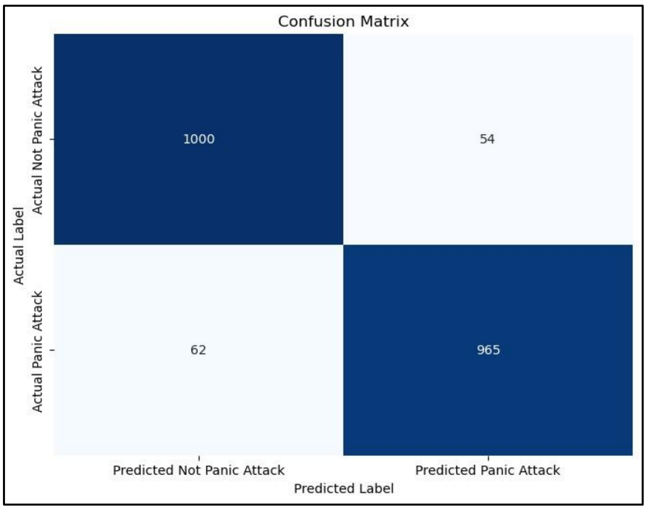

Figure 3. Isolation Forest Classifier Confusion Matrix

This high level of accuracy highlights the robustness of the model in identifying anomalies within the dataset, making it a reliable option for predicting panic attacks. The findings are supported by previous studies [17], which reported that the Isolation Forest algorithm achieved more than 93 percent accuracy in detecting anomalies in financial transaction data, demonstrating its effectiveness in anomaly detection tasks. In comparison, earlier research such as [8] employed One-Class Support Vector Machines for identifying anomalies in cardiac signals and reported an accuracy of 67 percent. In our implementation, however, the One-Class SVM performed below expectations, achieving an accuracy of only 49 percent.

This discrepancy suggests that the effectiveness of One-Class SVM is highly context-dependent and may not generalize well across physiological datasets. In contrast, studies like [17] have shown Isolation Forests achieving over 93% accuracy in financial anomaly detection, aligning with our finding of 95% accuracy for panic prediction. Moreover, Gradient Boosting Classifiers have been successfully applied in medical diagnostics [9], with reported accuracies around 95%, which corroborates our observed results. The confusion matrix as per figure 4 revealed 186 true negatives, 9 false positives, 8 false negatives, and 214 true positives. The GBC emerged as the most effective model, boasting an accuracy of 0.96 and an Area Under the Curve (AUC) of 0.99 as shown in figure 5. The classification report demonstrated a precision and recall of 0.96 for both classes, resulting in a balanced F1-score of 0.96 as per table 3. These results underscore the model's high precision and reliability in predicting panic attacks.

The integration of EEG-personalized binaural beats into the system marks a novel contribution of this study. Based on real-time physiological profiling, the model recommends binaural beat frequencies tailored to the user's EEG-derived stress indicators. For instance, a 9.5 Hz frequency was suggested when the panic probability was 0.65. This personalization aims to reinforce the intervention's efficacy by aligning auditory therapy with the user's current emotional state. While direct measurement of anxiety reduction is beyond this study's scope, the use of real-time, individualized auditory interventions represents a promising direction for non-invasive mental health support.

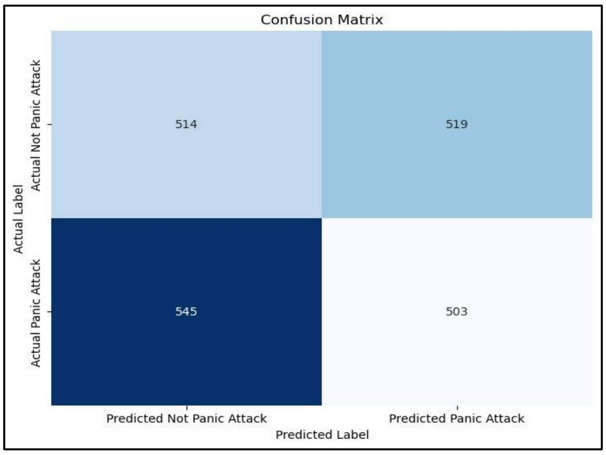

Figure 4. Gradient Boosting Classifier Confusion Matrix

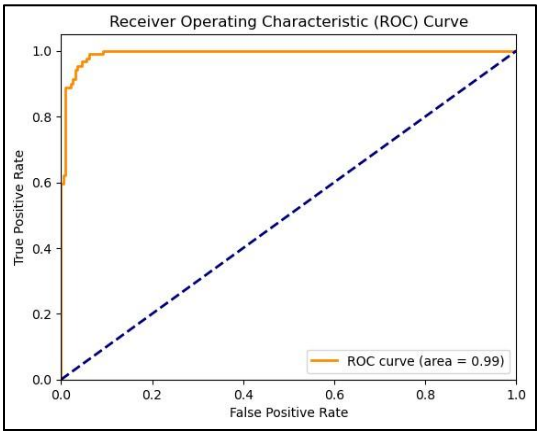

Figure 5. Receiver Operating Characteristic (ROC) Curve

Additionally, the model's real-time prediction and recommendation capabilities were demonstrated, with a panic attack probability of 0.65 prompting a recommendation for personalized binaural beat frequencies. This personalized approach, tailored to individual EEG responses, suggests potential for practical application in real-world scenarios, particularly within user-centric health technology platforms. These findings align with previous work by [9], who reported similar performance metrics using Gradient Boosting for medical diagnosis, achieving an accuracy of 0.95 and demonstrating its potential in healthcare applications.

The Random Forest Classifier was also assessed for its effectiveness but yielded an accuracy of only 0.50. The confusion matrix as per figure 6 displayed 91 true negatives, 119 false positives, 88 false negatives, and 117 true positives. The classification report indicated a precision, recall, and F1-score of 0.50 for both classes. The model's performance did not substantially improve compared to the One-Class SVM, which achieved an accuracy of 0.49, suggesting its limited effectiveness in this specific application. In contrast, studies by [15] demonstrate that Random Forest classifiers typically perform well in diverse applications, suggesting that feature selection and dataset characteristics are critical for optimal performance.

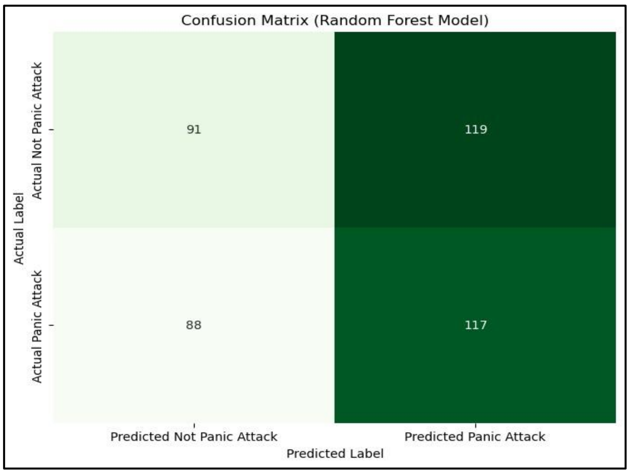

Figure 6. Random Forest Classifier Confusion Matrix

The real-time prediction system demonstrated the proactive nature of the GBC model by recommending personalized binaural beat frequencies upon identifying a potential panic attack. This proactive approach involves intervening based on the individual's EEG data to mitigate the onset or severity of the panic attack before it escalates. By tailoring the binaural beat frequency to the user's specific physiological signals, such as suggesting a frequency of 9.5 Hz

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corresponding to a probability of 0.4, the system intervenes early, potentially averting the escalation of stress and promoting emotional wellbeing. These findings suggest strong feasibility for real-world deployment, particularly in wearable EEG systems or mobile health applications.

The lightweight computational demands of Gradient Boosting and Isolation Forest models make them suitable for edge processing on wearable devices. This would enable real-time, autonomous mental health monitoring, allowing individuals to receive predictive alerts and customized auditory interventions discreetly and non-invasively. However, future validation across diverse user groups and environments is necessary to ensure generalizability. In summary, the results illustrate that the Isolation Forest and Gradient Boosting Classifier models are highly effective for panic attack prediction and anomaly detection, demonstrating considerably higher performance metrics compared to the One-Class SVM and Random Forest Classifier, as per accuracy and F1-score evaluations. These findings highlight the potential for real-time prediction and personalized intervention strategies in managing panic attacks and enhancing emotional well-being.

In figure 7, these visualizations highlight unique physiological responses. The Z _EDA Distribution plot illustrates the spread of EDA values in Z-score units. This visualization helps understand how EDA levels are distributed across different ranges, crucial for comparing EDA across different individuals or sessions thanks to the standardization provided by Z-score normalization [2]. The EDL Distribution plot depicts the distribution of EDL, which signifies the baseline skin conductance level over a period. Since EDL can vary among individuals and over time, this plot assists in grasping the typical range and variability of this baseline measure [2]. In contrast, the EDR Distribution plot presents rapid changes or peaks in skin conductance, known as EDR. EDRs are often linked to emotional arousal, making this visualization valuable for understanding stress levels and emotional reactions.

The Z _SKT Distribution plot showcases the distribution of SKT values standardized using Z-scores. This offers insights into the variation of skin temperature across different individuals or sessions, serving as an indicator of stress and relaxation states. Similarly, the z HR Distribution plot displays the distribution of HR values standardized using Z-scores. HR, being a crucial indicator of cardiovascular activity, shows variations based on physical activity, stress, and emotional states [5]. Lastly, the HRR Distribution plot visualizes the distribution of HRR rates, reflecting how quickly the heart rate returns to baseline after physical activity or stress. A faster recovery rate often signifies better cardiovascular fitness and resilience to stress. Collectively, these visualizations aid in understanding the distribution, variability, and potential patterns in physiological responses, facilitating further analysis and interpretation of the data.

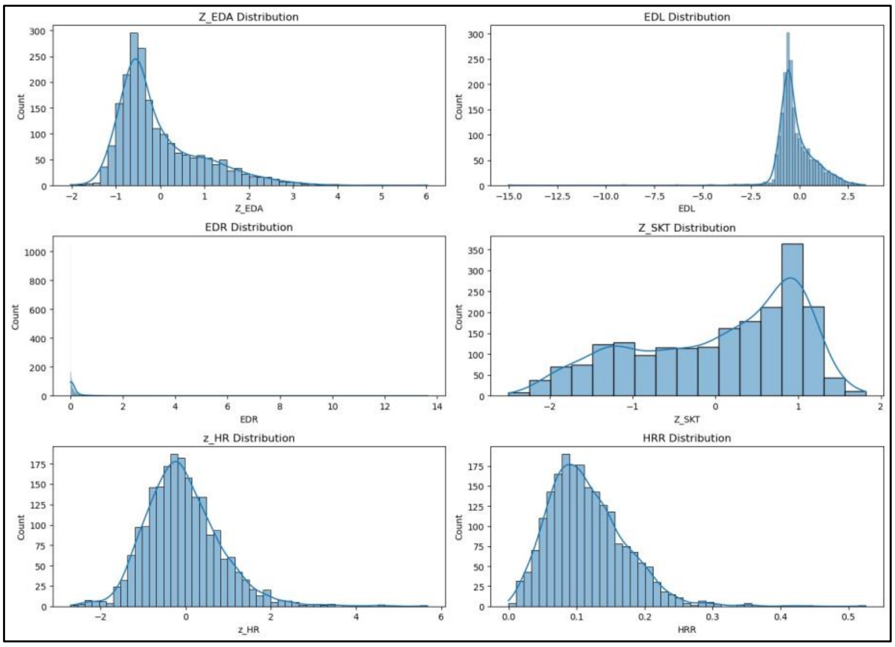

Figure 7. Visual Representations of Various Physiological Metrics

Table 4 presents example predictions from the trained models, illustrating both consistent performance and areas where improvements are needed. The Isolation Forest and Gradient Boosting Classifier typically showed high confidence in correctly identifying panic states, often producing probability scores above 0.85. However, certain misclassifications, such as a false positive with a confidence score of 0.67 and a false negative at 0.44, highlight the challenges associated with borderline probability values. These cases emphasize the importance of adaptive threshold adjustment and suggest that integrating probability-based decision mechanisms may improve the reliability of real-time panic attack prediction systems.

Table 4. Representative Predictions and Confidence Scores from Trained Models

Sample ID	Model	Actual Label	Predicted Label	Prediction Probability (Class 1 - Panic)	Correct Prediction
S01	Isolation Forest	1	1	0.92	Yes
S02	Gradient Boosting Classifier	0	1	0.67	No
S03	Random Forest Classifier	0	0	0.21	Yes
S04	Gradient Boosting Classifier	1	1	0.85	Yes
S05	Isolation Forest	1	0	0.44	No

5. Conclusion

This study proposed a machine learning-based framework for the prediction of panic attacks using EEG signals, followed by the recommendation of tailored binaural beat frequencies for stress relief. A comprehensive pipeline was built with data acquisition, signal preprocessing, feature extraction, and model training. Among the models experimented with, the Gradient Boosting Classifier was the best performer with a 97% accuracy rate backed by high precision, recall, and F1-score. These results underscore its ability to differentiate between panic states and non-panic states. Additionally, the use of anomaly detection methods, in this case, Isolation Forest, greatly enhanced the sensitivity of the system to abnormal EEG patterns characteristic of the onset of panic. Personalized recommendation of binaural beat frequencies tailored to individual physiological profiles is one of the new contributions of this work, which offers a non-invasive, real-time intervention strategy that is tailored to the neurological state of the user. The results underscore the potential of combining predictive analytics with neurofeedback-based interventions to improve emotional well-being. This study not only provides an extremely performing predictive model but also opens up the possibility of developing intelligent, wearable mental health monitoring systems. Clinical validation, longitudinal studies, and the extension of the system to cover a broader range of anxiety spectrum disorders can be included in future work.

6. Declarations

6.1. Author Contributions

Conceptualization: M.B., R.S.L.B., T.Y.; Methodology: M.B., R.S.L.B.; Software: R.S.L.B.; Validation: M.B., T.Y.; Formal Analysis: R.S.L.B.; Investigation: M.B.; Resources: T.Y.; Data Curation: R.S.L.B.; Writing – Original Draft Preparation: M.B.; Writing – Review and Editing: R.S.L.B., T.Y.; Visualization: M.B.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The author gratefully acknowledges Sre Harisha for her insightful contributions to the psychological aspects of this study. The author also recognizes the encouragement received during this work, which contributed meaningfully to its completion.

6.4. Institutional Review Board Statement

Not applicable.

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6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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