Diagnosis of Cardiac Disease and Panic Attacks: Through Wearable ECG Monitoring

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Abstract

Background: Wearable devices are increasingly important in mental health, monitoring physiological signals like ECG and HRV that reflect autonomic nervous system activity. While extensively researched for heart disease prediction, studies on predicting panic attacks are in early stages. Challenges include data collection difficulties, quantifying psychological factors, and analyzing different panic attack patterns.

Objective: To propose strategies for improving panic attack prediction using wearable devices, review methods that precedent studies accomplished in heart disease prediction, and addressing challenges in data collection, model development, and ethical considerations.

Methods: We propose a robust data collection and preprocessing protocol using wearable devices for long-term ECG and HRV monitoring. Also, we propose a comprehensive prediction model integrating both physiological signals and psychological factors (stress, anxiety, sleep patterns). Finally, we propose strict data privacy measures and ethical guidelines for handling sensitive personal information.

Results: In this paper, we propose an integration of psychological factors with physiological data for a more holistic prediction model. Implementation of ethical data collection practices, including explicit user consent and anonymized data management.

Conclusions: This approach offers a practical and scalable strategy for predicting panic attacks using wearable devices. It has the potential to improve the quality of life for individuals with panic disorders and introduce a new paradigm for preventive mental health management. The proposed service is expected to contribute significantly to the field of mental health care.

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Original Manuscript

Review

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KEYWORDS

Wearable Devices, Electrocardiogram (ECG), Heart Rate Variability (HRV), Panic Attack Prediction

Mental Health

Introduction

1.1 Advances in ECG Technology and Applications of Wearable Devices

Electrocardiography (ECG) is a test that records the heart's electrical signals, invented in 1902 by Dutch physiologist Willem Einthoven. This invention has become a powerful tool for diagnosing various heart diseases and has significantly contributed to distinguishing between normal and pathological states [1]. The original electrocardiograph used a string galvanometer to record the voltage difference caused by the heart's electrical activity across the limbs. However, due to a series of innovative discoveries and inventions by several key figures throughout the early 20th century, the 12-lead ECG system as we know it today was developed [2]. With the rapid advancement of information and communication technology (ICT) and the widespread adoption of the Internet of Things (IoT), portable devices have exponentially increased each year [3]. Additionally, an aging population has driven significant changes in the healthcare industry, focusing on the development of biosensors that enable real-time health monitoring. Among these devices, smartwatches are one of the most widely used wearable devices, capable of performing nearly all functions of a smartphone [3]. One such biosensor applicable to smartwatches is ECG, where these watches use a single electrode on the back of the watch face in contact with the wrist to record 1-lead ECG. Another electrode is placed on the front or side of the smartwatch, allowing users to activate the recording by touching the crown or surface with the opposite index finger (or hand). The list of smartwatches with ECG capabilities is continually expanding [4]. However, the ECGs captured by smartwatches still struggle to replace traditional 12-lead ECGs used clinically. This limitation is primarily due to critical issues like the uncertain tracings caused by noise in smartwatch recordings [5]. Nevertheless, recent studies demonstrate that smartwatches can detect certain levels of heart disease [6]. Additionally, with advancements in artificial intelligence (AI), heart disease prediction algorithms integrated with AI are continuously being proposed, suggesting that it may be possible to predict heart disease using single-lead or multi-lead data from smartwatches [7]. Current research indicates that a range of heart conditions can be detected and predicted through ECG-enabled smartwatches, with atrial fibrillation (AF) being the most extensively studied area [8]. Other conditions, such as arrhythmia, myocardial infarction, and heart failure, may also be predicted using smartwatches, though further studies are needed to improve accuracy and usability [9][10].

1.2 Association Between Mental Health and Cardiovascular Disease Through HRV Analysis

Association Between Mental Health and Cardiovascular Disease Through HRV Analysis Stress-related mental health disorders, such as anxiety and depression, have emerged as independent risk factors for cardiovascular disease (CVD) [11]. Anxiety and depression not only increase the risk of CVD but also impact the disease’s progression and course, potentially worsening it. Patients with anxiety disorders generally exhibit a tendency toward reduced heart rate variability (HRV), indicating excessive sympathetic nervous system activation. HRV, which reflects the balance of the autonomic nervous system, serves as a critical indicator in understanding the relationship between anxiety disorders and other mental health issues. Studies suggest that a similar physiological mechanism may underlie the heightened cardiovascular risk in patients with anxiety disorders [12]. Likewise, patients with major depressive disorder (MDD) also tend to show decreased HRV, which adversely affects cardiovascular health. Research indicates a close association between HRV and the severity of depression, with changes in HRV values before and after antidepressant treatment linked to symptom improvement [13]. This suggests that HRV may serve as a biological marker for depression. Furthermore, HRV can effectively distinguish specific mental health disorders, such as panic disorder, from generalized anxiety disorder. Existing research shows that machine learning models using HRV data can more accurately classify panic disorder and generalized anxiety disorder, demonstrating HRV's vital role in identifying subtle differences between anxiety subtypes [14]. Consequently, HRV has potential as a tool for developing personalized treatment strategies for individual patients.

However, predicting panic attacks presents a far more complex challenge than predicting heart disease. Panic attacks are challenging to predict as they may occur unexpectedly and are influenced by a range of factors, including psychological state and environmental elements. Therefore, a predictive model that integrates not only ECG data but also stress levels, sleep patterns, and environmental factors is essential [15]. With advances in wearable technology allowing for real-time physiological data collection, the importance of providing early warning signals before the onset of a panic attack and establishing preventive management services has increased. This paper explores the potential and challenges of predicting panic attacks using wearable devices and HRV analysis and proposes strategies to address these challenges. By establishing standardized data preprocessing protocols and combining psychological factors with physiological signals, a real-time predictive model can be developed to alert users before a panic attack occurs. This approach is expected to enhance the quality of life for those suffering from panic attacks and contribute significantly to the preventive management of mental health issues.

Potential

2.1 Opportunities in Wearable ECG-based Detection

2.1.1 Limitations of 12-Lead ECG

The 12-lead electrocardiogram (ECG) provides more accurate results compared to single-lead ECGs and is considered an essential tool for making clinical decisions regarding heart disease [16]. However, there are clear limitations. The primary limitation of the standard 12-lead ECG lies in the placement of the four limb electrodes and six precordial electrodes. For reliable measurements and interpretations, and to enable comparisons between successive ECG recordings, the electrodes must be correctly placed, particularly the precordial leads, where misplacement can lead to significant errors. This factor also makes it very challenging for patients to record a 12-lead ECG outside of a clinical setting [17]. The most commonly used method for obtaining long-term data with 12-lead ECG is Holter monitoring, which can record heart data for 24 to a maximum of 72 hours. However, Holter monitoring has its drawbacks. Often, symptoms of heart disease do not manifest during the monitoring period, and in several large-scale studies using mobile monitoring for syncope investigation beyond 12 hours, symptoms recurred in only 4% of cases, with an overall diagnostic yield of just 19% [18]. Therefore, a method allowing patients to record ECGs at home without needing the standard 12-lead ECG device would be highly beneficial.

2.1.2 Advantages and Potential of Real-Time ECG Data Collection via Wearable Devices

Real-time ECG monitoring using wearable devices presents an intriguing alternative to overcoming the limitations of 12-lead ECG tests. Wearable ECGs have consistently demonstrated non-inferiority in the detection of heart conditions, such as arrhythmias, when compared to current standard treatments. Various studies emphasize that these devices have the potential to improve patient care and reduce healthcare costs [19]. Multiple wearable ECG devices are currently available on the market, many of which are certified by the U.S. Food and Drug Administration (FDA) [20]. This suggests that ECG testing via wearable devices may have the potential to detect and predict heart disease at a clinical level. Wearable ECGs are particularly useful for continuously monitoring cardiovascular conditions in patients with chronic illnesses, as they provide superior accessibility by enabling monitoring outside of hospital settings. Additionally, continuous data collection allows physicians to tailor effective treatments to the specific characteristics of individual patients [21]. Although data limitations, noise, and reliability issues currently hinder wearable ECGs from fully replacing 12-lead ECG tests, the accumulation of more data, integration of artificial intelligence, and advancements in noise reduction techniques could make wearable ECGs a practical and highly accurate solution for patients with heart disease in the future. Meanwhile, data collection through wearable devices also plays a significant role in predicting mental health issues such as panic attacks. Wearable devices are particularly advantageous for real-time monitoring of physiological signals, including ECG and heart rate variability (HRV). Studies related to panic attacks have shown that data from wearable devices—such as heart rate, sleep stages (deep sleep, light sleep, and REM), and physical activity—are critical in predicting panic attacks, enabling long-term tracking of an individual's physiological state and daily variations for more precise prediction [15]. Physiological indicators like HRV are also useful for detecting mental fatigue or anxiety. In a study by S. Huang et al., HRV data collected via wearable devices detected fatigue states with over 75% accuracy, with the KNN algorithm showing the best performance [22]. Thus, the collection of physiological data using wearable devices demonstrates potential not only for the early detection of mental health issues like panic attacks but also for detecting psychological factors such as fatigue and anxiety. In conclusion, data collected through wearable devices plays a crucial role in the real-time detection of mental health issues, including panic attacks, fatigue, and anxiety. Furthermore, long-term and consistent data collection enables wearable devices to become an innovative approach to mental health management [23].

2.2 Effectiveness of Single-Lead-Based Prediction Models

2.2.1 Models for Detecting Panic Disorder and Panic Attacks

Recent studies highlight the potential of machine learning models based on electrocardiogram (ECG) and heart rate variability (HRV) data for predicting panic attacks (PA). Panic attacks, characterized by sudden physical and psychological symptoms, present a complex issue, and their early prediction and intervention can significantly improve patients' quality of life. Studies utilizing multiple physiological signals have applied various algorithms, such as Logistic Regression (LoR), k-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), and Multilayer Perceptron (MLP), to distinguish patients with panic disorder (PD) from healthy controls (HC). MLP, in particular, recorded a predictive accuracy of 75.61%, with ECG and peripheral temperature (PT) features derived from stress and recovery stages acting as key predictive indicators [24]. This demonstrates that multi-signal analysis based on ECG and HRV data can maximize the effectiveness of panic attack prediction.

However, it has been revealed that physiological signals alone are limited in further improving the accuracy of panic attack prediction. Consequently, recent studies have developed predictive models that integrate psychological factors alongside physiological signals. Research employing deep learning algorithms, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, has shown that initial psychiatric assessments—such as BDI (Beck Depression Inventory), BAI (Beck Anxiety Inventory), and STAI (State-Trait Anxiety Inventory)—serve as more significant predictive factors than physiological data. These models, combining physiological signals and psychological data, have raised prediction accuracy for panic attacks from 75.6% to 92.8%. Additionally, sleep duration has proven to be a critical protective factor, with sleep times between 6 hours and 23 minutes to 10 hours and 50 minutes showing a positive effect in preventing panic attacks [25]. Another study focuses on predicting panic attacks by integrating not only physiological and psychological signals but also environmental factors. Recent research demonstrates that a multi-factor predictive model, including environmental data like the air quality index (AQI), can enable seven-day predictions for panic attacks using machine learning. Specifically, a model using the Random Forest algorithm achieved a high prediction accuracy of 81.3%, with models that integrate physiological signals, psychological factors, and environmental data performing better than models using only a single data source [15].

2.2.2 Models for Detecting Other Mental Disorders

Efforts to detect mental health issues such as ADHD (Attention Deficit Hyperactivity Disorder) and CD (Conduct Disorder) through ECG signals are also underway. AI techniques, including machine learning (ML) and deep learning (DL), can analyze patients' ECG signals to classify ADHD and CD patients. In a study by Loh, H.W. et al., a 1D-CNN model was developed to classify ADHD, CD, and ADHD+CD patients using a small dataset, achieving a high accuracy of 96.04% [26]. ECG signals were divided into two-second segments for model training, and explainable AI (XAI) technology, specifically Grad-CAM, was employed to enhance the interpretability of the ‘black-box’ CNN model. Grad-CAM emphasized important ECG signal regions and provided temporal information on when these ECG features occurred. This study demonstrates the potential of applying explainable deep learning to diagnose ADHD and CD, supporting clinicians and mental health professionals in making more informed diagnostic decisions.

Methods for detecting sleep apnea (SA) using ECG data have also garnered attention, with research focusing on predicting sleep apnea based on real-time ECG signals collected from wearable ECG devices. Parbat, D. et al. proposed a multiscale entropy analysis methodology for detecting sleep apnea from ECG signals [27]. In this study, 60-second ECG signals were denoised with a 1D wavelet, and heart rate and respiration signals were subsequently generated to build a system that automatically detects sleep apnea events using various machine learning models, such as SVC, RF, and DT. Additionally, the ratio of breathing and heartbeat derived from ECG signals was calculated, capturing and analyzing respiratory sinus arrhythmia (RSA) phenomena during sleep. This approach enables continuous monitoring and real-time detection of sleep apnea using wearable devices at home, providing early warning signals to patients and caregivers. Moreover, mental health issues related to overwork are emerging as a major public health concern, particularly in East Asian countries, and wearable device-based systems for detecting mental fatigue show promise in effectively addressing these issues. In a study by S. Huang et al., HRV indicators were used to measure mental fatigue, and various machine learning algorithms, such as SVM, KNN, and Logistic Regression, were applied to develop a system that automatically detects fatigue [22]. Among these algorithms, KNN showed the highest performance, achieving an accuracy of 75.5% in cross-validation (CV). Key HRV indicators, such as NN.mean, PNN50, TP, and LF, were reported to play an important role in detecting mental fatigue. Studies like this reveal the significant potential of wearable ECG devices for real-time mental health monitoring and fatigue prediction, and advancements in this technology are expected to enable more precise mental health management and prevention in the future.

2.2.3 Models for Detecting Cardiovascular Diseases

Atrial fibrillation (AF) is one of the most extensively studied cardiac conditions that can be diagnosed through wearable ECGs. Patrycja S. Matusik and colleagues have shown significant progress in AF prediction and detection through machine learning-based heart rate variability (HRV) analysis [28]. Additionally, Buś et al. proposed AF detection using the MRMR algorithm, achieving an accuracy of up to 97.2% [29]. Numerous studies also support that traditional AI methods, such as Random Forest and SVM, can effectively predict AF [30]. Comparisons between wearables have been widely studied; for instance, a study comparing the Apple Watch Series 4 (AW4) with the KardiaBand (KB) in a cohort of elderly outpatients found that KB's automated algorithm outperformed AW4 in terms of accuracy and sensitivity in an outpatient setting [31]. However, there are limitations: automatic diagnosis alone is insufficient for clinical decisions regarding AF diagnosis and management. In a study comparing five wearable devices with single-lead ECGs to 12-lead ECGs for AF diagnosis, noise accounted for a quarter of the data, reducing diagnostic accuracy, and 99% of these errors were resolved when cardiologists manually reviewed the data [32]. Arrhythmias are also detectable using single-lead wearable ECGs, and research in this area is active. In a study by N. Sabor et al., the NEO-CCNN algorithm achieved an accuracy of 97.83% and a sensitivity of 96.46% in classifying arrhythmias, detecting over 99.79% of R-peaks in the MIT-BIH database [33]. Similarly, M.R. Thanka and colleagues developed an ensemble model based on CNN and LSTM, achieving 98.6% and 98.4% accuracy, respectively, in detecting five types of arrhythmias in the MIT-BIH dataset [34]. Thus, single-lead wearable ECG devices are effectively utilized for arrhythmia detection, providing users with timely arrhythmia alerts.

Wearable ECGs can also be applied to myocardial infarction (MI). Dimitrios Doudesis et al. used the CoDE-ACS score model to achieve excellent differentiation in MI diagnosis, showing that patients with a low likelihood of MI had lower 30-day and 1-year mortality rates compared to those with moderate or high likelihood [35]. Additionally, Gragnaniello et al. achieved accuracies of 89.4% and 94.76% for MI detection through a machine learning approach using normalization and a deep learning approach with spectrograms, respectively [36]. Gibson C.M. developed a CNN model using single-lead ECG data, achieving a detection accuracy of 90.5% for ST-elevation myocardial infarction (STEMI) [37]. Thus, wearable ECGs have the potential to provide reliable means for early treatment and improvement in MI outcomes.

E. Angelaki-Kaxiras and colleagues trained a Random Forest model to detect arterial hypertension from features derived from single-lead ECGs, achieving 81% accuracy, 80% sensitivity, and 83% specificity [38]. Additionally, A. Soysal demonstrated the capability of smartwatches in detecting supraventricular tachycardia (SVT), with cardiologists evaluating recordings made by a 6th-generation Apple Watch showing a sensitivity range of 66.0% to 76.6%. Although this is not yet clinically applicable, these studies prove the significant potential of AI in transforming smartwatch ECG signals into diagnostic tools.

2.3 Integration with Existing Healthcare Systems

Integrating wearable ECG monitoring technology with existing healthcare systems enables crucial interactions with platforms like hospital EMR (Electronic Medical Record) systems and telemedicine services. Integrating physiological data collected by wearable devices into EHR (Electronic Health Records) systems offers real-time data accessibility for hospitals and healthcare providers, enhancing patient monitoring effectiveness. Many healthcare institutions are undertaking projects to integrate wearable devices with EHR systems. For example, commercial EHR systems like Epic integrate data collected from devices like Apple HealthKit and Fitbit into patient portals, enabling remote tracking and management of patient health by healthcare providers [39]. This integration supports significant advancements, particularly in areas like chronic disease management, by allowing healthcare providers to make better clinical decisions based on collected data such as heart rate, blood pressure, weight, and physical activity levels. EMR integration of wearable devices is closely tied to telemedicine services, which are increasing in demand. Systems that allow data measured at home to be sent to hospitals in real-time, enabling immediate response from physicians, are in high demand. For example, real-time monitoring of psychological states such as panic attacks could send an alarm to the emergency room if necessary, enhancing the efficiency of wearable technology-based remote monitoring and emergency services. To enable these services, many healthcare systems and organizations are adopting user-centered design approaches to adjust workflows and integrate remote patient data in collaboration with third-party applications. Numerous healthcare providers have implemented wearable-EHR integration projects with Apple Health, Google Fit, Fitbit, Nokia, and Withings. Many devices on the market are equipped with the capability to connect directly to EHRs via HealthKit and Google Fit, allowing simple data like steps and weight to be collected and displayed, with more devices and data types being made available over time.

However, several challenges arise in the integration process, with interoperability issues and massive data processing posing major obstacles. Standardizing data communication between various devices and EHR systems is essential, as is the need for AI-based solutions that can efficiently process and interpret vast amounts of data. Another important issue is patient privacy and security; clear consent procedures and legal safeguards are required regarding how data collected by wearable devices is processed and which third parties are granted access rights. Addressing these challenges could lead to significant advancements in integrating wearable ECG monitoring technology into healthcare systems. This integration could not only allow for the monitoring of patients' health conditions but also contribute to enhancing preventive healthcare services. Early warning systems based on real-time data could detect early signs of disease, providing an environment where patients and healthcare providers can respond quickly, thereby improving treatment effectiveness and reducing unnecessary hospital visits. Ultimately, wearable ECG monitoring technology is set to become a crucial innovation that enhances personalized treatment, improves efficiency across healthcare systems, and raises the quality of healthcare services.

Limitations

3.1 Limitations of PPG Sensors

One of the main limitations of photoplethysmography (PPG) sensors, commonly used in smartwatches, is their high sensitivity to external factors, which can lead to signal distortion and reduce the accuracy and reliability of health monitoring results. PPG sensors operate by detecting changes in blood volume through light absorption, making them highly susceptible to variations caused by user movement, differences in skin tone, and ambient lighting conditions. These external interferences introduce substantial noise into the recorded signal, complicating the accurate measurement of physiological metrics such as heart rate variability (HRV), blood oxygen level, and respiration rate. Additionally, movement from physical activities like walking or exercising can significantly degrade signal quality, causing misreadings or complete signal loss. The fact that PPG sensors are often located at extremities like the wrist or fingertip exacerbates this issue, as these locations are more vulnerable to motion compared to centrally placed sensors like ECG electrodes. These design limitations pose a major challenge to consistently and reliably obtaining signals in real-world environments, which involve various environmental conditions and user activities. Furthermore, differences in sensor specifications and configurations across wearable devices lead to fluctuations in signal quality and consistency. The lack of standardized methodologies for acquiring and processing PPG data serves as a significant barrier to developing universally applicable health monitoring models.

3.2 Noise Issues in ECG Models

While ECG models are generally considered the standard for heart monitoring, they face limitations when applied in non-clinical or mobile environments. ECG models are highly sensitive to various interferences such as baseline wander, power line noise, and muscle contractions, which can obscure crucial signal elements like the P wave and T wave. Such distortions can make it challenging to detect subtle ECG signal patterns needed for accurately identifying cardiac arrhythmias like atrial fibrillation or ventricular tachycardia. In particular, baseline wander caused by respiration or body movements shifts the baseline of the ECG signal, making it difficult for machine learning algorithms to distinguish between normal and abnormal heart rhythms. Additionally, in wearable applications, issues such as changes in electrode placement and contact quality between the skin and sensor further exacerbate these interferences. For instance, improper electrode placement due to user movement or posture changes has been reported to lead to signal quality degradation or complete signal loss [40]. The impact exerted on wearable ECG sensors during physical activities also introduces additional noise, further degrading signal quality. These interferences pose particular challenges for machine learning models, as algorithms heavily depend on clean, high-quality data for effective training and accurate classification of cardiac events. Although signal processing techniques like wavelet decomposition and Independent Component Analysis (ICA) have been explored to mitigate these issues, their effectiveness remains limited when noise characteristics constantly change in dynamic environments. To overcome these limitations, advanced deep learning approaches that combine Long Short-Term Memory (LSTM) networks with adaptive noise cancellation techniques have been proposed. These methods enhance accuracy and robustness by allowing models to learn the temporal dependencies of ECG signals while filtering out noise. Additionally, hybrid models integrating attention mechanisms that selectively focus on clean signal segments have shown potential to improve the overall performance of ECG-based health monitoring systems. Research by Zhang et al. emphasized that combining such methods with emerging optimization techniques, such as Particle Swarm Optimization (PSO), can further fine-tune a model's ability to adapt to diverse signal conditions, providing a more comprehensive solution for reliable ECG signal processing on wearable devices [41].

3.3 Limitations in Predicting Mental Disorders

3.3.1 Data Bias and Difficulty in Generalization

Research on mental disorders often centers on Western adults, frequently failing to adequately reflect diverse racial, cultural, and socioeconomic backgrounds [15]. Models trained on data collected in specific environments may yield unreliable results in other settings. For example, as symptoms of panic attacks and anxiety manifest differently across cultures, models trained based on Western populations may perform poorly in regions like Asia or South America. Social context also plays a vital role, as the effects of similar stressors can vary depending on factors such as financial circumstances or family support systems. Furthermore, symptoms and triggers of mental disorders can vary widely from person to person. For instance, while some people with anxiety disorders experience symptoms in social situations, others may do so during extreme fatigue [14]. These factors complicate the development of universal prediction models, underscoring the need for broader data collection and algorithm improvements to create models that consistently perform well across various demographic groups and environments. Addressing data bias requires research that encompasses multicultural backgrounds and diverse populations, as well as the development of customized prediction models tailored to specific environments.

3.3.2 Challenges in Long-Term Data Collection and User Engagement

Consistent, long-term data is essential for predicting mental disorders through wearable devices. However, it is challenging to maintain sustained user engagement. While participants actively provide data at the start of studies, participation rates often drop sharply over time due to factors like fatigue, device discomfort, and concerns about data privacy [22]. Such data gaps negatively affect model training and performance, resulting in reduced predictive accuracy due to incomplete data. Enhancing the user experience is crucial for maintaining long-term data collection. Automated data collection systems and user-friendly interfaces can help improve engagement. For instance, features that automatically upload data such as heart rate or improvements in device comfort to reduce discomfort can encourage ongoing participation. Additionally, transparent data management policies and a clear consent process are needed to protect user privacy [15].

3.3.3 Challenges in Integrating and Analyzing Complex Data

Predictive models for mental disorders must consider a wide range of factors, including physiological signals (e.g., heart rate, HRV), psychological factors (e.g., anxiety, stress), sleep patterns, and environmental influences [25]. However, it is challenging to clearly analyze the interactions between these diverse data types. For example, when both sleep deprivation and stress are present, it is difficult to determine how each factor individually contributes to triggering a panic attack. The correlation between physiological data and psychological factors is complex, and traditional machine learning algorithms struggle to adequately capture the intricate interactions between these variables [24]. Advanced analytical techniques and deep learning-based models are necessary to effectively process complex data. For instance, deep learning models such as Long Short-Term Memory (LSTM) networks are advantageous for capturing temporal changes in data and handling complex interactions among variables. Moreover, multimodal models that can simultaneously analyze physiological, psychological, and environmental factors can improve prediction performance [26]. To enhance the prediction of mental disorders, it is essential to overcome the technical challenges arising from integrating and analyzing diverse data, requiring new analytical methodologies and data processing techniques.

Strategy

4.1 Data Collection and Preprocessing Strategy

Data Collection and Preprocessing Strategies Understanding the biomarkers of panic attacks in mental health research opens up significant potential for diagnosis, treatment, and prevention. ECG data offers crucial insights into the cardiovascular characteristics associated with these intense anxiety episodes. This study proposes ECG data collection and preprocessing strategies specifically tailored for panic attack research, presenting a goal-oriented approach that goes beyond existing datasets. The process of ECG feature extraction involves several stages. First, raw ECG signals are retrieved from the PTB ECG dataset, which serves as the foundation for all subsequent analyses. ECG processing is carried out using the ecg.ecg() function from the biosppy library, which applies various signal processing techniques to identify key features of the ECG waveform, especially the R-peaks. The R-peak, the most prominent peak in the ECG cycle, serves as the basis for calculating important ECG features. Primarily, heart rate variability (HRV) is calculated using the Root Mean Square of Successive Differences (RMSSD) method based on R-peaks. This method calculates the time intervals between successive R-peaks (RR intervals), determines their differences, and then computes the square root of these differences. RMSSD is a reliable indicator of short-term HRV, reflecting autonomic nervous system function. In addition to HRV, the biosppy library calculates the average RR interval to derive heart rate in beats per minute, while the detected R-peak count demonstrates heart rhythm and regularity over the analyzed period. The biosppy library also provides graphical visualizations of the ECG signal with marked R-peaks, enabling a quick evaluation of signal quality and R-peak detection accuracy. This allows for both quantitative and visual assessment of signal characteristics, facilitating exploration of their association with panic attacks.

4.2 Model Development and Optimization Plan

Model Development and Optimization Plan ECG signals possess complex temporal and spatial patterns, necessitating sophisticated analytical techniques. Traditional machine learning methods (e.g., decision trees, KNN, random forest, SVM) have been widely used in ECG classification but are limited in capturing the full complexity of these signals. Given that ECG characteristics encompass both immediate features and long-term heart rate patterns, a more advanced approach is required. This study proposes utilizing the ConvNetQuake model. This model was originally used in earthquake detection but has also been utilized as a deep-learning model for cardiologist-level myocardial infarction detection in ECG [42]. This model has proven to capture the temporal dependencies of the signal, essential for understanding the sequential characteristics and time-varying patterns in ECG data well. Additionally, dense layers are implemented for final classification, enabling the learning of complex, non-linear relationships among extracted features.

The initial development for the deep learning models for ECG analysis began with detailed data implementation of 507 ECG recordings from the PTB ECG Dataset. The data processing pipeline consisted of several key stages. First, we employed the BioSPPy library to calculate the Root Mean Square of Successive Differences (RMSSD) from the raw ECG signals loaded from channel_0. This calculation analyzed the successive differences between normal-to-normal (NN) intervals, providing a robust measure of beat-to-beat variability in heart rate. Quality control measures were implemented throughout, including range validation with strict boundaries for age (8-66 years), RMSSD (0.0048-2.3180), and heart rate (44.698-117.272 BPM), statistical verification through normal distribution assessment, and automated data integrity checks.

The target values were derived through an age-specific probability calculation based on established normal RMSSD ranges. We maintained a database of age-stratified ranges with distinct median and range values for each decade of life from ages 10 to 80+. For example, young adults aged 20-29 had reference values with a median range of 41.0-48.5 ms and overall range of 13.9-161.4 ms, while older adults aged 60-69 showed lower values with a median range of 20.4-20.7 ms and overall range of 5.6-104.8 ms, reflecting the natural decrease of RMSSD with age [43].

After converting RMSSD values to milliseconds and retrieving age-specific ranges, it calculated a standardized score based on median and range width, assuming a normal distribution where the range represents 96% of the data. For values within the normal range, the probability was calculated using the cumulative distribution function, while outlying values were assigned probabilities using an exponential decay function based on their distance from range boundaries. This approach provided a continuous measure of physiological normality that accounted for both age-specific variations and deviations from normal ranges. If the probability was over 0.5 we label the data as normal and the rest as abnormal.

The implementation of the ConvNetQuake deep learning model was conducted over 400 epochs, yielding the following results in ECG HRV anomaly classification. The final test results demonstrated a loss value of 1.1233 and an accuracy of 71.43%. The model achieved a precision of 83.72% and a recall of 70.59%, resulting in an F1 Score of 76.60%. Detailed metrics revealed 36 true positives, 7 false positives, 19 true negatives, and 15 false negatives, indicating a balanced performance in both normal and abnormal ECG detection capabilities.

The ConvNetQuake model's performance metrics demonstrate its potential as a viable tool for ECG-based HRV anomaly detection for panic disorder. Although there remains room for optimization. While the model shows strong precision in identifying abnormal cases (83.72%), the presence of false negatives suggests potential areas for improvement. Future work could focus on several key areas: (1) expanding the training dataset beyond the current 507 recordings to improve generalization, (2) implementing advanced data augmentation techniques to address class imbalance, (3) fine-tuning the model architecture with attention mechanisms to better capture subtle HRV variations, and (4) incorporating multiple ECG leads for more comprehensive analysis. Additionally, real-time processing capabilities could be developed to enable practical clinical applications. These enhancements, combined with the current foundation, could lead to a more robust system for automated ECG HRV analysis, potentially serving as a valuable tool for panic attack prediction in clinical settings.

Figure 1. Training & Validation Loss over time

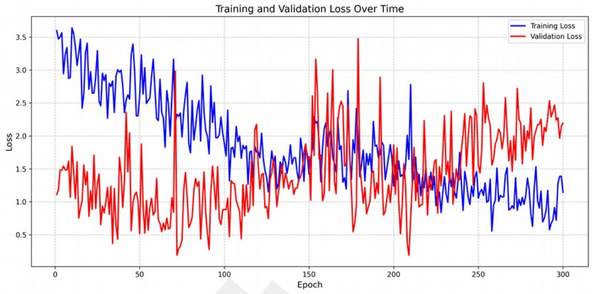
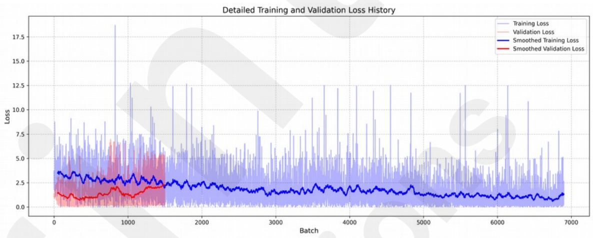


Figure 2. Detailed Training & Validation Loss History



4.3 Usability Evaluation of PanicMechanic and Integration Strategies for Mobile Applications

This study aims to draw on the PanicMechanic app as a case reference to develop a user interface (UI) design and functional integration plan for a mobile application that diagnoses heart and mental health conditions through wearable ECG monitoring. PanicMechanic focuses on monitoring the user’s heart rate (HR) during panic attacks (PA) and providing biofeedback to raise awareness of bodily responses during such episodes. In a similar manner, real-time monitoring of wearable ECG data can provide users with immediate feedback on HR-related fluctuations, contributing to early detection of cardiac and mental health issues. Findings from a pilot study of PanicMechanic indicated that participants subjectively reported an increase in HR during panic attacks, a key indicator supporting the efficacy of HR-based biofeedback. Notably, 90% of participants reported that using the app during panic attacks helped reduce the severity or duration of the attack, promoted personalized learning of fear responses, and enhanced their sense of physical control [44]. This user experience will serve as an essential reference for designing a mobile application that enables real-time monitoring of the user's condition and facilitates effective response to panic attacks or other heart-related conditions. Additionally, while 94% of participants in the PanicMechanic pilot study expressed a willingness to recommend the app, some found it challenging to open the app during a panic attack. To address this issue, push notifications can be used to prompt users to open the app when heart rate fluctuations are detected. By ensuring that the app is readily accessible in the early stages of a panic attack or cardiac event, diagnostic and intervention efficiency can be improved. This combination of real-time data detection and user alert systems will allow users to respond promptly at the onset of an attack. In terms of UI design, PanicMechanic's biofeedback feature serves as a highly useful reference. PanicMechanic provides users with a real-time HR graph, helping them intuitively understand bodily changes during panic attacks. Visualizing real-time ECG data, including heart rate and HR variability, will enable users to easily assess their condition. Additionally, features for logging symptom-related triggers and lifestyle data, as well as providing personalized insights based on this data, will be included. For instance, users can track signs of panic attacks or heart conditions and receive information on how lifestyle improvements may contribute to attack prevention, allowing for more effective self-management of health. Ultimately, with reference to PanicMechanic, the mobile application will be designed as a practical tool that enables users to monitor and manage panic attacks or heart conditions in real-time. Through this, users can enhance their control over their physical condition and contribute to early diagnosis and prevention of health issues.

4.4 Multimodal Panic Attack Detection Model Using Surveys

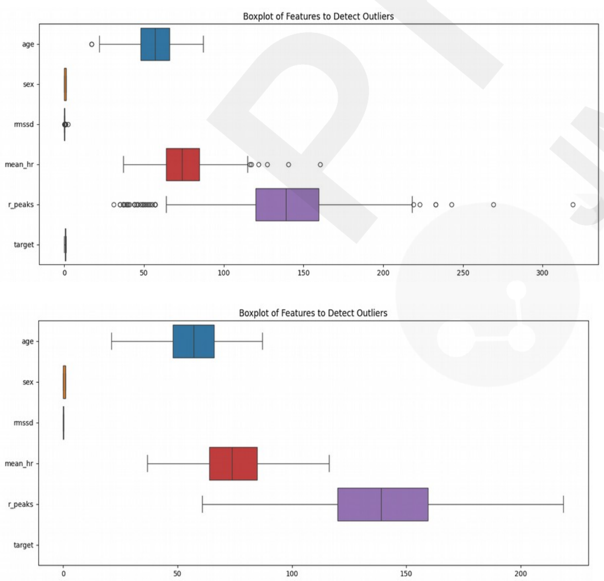
In a study implementing the Experience Sampling Method (ESM) using a smart speaker for 20 participants with mild depression, 93.8% preferred the Graphical User Interface (GUI), while only 3.5% preferred a mixed mode and 2.7% preferred the Voice User Interface (VUI). The results also showed that participants generally preferred GUI, but opted for VUI when they were physically occupied [45]. Based on these findings, we proposes a panic disorder prediction model that integrates the DSM-IV, a standard diagnostic tool for mental health professionals issued by the American Psychiatric Association, and the Panic Disorder Severity Scale (PDSS) survey into the existing prediction model. The DSM-IV consists of features across Axis 1 to Axis 5, including clinical disorders, personality disorders, and general medical conditions, while the PDSS comprises seven items. The DSM-IV will categorize the diagnostic criteria for panic disorder, while the PDSS will assess and monitor the severity. Using eight types of ECG biosignals—R-R intervals (RRIs), HR, SDNN of RRIs, sensitivity of parasympathetic activity (RMSSD, pNN50), VLF, LF, HF, and LF/HF ratio—the model will automatically detect panic disorder through machine learning [24]. By using this model in combination with GUI-based surveys as a multimodal tool, users can begin with a GUI-based survey upon starting the app. Based on these results, the next step will predict the likelihood of panic disorder by using a prediction model that incorporates physiological features measured from wearable ECGs, leading to more accurate diagnosis.

Appendix

The development and optimization of our machine learning models for ECG analysis began with detailed data implementation of 507 ECG recordings from the PTB ECG Dataset. The dataset comprised six distinct features: age (range 8-66 years), sex (categorical male/female), RMSSD (range 0.0048-2.3180), mean heart rate (range 44.698-117.272 BPM), R-peak count (range 881-2334), and target values (range 1.281217e-08 to 9.020004e-01).

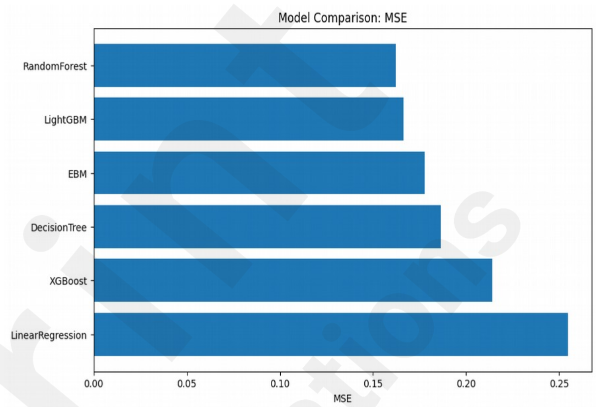
The preprocessing pipeline addressed several data challenges. Outlier treatment was performed through clipping, where extreme values were identified using the Interquartile Range (IQR) method and capped at the 5th and 95th percentiles, as shown in Figures 3. Multicollinearity was addressed through Spearman's rank correlation analysis, which revealed significant relationships between r_peaks and mean_hr (ρ > 0.85). This led to the creation of synthetic features that captured physiological relationships while reducing feature space redundancy. StandardScaler was applied for feature normalization, ensuring proportional contribution of all variables to the learning process.

Figure 3. Boxplot of features before and after clipping



Model development began with baseline exploration using multiple regression algorithms. We tested Linear Regression for linear relationship interpretation, Decision Tree Regression for non-linear pattern handling, and ensemble methods including XGBoost and LightGBM. Random Forest emerged as the superior choice, achieving an R^2 score of 0.6898 and Mean Squared Error (MSE) of 0.1622, as illustrated in Figure 4.

Figure 4. Model Comparison: Mean Squared Error



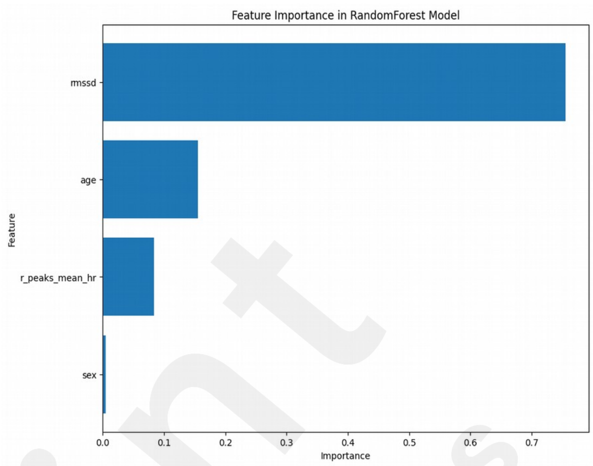
The Random Forest architecture was optimized through Bayesian optimization techniques, resulting in an optimal configuration of 226 decision trees with a maximum depth of 45 levels. This configuration balanced model complexity with generalization capability. Bootstrap sampling enhanced model robustness, while feature bagging increased sample diversity. Critical hyperparameters (min_samples_split, min_samples_leaf, max_features) were fine-tuned using cross-validated performance metrics. The optimization process employed a Gaussian Process model, proving more efficient than grid or random search methods, while incorporating both performance metrics and complexity penalties.

Model stability evaluation through cross-validation showed strong results: mean MSE of 0.1459, variance of 0.0006, and a coefficient of variation of 0.1636. Performance metrics were equally impressive, with 91.09% classification accuracy, 92.68% precision, 96.20% recall, and an F1 score of 94.41%. The confusion matrix showed excellent positive case identification, with 76 true positives against only 3 false negatives.

Illustrated in Figure 5, feature importance analysis through Random Forest's inherent ranking capability revealed that heart rate variability and age were the most significant predictors, validating the model's alignment with clinical knowledge. The final architecture demonstrated exceptional capability in handling non-linear relationships while maintaining interpretability. The ensemble nature provided natural uncertainty estimates through tree variance, offering valuable confidence metrics for clinical decision support. The implementation included efficient processing pipelines for both batch and streaming data scenarios, with a modular design ensuring adaptability to various clinical requirements while maintaining consistent performance.

This comprehensive approach resulted in a robust, clinically relevant model that effectively balances accuracy and interpretability.

Figure 5. Feature Importance in Random Forest



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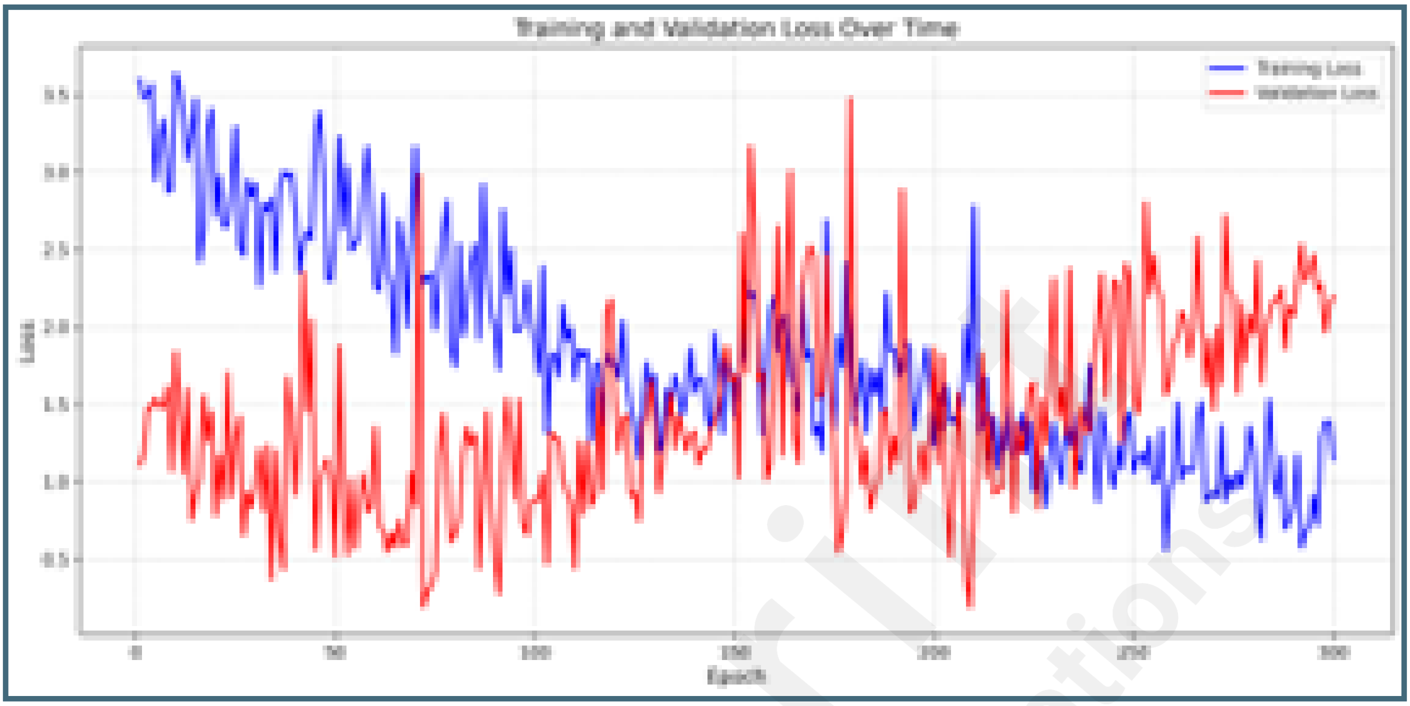
Supplementary Files

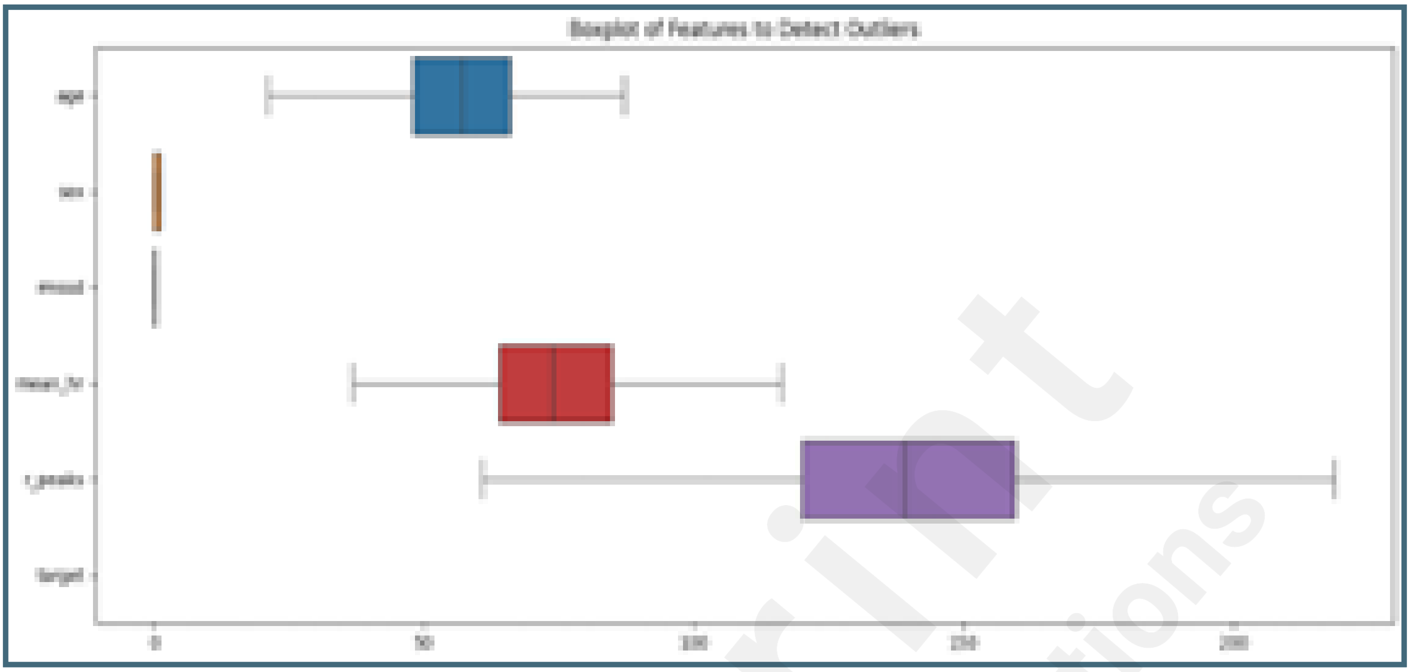
Figures

Training & Validation Loss over time.

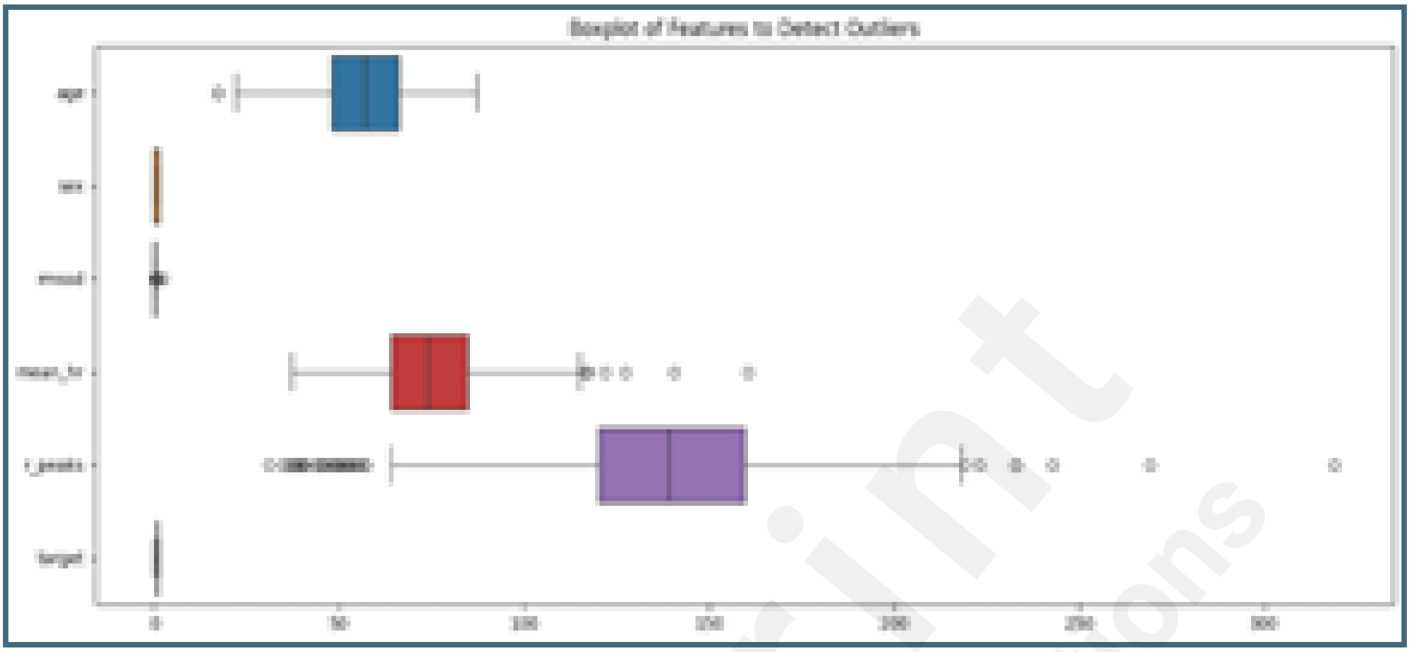


Detailed Training & Validation Loss History.

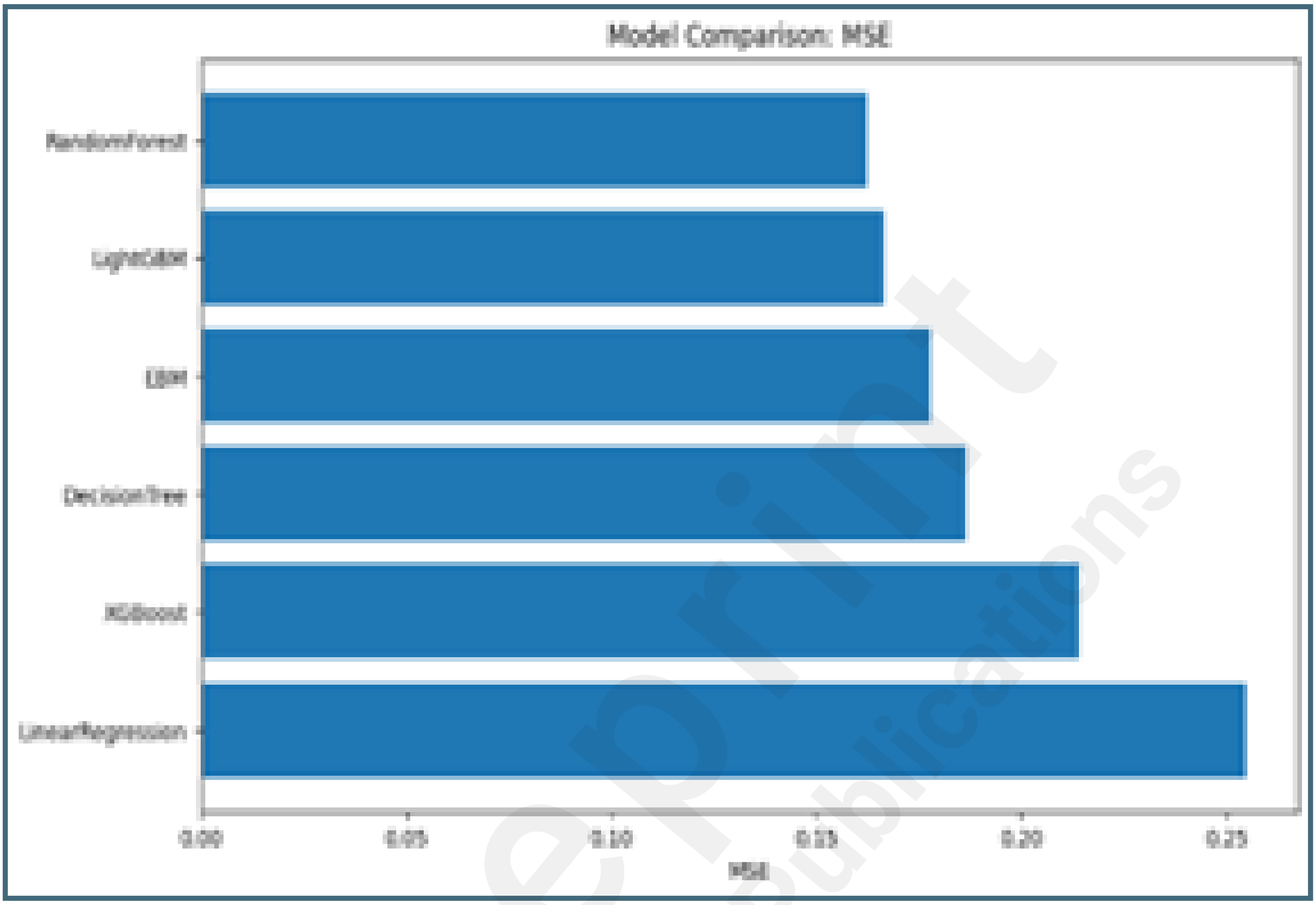
Boxplot of features before and after clipping.



Boxplot of features before and after clipping.



Model Comparison: Mean Squared Error.



Feature Importance in Random Forest.