Portable Holter with Cloud-Based Learning Analytics for Real-Time Health Monitoring

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ABSTRACT

The increasing prevalence of cardiovascular diseases underscores the need for efficient and user-friendly tools to monitor heart health. Traditional Holter monitors, while effective, are often bulky and inconvenient, limiting their use in real-world scenarios. This study introduces the Smart Portable Holter, a wireless device designed for real-time cardiac monitoring, enabling early detection of heart irregularities with enhanced accuracy and user convenience. The device captures continuous electrocardiogram signals and transmits them to a secure cloud platform for processing. Machine learning models, including Random Forest and Extreme Gradient Boosting (XGBoost), analyze the data to detect cardiac events. The system's performance was evaluated using real-world datasets, emphasizing accuracy and reliability in identifying cardiac arrhythmias. The Smart Portable Holter delivers an impressive 98% accuracy in detecting cardiac events. Its compact and wireless design enhances user comfort, allowing for seamless wear throughout the day. Coupled with advanced analytics, it offers detailed, time-stamped records that empower both users and healthcare professionals. These features facilitated early diagnosis and supported personalized treatment planning for patients with varying cardiac conditions. The Smart Portable Holter represents a significant advancement in cardiac care, combining portability, real-time analytics, and high diagnostic accuracy. By empowering patients and healthcare providers with actionable insights, it fosters proactive heart health management and contributes to improved clinical outcomes.

Keywords

Electrocardiogram; Early Diagnosis; Cardiac Arrhythmias; Holter Monitoring; XGBoost; Arrhythmias, Cardiac; Machine Learning

Introduction

Health is undeniably our most valuable asset, making its preservation and enhancement a top priority. The field of health sciences is expanding rapidly, integrating various disciplines such as medicine, biology, chemistry, and pharmacy. In parallel, advancements in technology, particularly electronics and information technology, have become integral to health management, leading to the development of e-Health. According to the World Health Organization (2024), e-Health is defined as the utilization of electronic tools to manage health resources and maintenance. E-Health covers three main areas, including a) the delivery and use of health information for health professionals based on the Internet and telecommunications devices, b) e-Health utilizes developments in information technology and e-Commerce to improve health services, and c) e-health uses e-Commerce and e-Business to manage the health system [1].

Cardiovascular diseases remain one of the leading causes of global mortality and a significant public health challenge [2]. Effective management of these conditions depends on early detection and continuous monitoring of irregular heartbeats using an Electrocardiogram (ECG) device. An ECG is a test that records the heart's electrical activity and provides a graphical representation to detect and monitor heart conditions. However, in regions with limited access to specialized ECG equipment and modern medical infrastructure, these monitoring efforts are often hindered, leading to delays in critical medical interventions [3]. Recent advancements in health monitoring systems based on Artificial Intelligence (AI) and the Internet of Things (IoT) have introduced practical solutions to these challenges [4,5]. These systems leverage cost-effective technologies such as Arduino for real-time ECG monitoring, enabling remote assessment and early detection of irregular heartbeats. Additionally, the integration of AI for automating heart rate pattern classification represents a major breakthrough, providing valuable resources for medical professionals working in resource-limited settings [6].

The increasing adoption of mobile ECG devices has significantly expanded remote monitoring capabilities, with comprehensive reviews highlighting their usability, technical features, and regulatory compliance. IoT-enabled portable ECG monitors have further enhanced real-time cardiac tracking by integrating cloud-based data transmission and emergency alert systems to improve patient safety [7,8]. Flexible and wearable electrodes have demonstrated significant improvements in ECG signal acquisition and durability, particularly in dynamic conditions such as exercise. These advances leverage nanomaterials and innovative structural designs to enhance comfort and signal fidelity [9]. Recent studies have also validated the efficacy of commercial wearable ECG sensors, such as Movesense HR+, in high-intensity sports activities, demonstrating their reliability for performance tracking [10]. Predictive analytics using ECG data has also emerged as a crucial tool in forecasting cardiovascular risks, particularly in underserved areas where healthcare access is limited [11]. Similarly, machine learning models, including hybrid CNN-LSTM architectures, have been developed to classify ECG signals with high accuracy, reducing the dependency on manual interpretation [12].

Building on this foundation, our research seeks to further increase the ECG monitoring technology's affordability and accessibility, particularly in Indonesia—a vast and developing nation with significant healthcare needs. Inspired by Qtaish and Wang [13,14] innovative IoT cloud-based ECG system, our project focuses on developing a cost-effective, user-friendly portable ECG device. This device, featuring an integrated algorithm to classify between abnormal and normal ECG signals, serves as an early warning system for identifying possible cardiac conditions [15,16]. We employed our custom-built portable ECG device, incorporating the ESP32 module, Arduino, and AD8232 sensor board, to collect and analyze ECG data from Indonesian university students. Using manual classification based on RR intervals and heartrate, we trained and validated a machine learning model with advanced techniques like Random Forest and Extreme Gradient Boosting (XGBoost) [17-19].

Our research aimed to advance portable ECG monitoring systems by addressing current technological gaps. We focused on providing a cost-effective, reliable tool for remote clinics and underserved areas, improving patient outcomes through early diagnosis and rapid response. The study details system design, manual classification, AI-based IoT integration, and implementation in resource-limited settings, promising enhanced cardiovascular monitoring and broad applicability.

Technical Presentation

This section outlines the development of a Portable Holter with Cloud-Based Learning Analytics for Real-Time Health Monitoring. The system integrates a wearable Holter device with cloud-based machine learning for continuous ECG monitoring and real-time analysis. The Holter device records ECG signals, transmitting them wirelessly to the cloud for preprocessing, feature extraction, and classification using machine learning models. The system detects cardiac anomalies and provides predictive insights, with real-time alerts and visualization for remote monitoring.

Hardware

The PCB design and schematics for the smart portable Holter monitor were created using KiCAD (open-source software for designing schematics and PCBs) software and printed on an FR4 board. This Holter design incorporates a NodeMCU ESP32 (a microcontroller with Wi-Fi and Bluetooth, ideal for IoT applications) microcontroller with Wi-Fi and Bluetooth capabilities, along with a SparkFun AD8232 module to monitor heartbeats and convert 3-lead signals into a single-channel analog output. The SparkFun AD8232 is an ECG signal acquisition board designed to amplify, filter, and condition the electrical signals generated by the heart for use in wearable health monitoring applications. The NodeMCU ESP32 receives data from the AD8232 module and transmits it via the Message Queuing Telemetry Transport (MQTT) protocol over Wi-Fi. MQTT is a lightweight communication protocol enabling real-time data transfer between the ESP32 and a cloud server. It also manages a Micro SD card module for offline data storage. This research led to the development of a smart portable Holter that integrates data archiving and online classification processing through an IoT-based database and real-time server. The system operates with a Raspberry Pi, supported by a Python algorithm, records data, and transmits it via Bluetooth to the database using MQTT.

Experiment Scenario

During the experiment, 30 participants provided data under three conditions: relaxed sitting, casual walking, and running. However, only 27 participants' data were recorded in the sitting scenario, likely due to communication errors during data transmission from the mobile ECG to the cloud, possibly caused by internet connectivity issues. The study employed essential tools and materials for ECG data collection, processing, and analysis. Each participant's ECG was recorded using the portable ECG device. This device, equipped with an AD8232 sensor board linked to an Arduino and an ESP32 module, enabled real-time ECG signal capture. Its compact design made it suitable for various environments, including resource-limited settings and remote monitoring. The lead placement is following the standard chest limb 3-leads.

Data Recording

Data collection was conducted through an experimental scenario in which each subject's ECG recording was taken while sitting and running. ECG electrodes were attached to specific points on the subjects' bodies prior to recording. Electrode placement on the chest was done on clean, dry skin, adhering to medical standards, and the conductive gel was applied to enhance conductivity between the electrodes and the skin. Correct electrode placement was allowed for accurate monitoring of heart electrical activity during the ECG signal recording. The signals were immediately read by an ESP32 microcontroller connected to a Wi-Fi network. The experiment was conducted with all subjects under identical conditions and durations. Each participant was recorded three times, with each recording session lasting approximately one minute. This approach ensured that the collected data was robust for in-depth analysis and model training. Before recording, each participant rested for

15 minutes, removed any jewelry, and remained still and silent during recording. The collected data was then transmitted, processed, and stored in the cloud.

Data Processing: Filtering, Feature Extraction, and Classification

At this stage, we present the design and evaluation process of a portable ECG monitoring system that allows for automatic heart classification. A comprehensive explanation is provided for the steps involved in data collection, preprocessing methods, and the implementation of Random Forest using XGBoost. A Kaiser windowed Finite Impulse Response (FIR) filter was used to improve the signal-to-noise ratio and reduce noise, ensuring the accuracy and reliability of the subsequent analysis in the preprocessing step. The key features extracted from the ECG signal include heart rate, PR interval, RR interval, QT interval, and ST segment, with typical values ranging from 60-100 bpm, 120-200 ms, 600-1200 ms, 350-420 ms, and 80-120 ms, respectively, in this order. When utilizing the Random Forest Classification algorithm, decision tree nodes are split based on the Gini Index as the criterion. The Gini Index (equation (1)) measures the impurity or disorder of a node by considering the class distribution and the associated probabilities of each branch, which helps determine the most likely branch for classification. In this context, 'pi' denotes the relative frequency of each observed class in the dataset, while 'c' represents the total number of distinct classes present in the data. The use of Random Forest combined with XGBoost provides a robust mechanism for classifying ECG signals. XGBoost's gradient boosting improves the model's performance by iteratively adjusting weights to minimize errors, thus enhancing classification accuracy. Moreover, the evaluation of model performance, including metrics such as accuracy, precision, recall, and F1 score, is essential for determining the system's effectiveness in real-world applications. With these steps, we aim to create an automated, reliable ECG classification tool capable of providing timely and accurate heart health assessments in a portable format, facilitating early detection of cardiac abnormalities [20-22].

$$Gini = 1 - \sum_{C=1}^{i} \left(p_i\right)^2 \tag{1}$$

XGBoost, a powerful open-source library known for its XGBoost method, introduces an advanced boosting mechanism to the machine learning pipeline. Boosting is an ensemble technique that involves sequentially training decision trees on randomly sampled subsets of data, where each tree is specifically trained to correct the errors made by its predecessor. This method is particularly effective for improving models with high bias and low variance, as it focuses on reducing bias over successive iterations. During each step of the process, the algorithm assigns more weight to misclassified data points, increasing the likelihood that the next tree will correctly classify these previously misclassified examples. This iterative process of refining weak learners leads to a much stronger and more accurate model over time. The mathematical representation of the Gradient Boosting process is provided in equation (2), which highlights the importance of adjusting the model to minimize cumulative errors across all trees. This approach can significantly enhance predictive performance by focusing on the correction of previous mistakes, allowing the model to converge to a highly effective solution [23,24].

$$F_0\left(x\right) = argmin \sum_{i-1}^{n} L\left(y_i, y\right) \tag{2}$$

For each, i starts from 1 to n, the pseudo-residuals are computed as follow:

$$r_{im} = \left[\frac{\delta L\left(y_i, F\left(x_i\right)\right)}{\delta F\left(x_i\right)}\right] for\, i = 1,\ldots,n \tag{3}$$

by fitting a base learner (e.g. tree) $h_m(x)$ to pseudo-residuals with input data training set of $\{(x_i, r_{im})\}_{i=1}^{n}$. The multiplier γ_m is then computed by solving the following one-dimensional optimization problem.

$$\gamma_m = argmin \sum_{i-1}^{n} L\left(y_i, F_{m-1}\left(x_i\right) + \gamma h_m\left(x_i\right)\right) \quad (4)$$

Then, the model is updated as follow:

$$F_m\left(x\right) = F_{m-1}\left(x\right) + \gamma_m h_m\left(x\right) \quad (5)$$

In this context, $L(y,F(x))$ represents the loss function, which could be log-loss, linear loss, hinge loss, or similar functions, while 'M' denotes the total number of base models. These models are constructed sequentially, making Gradient Boosting Decision Trees (GBDT) a non-parallelizable process, resulting in longer training times compared to Random Forests. Gradient boosting is based on learners with inherently high bias and low variance. GBDT follows a sequential approach, creating each tree to minimize the overall loss. This sequential training process often leads to longer training times than Random Forests, which build multiple decision trees independently and in parallel, significantly reducing the training duration.

By combining Random Forests with XGBoost, we create a hybrid model that leverages the strengths of both methods. Random Forests enhance ensemble diversity and reduce overfitting by aggregating independently trained decision trees in parallel, which also speeds up training. On the other hand, XGBoost's boosting mechanism, when applied within the Random Forest framework, improves the predictive accuracy of individual trees, especially when using Gradient Boosting Decision Trees with shallow depth values. This synergy results in a robust and balanced ensemble model that effectively addresses both bias and variance, leading to superior performance and efficiency across a range of machine learning tasks. Finally, we use performance metrics to assess the algorithm's ability to detect abnormalities in ECG readings. The schematic of the Wireless ECG monitoring system using the Random Forest with XGBoost classifier is shown in Figure 1.

Results

Figure 2 illustrates a portable ECG Holter monitoring system that integrates embedded hardware, cloud-based processing, and real-time web visualization for continuous cardiac monitoring. The system consists of electrodes, a SparkFun AD8232 ECG sensor, and a NodeMCU ESP32 microcontroller, which together capture and process ECG signals. These signals are then transmitted to a Raspberry Pi for further analysis using machine learning models (Python, TensorFlow) and stored in a MySQL database. The processed data is sent to a web-based platform using MQTT and JavaScript, allowing users to access real-time heart health insights remotely. The final image in the Figure 2 shows a compact portable ECG

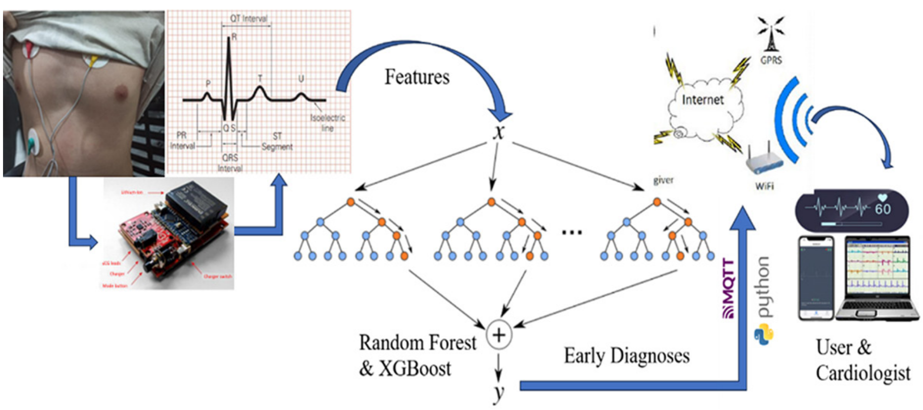

Figure 1: Scheme of wireless Electrocardiogram (ECG) monitoring using Random Forest with Extreme Gradient Boosting (XGBoost) Classifier

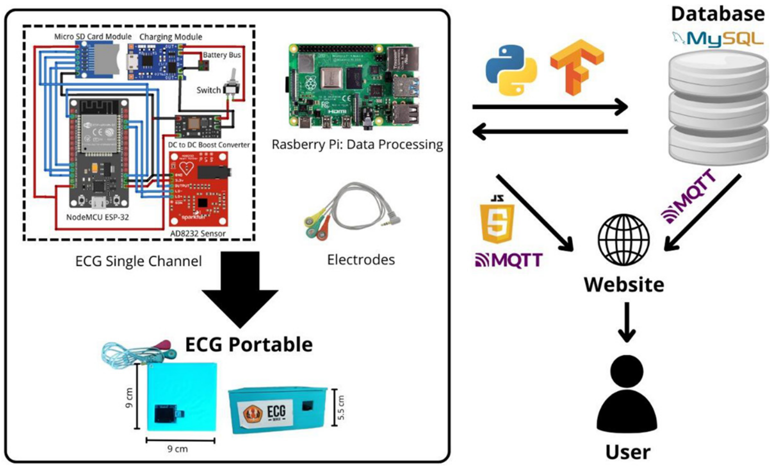

Figure 2: Schematic diagram of the Portable Holter System (ECG: Electrocardiogram, MQTT: Message Queuing Telemetry Transport)

device, indicating its real-world implementation.

This ECG Portable Holter is highly portable, designed to be lightweight, compact, and wireless, making it convenient for continuous monitoring without restricting movement. Its ease of use is enhanced by automated data acquisition, wireless connectivity (ESP32, MQTT), and cloud-based analytics, eliminating the need for complex setups. The system is also durable, as it is built with robust electronic components and a protective casing, ensuring long-term reliability and stable ECG signal acquisition in real-world conditions. With its combination of portability, user-friendliness, and durability, the ECG Portable Holter is well-suited for personal health monitoring and clinical use, facilitating early detection of cardiac abnormalities and proactive management of heart health.

The research and experiments were conducted in two locations: the Cogno-Technology & Artificial Intelligence Laboratory at the Department of Electrical Engineering (Building C), the Universitas Padjadjaran, and at the Universitas Prima Indonesia, Indonesia. Data was collected from 30 male participants aged 19–24, each of whom provided informed consent, supported by ethical clearance from the medical ethics commission. Preprocessing was applied to the recorded ECG data, shown in Figure 3a, to enhance its quality and extract relevant features. Following preprocessing, the PQRST complexes of each ECG waveform were extracted. These complexes represent the various stages of the cardiac cycle and provide essential information for analyzing heart rate patterns. Interval data, such as QT, RR, and ST intervals, were derived from the PQRST complexes. These intervals serve as features for classification and are key to understanding the time-dependent characteristics of ECG signals. The data collection and preprocessing steps described here were critical in producing a high-quality dataset for training and evaluating our machine learning model. By following rigorous data collection protocols and employing appropriate preprocessing techniques, we ensured the accuracy and dependability of the ECG.

In this study, we carefully preprocessed the dataset to guarantee high-quality input for our models. This preprocessing included applying feature scaling using the Standard Scaler, as shown in Figure 3b. We selected a comprehensive set of features for classification, such as the RR interval, PR interval, QT interval, Q-wave, ST segment, heart rate, and their

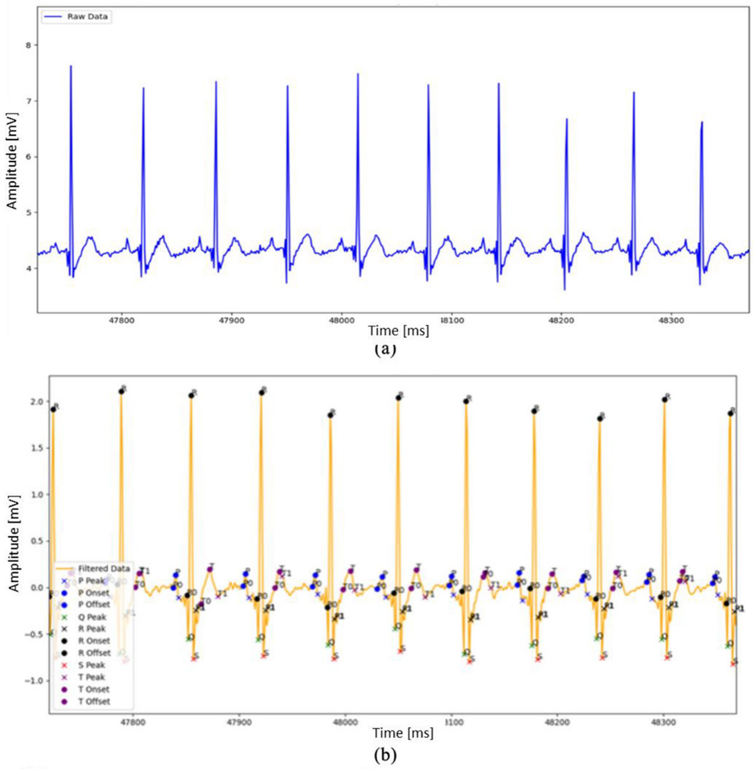

Figure 3: **a**) The recorded Electrocardiogram (ECG) signal **b**) processed and scaled ECG data

respective standard deviations. To preserve the integrity and reliability of the dataset, we employed an 80%-20% train-test split. This approach ensured that the evaluation of our model was unbiased and provided a clear measure of its generalization ability. By using this methodology, we aimed to optimize model performance and minimize the risk of overfitting, thereby ensuring more accurate and robust results.

To enhance predictive performance and mitigate overfitting, we adopted a hybrid approach that integrates the XGBoost algorithm with Random Forest. The Random Forest model, leveraging an ensemble of decision trees, significantly reduced the errors typical of individual trees, thereby increasing the model's robustness and generalizability. Meanwhile, XGBoost contributed to its sophisticated optimization methods, which further improved the accuracy of the predictions. The combination of these two powerful algorithms fostered a highly accurate and reliable classification model. Through extensive training and thorough evaluation of separate test datasets, our system consistently demonstrated superior performance and dependability, showcasing its potential for real-world application. This hybrid approach not only mitigates the weaknesses of each individual model but also capitalizes on their strengths, resulting in a more robust and scalable solution.

The accuracy of the developed early detection of heart irregularities is significantly influenced by various factors, some of which are discussed in this paper. Therefore, it is essential to examine the correlation among these variables to better understand their impact on performance. Furthermore, we generated a feature correlation heatmap, as shown in Figure 4, to investigate the physiological interrelationships within our dataset. The heatmap revealed several noteworthy correlations among various features.

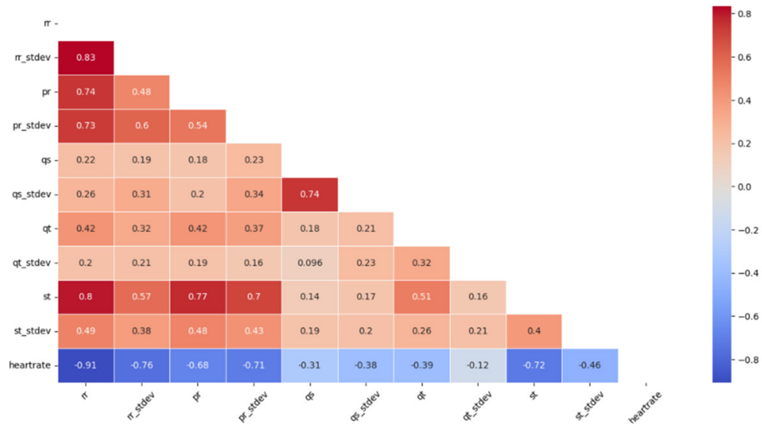

Figure 4: Feature correlation heatmap

For example, a strong positive correlation was observed between the standard deviations of the RR and ST intervals, suggesting a shared variability in these measures. Additionally, the standard deviations of the PR and RR intervals also showed a strong positive association, which raises the possibility of common regulatory mechanisms governing these intervals. The heatmap further highlighted consistent patterns, with a strong positive correlation between QS intervals and their respective deviations, as well as between ST and PR intervals. Conversely, a negative correlation between heart rate and several other variables was identified, indicating a potentially unfavorable relationship. This finding warrants further investigation to better understand its implications. Future studies are crucial to elucidate the nature and significance of this negative association, particularly in the context of cardiovascular health monitoring, as emphasized in the works of [14,25]. Expanding on this line of research could provide valuable insights into how these physiological parameters interact and influence cardiovascular function, ultimately enhancing monitoring systems for early detection and prevention of heart-related issues.

Figure 5 provides a detailed overview of key ECG features and their respective standard deviations, including parameters such as the RR interval, PR interval, Q-wave duration, QT interval, ST segment duration, and heart rate. These features, along with their standard deviations, serve as the foundation for automated classification into four categories: abnormal (AB), normal (N), potentially arrhythmic (PA), and highly potential arrhythmic (HPA).

The analysis reveals a weak positive correlation (0.128) between RR intervals and heart rate, indicating that longer RR intervals tend to be associated with slightly higher heart rates. However, this correlation is weak, suggesting that additional factors may also influence heart rate dynamics. A weak negative correlation (-0.196) is observed between PR intervals and heart rate, implying that shorter PR intervals may correspond to a slightly higher heart rate. Given the importance of PR intervals in assessing atrioventricular conduction, this relationship is critical for evaluating cardiac health. The correlation between QT intervals and heart rate is nearly zero (0.002), suggesting no linear relationship between the two. This lack of a linear connection emphasizes the need to consider potential nonlinear interactions and other physiological factors that could influence QT interval behavior. These findings highlight the complexity of ECG signal analysis and underscore the importance of accounting for a range of variables when assessing heart health and arrhythmic potential.

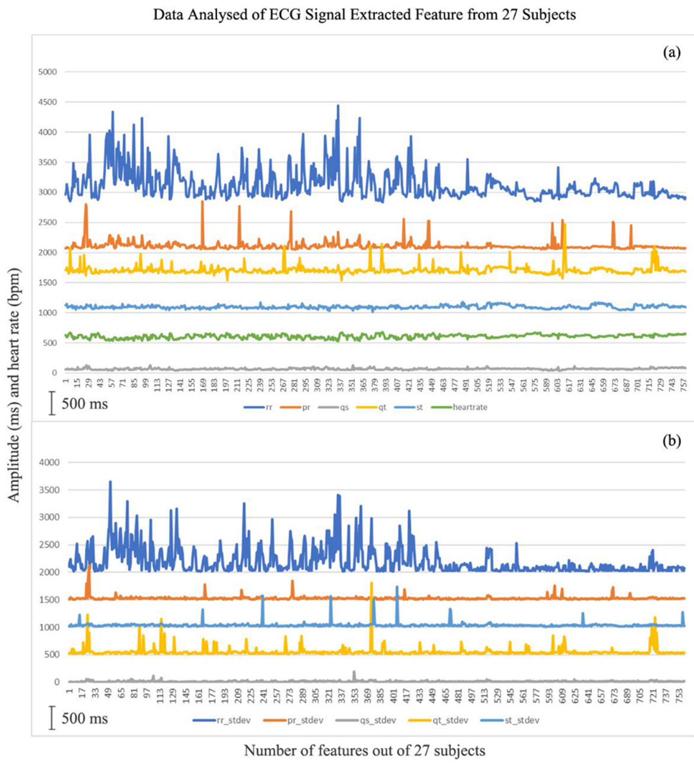

Figure 5: **a**) Data analyzed of Electrocardiogram (ECG) signal extracted feature from 27 subjects (blue, orange, gray, yellow, blue sky, green are RR, PR, QS, QT, ST, and heart rate intervals, respectively) **b**) Its standard deviation.

The standard deviations for the RR, PR, QS, QT, and ST intervals indicate significant variability within the dataset (Figure 5b), suggesting that these measures fluctuate across different individuals or conditions. Understanding the underlying factors contributing to this variability is essential for accurate clinical interpretation. The broad range was observed in RR intervals points to potential variability in the autonomic nervous system's regulation of heart rate. Additionally, the moderate variability in PR intervals, combined with their negative correlation with heart rate, may suggest possible issues in Atrioventricular (AV) conduction, which could affect electrical signal transmission between the atria and ventricles. The wide variation in QT intervals, along with moderate variability, raises concerns about the potential for arrhythmias, particularly if the QT duration exceeds normal limits, signaling a heightened risk for abnormal heart rhythms. Similarly, the moderate variability in ST intervals, coupled with their weak positive correlation with heart rate, could imply an association with cardiac stress or ischemia, conditions that may compromise heart function due to reduced blood flow. Overall, the high standard deviations across these measures emphasize the importance of considering individual patient variations, which underscores the need for personalized approaches to medical interpretation. This dataset offers valuable insights into the variability of ECG intervals and their relationship with heart rate, offering a starting point for further clinical investigations. Incorporating patient history, along with additional diagnostic testing, is essential for a more comprehensive understanding of cardiac health, enabling better-targeted treatments and interventions.

Our portable ECG monitoring system, utilizing both XGBoost and Random Forest algorithms, achieved an impressive classification accuracy of 98.03% for distinguishing among Abnormal (AB), Normal (N), Potential Arrhythmia (PA), and High-Potential Arrhythmia (HPA) cases, as presented in Table 1.

This high accuracy underscores the system's strengths in robustness, computational efficiency, and precise classification, highlighting its effectiveness for real-world applications. The system enables reliable, automated identification of irregular heart rate patterns, enhancing diagnostic precision and therapeutic decision-making with a classification accuracy exceeding 98%. Compared to related studies and existing techniques, our approach demonstrates competitive accuracy, confirming its potential for precise and effective ECG signal classification.

Achieving an overall accuracy of 98.03% reflects the system's capability to accurately categorize ECG data across different cardiac conditions. Notably, the Random Forest algorithm effectively manages this classification task's complexity. The relatively short execution time of 0.55 seconds further supports the system's suitability for real-time applications, as it allows for rapid processing and classification, which is essential for continuous monitoring settings. Cross-validation results reinforce the model's reliability, with accuracies ranging from 96.32% to 100% across folds, yielding an average accuracy of 98.68% with a low standard deviation of 1.42%. This stability across different dataset subsets suggests the model generalizes well without overfitting or underfitting the data.

Table 1: Confusion matrix of random forest prediction

		PREDICTED			
		AB	HPA	N	PA
ACTUAL	AB	13	0	0	0
	HPA	0	36	0	0
	N	1	0	20	0
	PA	0	2	0	80

AB: Abnormal, HPA: High Potential for Arrhythmia, N: Normal, PA: Potential for Arrhythmia

The system also demonstrates high precision (98.14%), recall (98.03%), and F1-score (98.04%), indicating its effectiveness in not only accurately classifying positive cases but also minimizing false positives and false negatives. This balance between sensitivity and specificity is crucial for reducing misclassification risks in medical applications, where diagnostic accuracy directly impacts patient outcomes. The cross-validation execution time of 2.73 seconds remains practical, given the additional computational demands. Overall, the high accuracy, low computational cost, and rapid processing capabilities of our ECG monitoring system establish it as a practical solution for real-time, continuous cardiac health monitoring, with significant potential for clinical applications and remote patient care.

The high overall accuracy, consistent cross-validation results, and strong precision, recall, and F1-scores indicate that the Portable Wireless ECG Monitoring System using Random Forest performs exceptionally well in automated ECG classification. The model's low execution time in both individual classification and cross-validation stages enhances its suitability for real-time applications, where rapid ECG data interpretation is essential. Additionally, the low standard deviation observed in cross-validation results suggests robust model performance, indicating that it effectively generalizes across different subsets of data, a vital trait for reliable deployment in diverse, real-world scenarios.

However, these results are promising, continuous monitoring systems often require an optimal balance between accuracy and computational efficiency to meet the demands of real-time use. Further optimization could be explored to reduce execution time even more, without sacrificing classification accuracy. It would also be valuable to compare the Random Forest model's performance with that of the XGBoost algorithm, as XGBoost is known for its speed and efficiency in handling large datasets. Such a comparative analysis could shed light on the trade-offs between the two algorithms, offering insights into selecting the most suitable model for this application, particularly when both accuracy and processing speed are prioritized.

Table 2 presents data on activity classifications across four health-related categories: Normal, Abnormal, Potential for Arrhythmia, and High Potential for Arrhythmia across three physical conditions: sitting (27 participants), walking, and running (each with 30 participants). A few cases were recorded in the Abnormal category: 2 cases during sitting and just one case during walking and running, indicating that precise abnormal heart rhythms were rarely detected regardless of physical activity. For the Normal category, participants increased physical activity by six during sitting, 12 during walking, and 15 during running, suggesting that higher activity levels may promote or reflect more stable cardiac function. The highest numbers were observed across all conditions in the Potential for Arrhythmia category, with 17 during sitting, 16 during walking, and 14 during running. This highlights a persistent presence of mild or early signs of arrhythmia, though slightly decreasing with increased activity. The High Potential for Arrhythmia category appeared only during sitting (2) and walking (1), with no cases during running. This category may indicate that intense physical activity either masks these high-risk patterns or helps regulate them temporarily. These findings suggest that sitting conditions are more effective for detecting arrhythmia risk, especially in high-potential cases, while physical activity improves or masks cardiac irregularities.

Table 2: Chart of classification result

	Sit	Walk	Run
Abnormal (AB)	2	0	1
Normal (N)	5	12	15
Potential for Arrhythmia (PA)	17	16	14
High Potential for Arrhythmia (HPA)	3	2	0

Discussion

Understanding these patterns can be valuable for refining classification models in medical diagnostics. Including additional features such as heart rate variability, duration of each activity, or other physiological parameters could enhance the model's accuracy in identifying early signs of arrhythmia. It is also important to recognize potential class imbalances within the data, as disproportionate representations of certain classes (e.g., more instances of sitting than walking or running) can bias machine learning models, potentially skewing their predictive performance. Addressing this might involve techniques like oversampling or weighting to ensure balanced representation during model training. In implementing a portable ECG monitoring system in rural and resource-constrained areas, challenges such as inconsistent power and limited internet connectivity must be considered. Ensuring device reliability in these environments requires robust power solutions, possibly using renewable energy sources like solar. Furthermore, training healthcare providers in these areas to operate and troubleshoot the system is essential for maximizing its efficacy. Tailored support for local users, along with minimal reliance on continuous connectivity, can make the system more resilient and effective in remote locations.

Our system stands out due to a suite of groundbreaking features tailored for high-impact healthcare applications in resource-limited areas. We have engineered a specialized algorithm with advanced signal processing techniques that not only enhances diagnostic accuracy but also significantly improves computational efficiency. These optimizations empower our portable ECG technology to provide early detection and intervention for heart-related conditions, which can lead to markedly better patient outcomes in underserved communities. Our technology is uniquely suited to meet the demands of these settings by leveraging cost-effective, readily available components and integrating sophisticated machine learning models. This design yields a highly dependable tool for detecting and categorizing heart rate anomalies, while maintaining affordability and accessibility. Additionally, our system is customized to align with local healthcare practices and environmental factors, enhancing its practical value and effectiveness for end-users in specific regions.

Looking ahead, we plan to rigorously validate our system across diverse real-world scenarios, including long-term monitoring studies and pilot programs. This next phase will address essential logistical and infrastructural challenges, such as connectivity limitations and user training requirements. To optimize usability, we will actively seek feedback from healthcare professionals and refine our training protocols, ensuring the system meets real-world needs effectively. Our ultimate goal is to drive widespread adoption, helping bridge healthcare gaps and improve cardiac care in areas where it is needed most.

Conclusion

This research successfully developed a Smart Portable Holter to address the growing need for efficient and user-friendly cardiac monitoring tools amid the rising prevalence of cardiovascular diseases. Traditional Holter monitors, while effective, are often bulky and inconvenient, limiting long-term and real-world usability. In contrast, the proposed system integrates XGBoost with a Random Forest classifier to analyze ECG signals, achieving 98.03% accuracy in classifying heart rate patterns and detecting anomalies. Using the Portable Wireless ECG Monitoring System dataset, the model demonstrated swift execution times of 0.55 seconds per classification and 2.73 seconds for cross-validation, ensuring suitability for real-time applications. Its reliability is reinforced by cross-validation accuracy ranging from 96.32% to 100% with a low standard deviation of 1.42%, indicating strong generalization across different datasets. By combining portability, real-time analytics, and high diagnostic accuracy, this device enhances cardiac care, empowering both patients and healthcare providers with actionable insights for early detection and proactive heart health management, making it a practical alternative to traditional Holter monitors.

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Authors' Contribution

A. Dharma, as the corresponding author, made substantial contributions to the design of the study and supervised the overall research. P. Sihombing was responsible for the theoretical framework and provided expert advice on the methodologies used. S. Efendi contributed significantly to the data analysis and algorithm development. H. Mawengkang, as a mathematics expert, assisted with the statistical modeling and computational aspects of the study. A. Turnip provided critical insights into the electrical engineering applications, contributing to the development of the hardware interface for the study. All authors read and approved the final manuscript.

Ethical Approval

The protocol of the human study was approved by the local ethical committee, Universitas Prima Indonesia, Medan, North

Sumatera, Indonesia, under approval number: 072/KEPK/UNPRI/V/2023.

Informed Consent

This study was approved by the Universitas Prima Indonesia, Faculty of Science and Technology, and written informed consent was obtained from all participants in this study.

Conflict of Interest

None

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