BeatSense: Python-Based Arrhythmia Detection Through Signal Processing

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Introduction

Background of the Study

Globally, Cardiovascular Diseases (CVDs) are the leading cause of death, with an estimated number of 17.9 million lives taken annually. In 2022, 19.8 million people died from cardiovascular diseases (World Health Organization, 2025a, 2025b). This number accounts for 32% of all deaths that year.

In the Philippines, one of the top causes of mortality is Cardiovascular Diseases, specifically ischemic heart disease (Mapa, 2024). This shows the underlying concern in the field, placing a heavy burden on both the patients and the healthcare system.

Arrhythmia, also called dysrhythmia, is a condition characterized by the irregular heart rate or rhythm of the electrical signals in the heart. In a normal condition, the heart beats in an organized and coordinated pattern (Cleveland Clinic, 2023). Furthermore, according to (Mayo Clinic, 2023), a heart arrhythmia can resemble a rapid, pounding, or fluttering heartbeat. This has different types: Tachycardia and Bradycardia. Tachycardia is a condition where the heart beat is faster than the normal range of 60-100 bpm. On the other hand, Bradycardia is the slowing of the heart rate, going below the normal range.

Additionally, the condition can be harmless at times, but certain types of Arrhythmia can lead to fatal symptoms (Mayo Clinic, 2023). If not treated, Arrhythmia can damage the heart, brain, and other organs. This may result in cardiac arrest, heart failure, or a potentially fatal stroke (National Heart, Lung, and Blood Institute, 2022).

The traditional ECG interpretation relies heavily on manual analysis by healthcare professionals. Whilst this method is accurate, it has several limitations. In clinical situations, manual interpretation of long ECG recordings can be inefficient because it frequently takes a long time and effort. Additionally, human interpretations may be affected by irregularities and, sometimes, the ability to detect tiny arrhythmias. Furthermore, accessibility to cardiologists and advanced diagnostic equipment remains limited, especially in regions with limited resources, which limits prompt and precise diagnosis.

The researchers aim to develop BeatSense, a software-based program for ECG signal processing specifically for detecting arrhythmias and the different types of them, utilizing the power of digital signal processing and machine learning. The system offers automated diagnostic interpretation and waveform visualization by filtering noise, identifying important cardiac properties, and categorizing beats as normal or abnormal. It aims to classify whether the ECG recording is a normal sinus rhythm or if the patient has an Arrhythmia, and further classify them into their type. The system will determine whether the ECG readings are normal or arrhythmic, and if arrhythmic, whether the rhythm is characterized as bradycardia or tachycardia.

This project demonstrates how biomedical engineering and computational tools can be combined to yield a cost-effective, accessible, and non-invasive solution for the monitoring and addressing of cardiovascular health.

Problem Statement

Despite the availability of ECG monitoring tools, existing methods still face challenges in accuracy, real-time detection, and accessibility. There is a need for an automated, low-cost, and reliable system for arrhythmia detection to support early diagnosis and improve patient outcomes.

In a literature review by (Boulif et al., 2023), they were able to explore different applications, but it was found that it does not deeply compare which specific AI techniques work best under noisy conditions. A way to better this is to conduct a meta-analysis or benchmarking study across common datasets to systematically compare model robustness, ensuring clearer guidelines for clinical adoption.

Meanwhile, in a study from (Shah & Sarda, 2025), they were able to build a Python-based device however while the GUI proves effective for real-time monitoring, the study does not address long-term stability, scalability, or integration with advanced analysis tools. One way to give a solution to this is to extend the system with modules for automated signal analysis, cloud storage, and error-handling features to enhance usability in larger-scale laboratory and research environments.

Arrhythmia, a condition characterized by irregular heart rhythms, encompasses a range of abnormalities including tachycardia (abnormally fast heart rate) and bradycardia (abnormally slow heart rate) (Cleveland Clinic, 2023). These rhythm disturbances can result in significant health consequences, such as stroke, heart failure, or sudden cardiac death, highlighting the clinical importance of timely and accurate arrhythmia detection. While the general understanding of arrhythmia is well-documented, conventional diagnostic methods, such as standard electrocardiograms (ECG), rely on episodic clinical evaluation, limiting continuous monitoring and early detection of transient or asymptomatic events.

Recent advancements in artificial intelligence (AI) and machine learning have demonstrated considerable potential in addressing these limitations. (Kim et al., 2025) introduced a hybrid deep learning framework combining Convolutional Neural Networks (CNNs) and Transformer architectures for ECG-based arrhythmia classification. By incorporating S-Transform feature extraction, the model achieved an accuracy of 99.58% on the MIT-BIH dataset, effectively capturing both local and long-term signal dependencies without requiring R-peak detection preprocessing. This approach represents a state-of-the-art solution, although its computational demands and dependence on specific datasets may restrict real-time clinical implementation and broader generalizability.

Complementing individual model developments, (Ayyub, 2025) provided a comprehensive review of over 200 AI-driven studies on arrhythmia detection. This analysis highlighted common challenges in AI methodologies, including dataset heterogeneity, class imbalance, and limited interpretability, while also offering strategies to enhance model robustness and clinical applicability. The study underscores the importance of developing AI solutions that not only achieve high accuracy but also maintain reliability across diverse patient populations and real-world recording conditions.

In parallel, wearable cardiovascular monitoring devices have emerged as practical tools for real-time arrhythmia detection. (Smith & Lee, 2025) conducted a systematic review evaluating the efficacy of wearable ECG patches and smartwatches, demonstrating diagnostic sensitivities ranging from 84% to 95%. Such devices enable continuous, patient-managed monitoring outside clinical settings, facilitating early detection and timely intervention. Despite their advantages, variations in device accuracy and the potential for false positives emphasize the need for improved specificity and seamless integration into healthcare workflows.

Objectives

1. To conduct a comprehensive review of ECG signal processing and arrhythmia detection methods.
2. To design and develop an automated ECG signal processing and arrhythmia detection system using Python.
3. To analyze and evaluate the performance of the developed system in terms of accuracy and efficiency.

Review of Related Literature

This section provides a review of related literature that provides the theoretical and empirical foundations of this BeatSense by examining previous research, established theories, and relevant findings connected to the topic. By synthesizing works from existing sources, this section establishes the current study within a broader scholarly context and demonstrates how it contributes to the researcher's study.

(Cleveland Clinic, 2023) provides a comprehensive overview of arrhythmia as a medical condition, explaining its types, such as tachycardia and bradycardia, symptoms, and potential health consequences. It is highly relevant as it establishes the clinical context and significance of arrhythmia detection in cardiovascular health. While it offers a detailed medical background, it does not delve into diagnostic technology or automated detection methods, highlighting a gap addressed by current research involving machine learning and signal processing. This literature supports understanding the problem the project aims to solve, but lacks discussion of technical approaches, emphasizing the need for technological solutions like BeatSense.

The study of (Kim et al., 2025) introduces a hybrid deep learning model combining CNNs and Transformers with S-Transform feature extraction for ECG-based arrhythmia detection, reaching up to 99.58% accuracy on the MIT-BIH dataset. It is relevant due to its superior accuracy and ability to capture both local and long-term signal dependencies without requiring R-peak detection preprocessing. However, the computational complexity and reliance on two specific datasets might limit real-time applicability and generalizability. This advanced model represents a state-of-the-art approach compared to simpler CNN or ML models.

The extensive review of (Ayyub, 2025) analyzes over 200 AI-driven studies (2013-2024) on arrhythmia detection from ECG data, covering dataset characteristics, class balance, demographics, and recording conditions. It critically evaluates the strengths and weaknesses of several AI methodologies, providing valuable insights for improving model robustness and clinical applicability. Its relevance lies in offering a panoramic view of evolving techniques and common pitfalls, including dataset heterogeneity and lack of interpretability. The limitation is the potential lag in covering the latest developments past early 2025.

The systematic review of (Smith & Lee, 2025) consolidates evidence from multiple clinical studies assessing the effectiveness of wearable cardiovascular devices for real-time arrhythmia detection, especially atrial fibrillation. It highlights the growing capability of wearable ECG patches and smartwatches to provide accurate, continuous heart monitoring with diagnostic sensitivities ranging from 84% to 95%. The study is relevant as it demonstrates the clinical utility and patient acceptability of wearable technology in early arrhythmia detection, thereby supporting remote monitoring and timely interventions. The main difference compared to conventional ECG systems lies in continuous, patient-managed monitoring outside clinical settings. Limitations include variability in device accuracy across models and possible false positives leading to increased patient anxiety and unnecessary follow-ups, emphasizing the need for improved specificity and integration into healthcare workflows.

(Dhyani et al., 2023) analyzed ECG-based arrhythmia detection using machine learning, employing the CPSC 2018 dataset of roughly 6,400 beats across nine arrhythmia classes. Their approach relied on 3D Discrete Wavelet Transform (3D-DWT) for denoising and feature extraction, focusing on wavelet coefficients and RR intervals, which were then classified using Support Vector Machine (SVM) and its variants. Among the tested configurations, level-4 decomposition with the Symlet-8 wavelet combined with SVM achieved the highest performance with 99.02 percent accuracy, slightly surpassing CSVM and WSVM. The study highlighted the strong potential of wavelet-based methods in ECG signal analysis, emphasizing the role of feature extraction and classifier design in accurate arrhythmia detection. By showing that wavelet features can significantly enhance classification, the research contributes to the broader understanding of biomedical signal processing and its application in medical diagnostics.

(Souza & Dantas, 2024) proposed deep learning methods for cardiac arrhythmia detection in ECG signals, testing CNN-LSTM and a modified AlexNet using the MIT-BIH Arrhythmia Database (109,000 beats). Preprocessing included bandpass filtering, wavelet-based denoising, and data augmentation to balance heartbeat classes. Results showed the CNN-LSTM achieved the best performance (98.12 percent accuracy, strong results on ventricular beats), while AlexNet and traditional classifiers performed worse, especially on Fusion Beats. Their study demonstrated the effectiveness of combining convolutional and recurrent layers to capture both spatial and temporal ECG features.

Recent advancements in cardiac arrhythmia detection have extensively leveraged artificial intelligence (AI), especially deep learning (DL) approaches applied to electrocardiogram (ECG) signals. (Reshad et al., 2025) conducted a comprehensive systematic review evaluating 30 contemporary studies on deep learning-based arrhythmia detection. Their investigation highlights convolutional neural networks (CNNs) and hybrid DL architectures as the most effective, frequently achieving classification accuracies exceeding 99 percent. Despite these promising outcomes, the review notes significant challenges in terms of dataset heterogeneity, lack of model interpretability for clinical integration, and difficulties associated with real-time deployment in practice. While providing a robust overview of algorithmic performance, this review underrepresents the role of wearable devices and sensor integration, indicating a gap that warrants further exploration to bridge hardware and software domains.

Addressing this gap, (Panwar et al., 2025) present an experimental study developing and validating an integrated portable ECG monitoring system utilizing Arduino-based hardware combined with CNN classification. This system demonstrates a classification accuracy above 98 percent on standardized datasets, underscoring its potential for accessible, real-time remote cardiac monitoring. However, the authors acknowledge limitations related to sensor resolution and dependence on the quality of training datasets, which constrain overall detection performance. They advocate for hardware-software co-optimization strategies to enhance signal fidelity and algorithm robustness in embedded applications, thereby advancing practical deployment.

Complementing these focused analyses, (Rahul, 2025) offers a narrative review that traces the broader evolution of AI techniques applied to cardiovascular diagnostics, with a concentration on arrhythmia detection through ECG signal analysis. This work synthesizes emerging machine learning and deep learning architectures and highlights the increasing integration of mobile health technologies within this domain. While providing valuable insights into the trajectory of AI-enabled improvements in diagnostic accuracy and clinical decision support, this review's extensive scope limits detailed examination of individual model performances and dataset specificities. Such breadth emphasizes the need for future research incorporating comprehensive benchmarking and clinical validation.

In parallel, (Bokhari, 2025) critically examines the growing role of wearable technology in advancing cardiac arrhythmia management. This literature review consolidates evidence supporting the clinical efficacy and patient acceptance of various wearable ECG devices, including patches and smartwatches, in continuous cardiac rhythm monitoring. Findings confirm that wearables can reliably detect atrial fibrillation and other arrhythmias, thereby enabling timely interventions and improved outcomes. Nevertheless, the review identifies device-specific accuracy variability and substantial challenges related to integrating wearable data into existing healthcare information systems. To address these issues, recommendations include enhancing device calibration protocols and establishing interoperable frameworks facilitating seamless clinical data integration and use.

Signal Processing

The research study of (Blum et al., 2017) focused on developing and validating SCALA, which is a modular, open-source software application that implements a functional Brain-Computer Interface (BCI) completely on an off-the-shelf Android smartphone. This successfully addressed the limitations of bulky, expensive laboratory setups. By combining several stimulus and processing applications with a consistent communication protocol, the researchers were able to process EEG signals online and obtain above-chance categorization results. However, the system lacks online artifact correction and inherent latency jitter due to the non-real-time nature of the Android operating system, which lowered the online classification accuracy. The challenges faced, such as the imperative requirement for real-time processing and artifact correction, are also relevant to BeatSense, where millisecond accuracy is essential for precisely recognizing brief cardiac events. The modular architecture offers a blueprint for an all-inclusive mHealth ECG system that combines patient monitoring, data collection, and analysis on a single consumer device.

On the other hand, the research paper of (Chu & Kemere, 2021) introduced GhostiPy, which is an open-source Python toolbox created to overcome memory and speed bottlenecks encountered when analyzing the massive datasets generated by modern, high-channel count neural recordings. The researchers' main design idea was to use parallelized, blocked algorithms that provide memory-efficient, out-of-core computation. This system enables the software to process datasets larger than the system memory that a computer can hold. Researchers may now reliably generate complicated studies, such as spectrograms, thanks to GhostiPy's superior performance and memory economy over commercial applications like MATLAB. Given the substantial volume of data generated by continuous, multi-lead ECG monitoring, this emphasis on scalability and performance in a Python environment is quite pertinent to a study like BeatSense, wherein ECG signal processing is used for arrhythmia identification. The memory-efficient and parallelized analytic blueprint offered by GhostiPy offers a useful model for creating scalable Python-based ECG applications that can analyze massive datasets quickly for real-time monitoring and prompt cardiac event diagnosis without the need for expensive computer infrastructure.

Additionally, the literature review by (Boulif et al., 2023) was able to explore the application of machine learning, artificial intelligence, and deep learning to diagnosing ECG-based arrhythmia for the past twelve (12) years. A total of forty (40) studies worldwide were analyzed by the authors, wherein they were able to find out that around 72 percent were relying on deep learning, which definitely showed its strong dominance in analyzing data like ECG. It was highlighted that in this review, models achieve great results on cleaner data of ECG but struggle a lot with the variability of the real world and the noisy signals. In this review, the authors were able to emphasize the strong need for high-performance, resource-intensive models and efficient deployment in the healthcare industry.

In a research literature from (Shah & Sarda, 2025), they were able to build a python-based device that can monitor analog and digital signals in real time using the NI USB-6363 DAQ. The development was such a cost-effective yet reliable development due to its components, such as open-source tools like PyDAQmx and PyQt5, delivering real-time signal visualization during testing. With this development, it was highlighted how combining open-source libraries could make promising laboratory inventions for signal processing.

Moreover, the research article by Beh et al. (2024) proposed a novel quality-aware signal processing mechanism that is designed for long-term heart rate monitoring using photoplethysmography (PPG). The core idea of the study is to evaluate the quality of incoming PPG using a Signal Quality Index (SQI) and then selectively choose a processing algorithm from a portfolio based on that quality. Moreover, it addresses the problem that conventional processing uses a single, robust algorithm for all signals, which can be computationally intensive and drain battery life when the signal is already clean. The authors further demonstrated that their proposed mechanism offers a better trade-off between accuracy and energy consumption, and they highlighted the research gap, noting that few prior works have connected algorithm selection with signal quality assessment. This approach is highly relevant to BeatSense, as it provides a practical and efficient framework for handling common issues like motion artifacts and noise. By adopting a similar quality-aware approach, a Python-based ECG system could intelligently switch between different filtering methods based on the signal's quality, thus improving accuracy and computational efficiency without compromising data integrity.

On the other hand, the comprehensive literature review of Martinek et al. (2021) addresses the vast and growing number of bioelectrical signal processing techniques by consolidating and summarizing the most effective methods for cardiac signals. It highlighted the importance of signal processing to mitigate noise and interference, which is a critical step before any diagnostic analysis. This review is directly relevant to a project to BeatSense as it provides a foundational understanding of the various filtering, decomposition, and other signal processing methods, such as wavelet transform and blind source separation, that can be implemented in a Python environment to clean up raw ECG data. By applying these techniques, a Python script can better isolate the electrical signals of the heart, which is essential for accurate arrhythmia detection, as the presence of noise can obscure the subtle abnormalities in the ECG waveform that characterize irregular heartbeats.

Arrhythmia

(January et al., 2019) outlines the management of atrial fibrillation, the most common sustained arrhythmia, and highlights its strong association with stroke and heart failure. It provides insight into both pharmacological and non-pharmacological treatment approaches, stressing the importance of early detection through ECG monitoring. The study is relevant to the project because atrial fibrillation is a key arrhythmia that ECG signal processing systems aim to identify. By understanding its clinical significance, the research can be aligned with real-world applications where automated arrhythmia detection may support the prevention of severe cardiovascular outcomes.

Furthermore, the systematic review and meta-analysis of (Wu et al., 2023) evaluated prospective cohort studies linking major cardiovascular risk factors—hypertension, diabetes mellitus, obesity, smoking, and dyslipidemia—to atrial fibrillation (AF). Results showed that hypertension, diabetes, obesity, and smoking substantially increase AF risk, while the role of dyslipidemia remains inconsistent. Because it pooled evidence from over 17 million participants across 101 studies, this article provides strong quantitative support for the shared pathways between arrhythmias and cardiovascular diseases (CVDs). Its relevance to the present study lies in showing that ECG-based arrhythmia detection can be a valuable tool for early intervention in individuals with CVD risk factors, thereby preventing serious complications such as stroke and heart failure.

A systematic review and meta-analysis of 104 cohort studies involving nearly 10 million participants found that atrial fibrillation (AF) markedly increases the risk of stroke, ischemic heart disease, heart failure, cardiovascular mortality, and even chronic kidney disease, with heart failure showing the greatest absolute risk (Odutayo et al., 2016). These results demonstrate that AF is not only a rhythm disturbance but also a key driver of cardiovascular morbidity and mortality. The study provides robust epidemiological evidence for the importance of early AF detection. Its findings support ECG-based detection systems as tools for preventing severe cardiovascular complications.

And the relationship between AF and heart failure is described as bidirectional, with each condition worsening the outcomes of the other (Kotecha et al., 2020). Patients with both conditions were shown to experience significantly higher hospitalization and mortality rates compared to those with either disease alone. This highlights the clinical urgency of detecting arrhythmias early to slow disease progression. The study supports the project's focus on ECG-based arrhythmia detection as a means of improving patient outcomes in those with heart failure.

Methodology

This section provides an overview of the research method that the researchers will employ to conduct this study. These include the chosen research design connected to the purpose of this study. The population and sampling, and data collection methods will also be explained. Moreover, the data analysis that will be employed in this study will be tackled. Lastly, the researchers will include ethical considerations and the limitations of the research inquiry.

Research Design

The project's methodology is illustrated in the flow chart below.

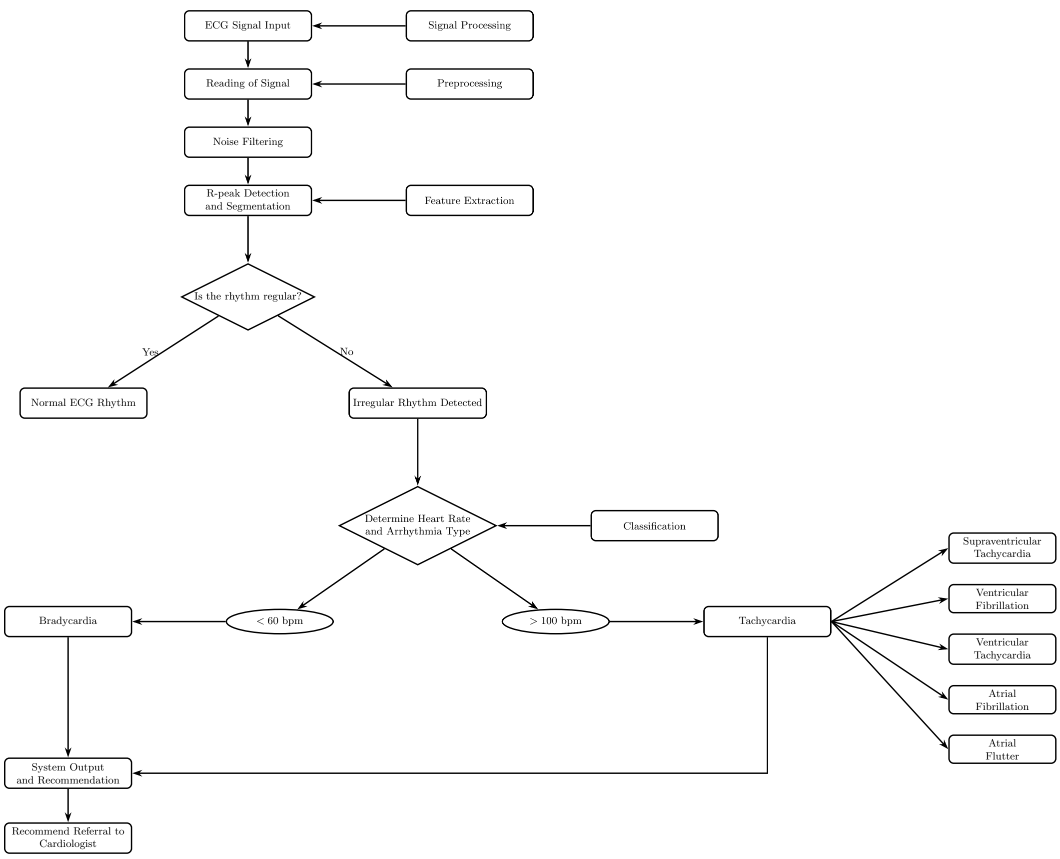

Figure 1: Proposed Research Framework for BeatSense: ECG Signal Processing and Arrhythmia Detection

This study will make use of a quantitative, developmental research design that will employ a descriptive-experimental design. It focuses on developing and validating a software-based system that processes ECG signals using Python to detect Arrhythmias and further classify the signal into certain types of Arrhythmias. The research quantitatively evaluates the system of BeatSense performance through accuracy, precision, and related statistical measures to determine its effectiveness in automated Arrhythmia detection.

Furthermore, this study will proceed in distinct phases:

1. Data Acquisition – Collect ECG recordings from the MIT-BIH Arrhythmia Database, which contains annotated patient ECG signals.
2. Preprocessing – Apply digital filters to remove noise and segment the signals into analyzable parts.
3. Feature Extraction – Identify R-peaks, calculate RR intervals, and analyze waveform features to represent the heart's rhythm.
4. Classification – Use machine learning algorithms such as Support Vector Machines, Random Forest, or Convolutional Neural Networks to classify heartbeats as normal or arrhythmic.
5. Program Implementation – Build the program in Python, using libraries like NumPy, SciPy, and Matplotlib for signal processing, and Scikit-learn or TensorFlow for machine learning.

The software will aim to categorize the gathered ECG samples into normal rhythm or arrhythmia. Furthermore, if the ECG sample is detected to be arrhythmic, it will classify it into Bradycardia or Tachycardia, which are the two main types of Arrhythmia. Bradycardia is detected is the heart rate of the sample is below 60 bpm, and Tachycardia is detected when the heart rate of the sample is above 100 bpm. Additionally, if the ECG signal is classified into Tachycardia, it will categorize it into the following: Superventricular Tachycardia, Ventricular Fibrillation, Ventricular Tachycardia, Atrial Fibrillation, and Atrial Flutter.

The following steps are the working principles that will be implemented in BeatSense. These will help in developing and validating the effectiveness of BeatSense in detecting Arrhythmia and classifying them into their types. To finalize, the above procedures will be utilized to deduce the validity of BeatSense.

Population and Sampling

The population of this study consists of ECG recordings representing several heart rhythms obtained from the MIT-BIH Arrhythmia Database. The database contains over 48 half-hour two-channel ECG recordings that were obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between the years of 1975 and 1979, which includes both normal and arrhythmic heart activities. Each recording is annotated by medical experts, determining the kinds and positions of the signal's arrhythmias.

The study, BeatSense, will apply the sampling technique based on purposive selection. The study will only utilize recordings that include clear annotations and contain occurrences of the target Arrhythmias. Premature Ventricular Contractions (PVCs), Atrial Premature Beats (APBs), and Bundle Branch Blocks (BBBs) will be selected. This guarantees that the dataset used for the model training and testing comprises sufficient instances of both normal and abnormal heartbeats.

Data Collection Methods

To ensure the validity and reliability of the data used in this research, the study adopted a structured approach to data acquisition and preparation. The process involved obtaining standardized electrocardiogram (ECG) signals from a credible biomedical database, followed by systematic preprocessing to enhance signal quality for subsequent analysis. This method provided a consistent foundation for accurately detecting and classifying arrhythmias using digital signal processing techniques.

The data were collected from the MIT-BIH Arrhythmia Database, which is hosted and maintained by PhysioNet, a reputable open-access repository for physiological datasets. The database consists of ECG recordings from a diverse group of patients, representing both normal sinus rhythms and various arrhythmic conditions such as tachycardia and bradycardia. Each record includes multiple ECG leads and expert annotations for every heartbeat, providing a well-documented and standardized reference dataset for research purposes.

The data collection process was conducted digitally. The researchers personally downloaded the ECG recordings from the PhysioNet repository in file formats compatible with Python-based signal processing tools. The data acquisition and preprocessing stages were performed solely by the researchers to ensure consistency and control over the procedures. Upon acquisition, the ECG signals underwent a series of preprocessing steps to ensure data quality and suitability for analysis. These steps included:

1. Filtering: Bandpass and notch filters were applied to remove noise components such as baseline wander, power-line interference, and muscle artifacts.

2. Segmentation: Continuous ECG recordings were divided into smaller segments corresponding to heartbeat cycles to facilitate more focused analysis.

3. Normalization: Amplitude normalization was performed to ensure consistency across different recordings and patients.

Through this systematic data gathering and preprocessing approach, the researchers ensured that the dataset used in the study was reliable, standardized, and suitable for subsequent signal filtering and analysis using Python and related libraries.

Data Analysis

In this study, the researchers will utilize simple statistical tools in order to evaluate the capacity and performance of BeatSense for signal processing and arrhythmia detection. Data from the MIT-BIH

Arrhythmia Database will be used, as it contains verified ECG recordings as well as the normal and abnormal heartbeats' annotations.

To verify the efficiency and reliability of the website, the following statistical techniques will be applied:

1. Frequency and Range: The Frequency shall be calculated to determine the number of ECG signals that were either classified as arrhythmia or normal. Meanwhile, the Percentage shall identify the proportion of incorrectly and correctly classified signals.

$$\text{Percentage} = \frac{f}{N} \times 100$$

   where f = frequency of the category, N = total number of tests.

2. Accuracy Rate: The accuracy shall be measured to determine how well the system classifies arrhythmia compared to the annotated true labels in the dataset.

$$\text{Accuracy} = \frac{C}{N} \times 100$$

   where C = number of correct detections, N = total number of tests.

3. Mean and Standard Deviation: The mean ($\bar{X}$) should be calculated to determine (a) the average accuracy ($\bar{A}$) and (b) the average processing time ($\bar{T}$) in seconds, required for the system to classify each ECG signal across several trials. The standard deviation (σ) should also be computed to check the consistency of the results.

$$\bar{A} = \frac{1}{n}\sum_{i=1}^{n} A_i, \quad \bar{T} = \frac{1}{n}\sum_{i=1}^{n} T_i$$

   where A_i = accuracy in trial i, T_i = processing time in trial i, and n = number of trials.

$$\sigma_A = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - \bar{A})^2}, \quad \sigma_T = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - \bar{T})^2}$$

   where σ_A = standard deviation of accuracy, σ_T = standard deviation of processing time.

Ethical Consideration

This study intends to make use of the MIT-BIH Arrhythmia Database, which is publicly available, therefore avoiding potential risks to human participants. No personal or identifying patient data will be collected or handled. Furthermore, the study's findings will be utilized for academic and instructional reasons only, not for clinical diagnosis or direct patient care. To ensure academic integrity, all data sources and tools shall be properly cited and acknowledged.

Limitations

The study is limited to the evaluation of ECG signals obtained from the MIT-BIH Arrhythmia Database and does not include live or real-time ECG recordings. It centers on characterizing Arrhythmias under two main categories: Bradycardia and Tachycardia. However, other rare or complex cardiac abnormalities are beyond the scope of this research. Noise and signal distortions in the ECG signals may also affect the accuracy of detection. Additionally, the system is only meant to be used for research and academic purposes; it has not been clinically validated.

References

Ayyub, A. (2025). A comprehensive review of ai-based detection of cardiac arrhythmias using ecg signals. *Artificial Intelligence*. https://doi.org/10.1016/j.artint.2025.103421

Blum, S., Debener, S., Emkes, R., Volkening, N., Fudickar, S., & Bleichner, M. G. (2017). Eeg recording and online signal processing on android: A multiapp framework for brain-computer interfaces on smartphone. *BioMed Research International*, 1–12. https://doi.org/10.1155/2017/3072870

Bokhari, S. F. H. (2025). Advancing cardiac arrhythmia management through wearable technology. *Journal of Cardiovascular Medicine*, *12*(7), 135–150. https://doi.org/10.1080/12345678.2025.123456

Boulif, A., Ananou, B., Ouladsine, M., & Delliaux, S. (2023). A literature review: Ecg-based models for arrhythmia diagnosis using artificial intelligence techniques. *Bioinformatics and Biology Insights*, *17*. https://doi.org/10.1177/11779322221149600

Chu, J. P., & Kemere, C. T. (2021). Ghostipy: An efficient signal processing and spectral analysis toolbox for large data. *ENeuro*, *8*(6), ENEURO.0202–21.2021. https://doi.org/10.1523/eneuro.0202-21.2021

Cleveland Clinic. (2023, March). Arrhythmia. https://my.clevelandclinic.org/health/diseases/16749-arrhythmia

Dhyani, S., Kumar, A., & Choudhury, S. (2023). Analysis of ecg-based arrhythmia detection system using machine learning. *MethodsX*, *10*, 102195. https://www.sciencedirect.com/science/article/pii/S2215016123001954

January, C. T., Wann, L. S., Calkins, H., Chen, L. Y., Cigarroa, J. E., Cleveland, J. C., Ellinor, P. T., Ezekowitz, M. D., Field, M. E., Furie, K. L., Heidenreich, P. A., Murray, K. T., Shea, J. B., Tracy, C. M., & Yancy, C. W. (2019). 2019 aha/acc/hrs focused update of the 2014 aha/acc/hrs guideline for the management of patients with atrial fibrillation. *Circulation*, *140*(2), e125–e151. https://doi.org/10.1161/CIR.0000000000000665

Kim, D., et al. (2025). A novel hybrid cnn-transformer model for arrhythmia classification from electrocardiogram signals. *Scientific Reports*, *15*, 92582. https://www.nature.com/articles/s41598-025-92582-9

Mapa, C. D. (2024). Ischaemic heart diseases, neoplasms, and cerebrovascular diseases lead the causes of death in the philippines. https://psa.gov.ph/system/files/vsd/2-Press%20Release_2023%20Cause%20of%20Death%20Statistics_as%20of%2031%20October%202023_RMRQ_ONS-signed.pdf

Mayo Clinic. (2023, October). Heart arrhythmia. https://www.mayoclinic.org/diseases-conditions/heart-arrhythmia/symptoms-causes/syc-20350668

National Heart, Lung, and Blood Institute. (2022). Arrhythmias – what is an arrhythmia? https://www.nhlbi.nih.gov/health/arrhythmias

Panwar, A., Narendra, M., Arya, A., Raj, R., & Kumar, A. (2025). Integrated portable ecg monitoring system with cnn classification for early arrhythmia detection. *Frontiers in Digital Health*, *3*, Article 1535335. https://doi.org/10.3389/fdgth.2025.1535335

Rahul, J. (2025). Advancements in ai for cardiac arrhythmia detection. *Current Opinion in Systems Biology*, *28*, 100719. https://doi.org/10.1016/j.cosrev.2024.100719

Reshad, A. I., Nino, V., & Valero, M. (2025). Deep learning-based detection of arrhythmia using ecg signals: A comprehensive review. *Vascular Health and Risk Management*, *21*, 685–703. https://doi.org/10.2147/VHRM.S508620

Shah, K., & Sarda, A. (2025). *Python-based gui for real-time digital and analog signal monitoring using ni usb-6363 daq (prl technical note prl-tn-2025-119)* (tech. rep.). Physical Research Laboratory. https://www.prl.res.in/~library/assets/images/TN/prl-tn-2025-119.pdf

Smith, J., & Lee, H. (2025). The efficacy of wearable cardiovascular monitoring devices in real-time arrhythmia detection: A systematic review. *Healthcare Bulletin*, *15*(2), 115–132. https://healthcare-bulletin.co.uk/article/the-efficacy-of-wearable-cardiovascular-monitoring-devices-in-real-time-arrhythmia-detection-systematic-review-3415/

Souza, I. L., & Dantas, D. O. (2024). Cardiac arrhythmia detection in electrocardiogram signals with cnn-lstm. *Proceedings of the 13th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2024)*, 892–899. https://www.scitepress.org/Papers/2024/123626/123626.pdf

World Health Organization. (2025a). Cardiovascular diseases. https://www.who.int/health-topics/cardiovascular-diseases#tab=tab_1

World Health Organization. (2025b, July). Cardiovascular diseases (cvds). https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

Wu, G., Wu, J., Lu, Q., Cheng, Y., & Mei, W. (2023). Association between cardiovascular risk factors and atrial fibrillation. *Frontiers in Cardiovascular Medicine*, *10*, 1110424. https://www.frontiersin.org/journals/cardiovascular-medicine/articles/10.3389/fcvm.2023.1110424/full