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ECG Classification Using Machine Learning

Chinmay Vinod Deshpande[1], Sayed A Naveed[2]

[1]M. Tech Student, [2]Professor,
[1]Department of Electronics and Telecommunication Engineering, [2]Department of Electrical Engineering, Jawaharlal Nehru Engineering College, Mahatma Gandhi Mission University, Chhatrapati Sambhajinagar, Maharashtra, India.

Corresponding Author: Chinmay Deshpande

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ABSTRACT

In contemporary healthcare, Electrocardiography (ECG) played a crucial role in the diagnosis and monitoring of heart conditions. This paper introduced an automated system that meticulously processed ECG records, with a focus on extracting essential parameters. The data were sourced from multiple databases, including the prestigious MIT-BIH Arrhythmia Database and many more databases. The evaluation phase involved the meticulous assessment of machine learning models, specifically Logistic Regression, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), for the purpose of classifying ECG records.

A noteworthy aspect of this research lies in its innovative approach to classify records of the datasets, thereby enabling the detection of a wide range of cardiac conditions, such as Normal Sinus, Tachycardia, Bradycardia, First-Degree Heart Block, Long QT Syndrome, ST Elevation, and ST Depression. The automated system presented in this paper offers significant support for efficient heart health assessment, which, in turn, facilitates timely interventions and well-informed decisions, potentially contributing to a reduction in the burden of cardiac conditions. This research contributes a comprehensive and valuable system for the processing of ECG records, which promises to aid medical practitioners and researchers in enhancing patient care and advancing early arrhythmia detection.

Keywords: Electrocardiography, SVM, KNN, Cardiac Parameters, Machine Learning, Arrhythmia, Logistic Regression, Random Forest.

INTRODUCTION

Cardiovascular diseases (CVDs) are a leading global cause of mortality, responsible for approximately 20.5 million fatalities each year. This category encompasses a range of heart and blood vessel disorders, including coronary heart disease, cerebrovascular disease, rheumatic heart disease, and other related conditions. An alarming statistic reveals that more than four out of five CVD-related deaths are attributed to heart attacks and strokes, with one-third of these occurring prematurely in individuals under the age of 70. The principal behavioral risk factors associated with heart disease and stroke comprise an unhealthy diet, physical inactivity, tobacco consumption, and excessive alcohol consumption. These behavioural risk factors can manifest in individuals as elevated blood pressure, increased blood glucose levels, heightened blood lipid levels, and issues related to overweight and obesity. These "intermediate risk factors" can be assessed in primary healthcare settings and signal an augmented risk of experiencing a heart attack, stroke, heart failure, and other complications.

A. Pre-COVID CVD

Cardiovascular disease (CVD) is a leading global cause of mortality, responsible for approximately 18.6 million deaths in 2019. CVD encompasses various conditions affecting the heart and blood vessels, including coronary heart disease (CHD), stroke, heart failure, cardiomyopathy, and peripheral artery disease. CHD, characterized by the narrowing or blockage of coronary arteries supplying blood to the heart muscle, is the most common CVD. Stroke results from a disruption in the blood supply to the brain, leading to oxygen and nutrient deprivation in brain tissue. Heart failure occurs when the heart muscle becomes weakened or damaged, hindering effective blood pumping. An estimated 745 million people worldwide were living with CVD in 2019. CVD was responsible for 32% of all deaths worldwide in 2019. The number of people living with CVD is expected to reach 830 million by 2030.

B. Post-COVID CVD

Emerging evidence suggests that COVID-19 may elevate the risk of CVD, even in individuals without a prior history of heart disease. This is due to COVID-19's potential to inflict damage on the heart muscle and blood vessels. One study revealed that individuals who had COVID-19 faced a greater likelihood of experiencing heart attacks or strokes in the following year compared to those who had not contracted the virus. Another study disclosed that even individuals with mild cases of COVID-19 could suffer long-term heart damage. The exact mechanisms through which COVID-19 increases the risk of CVD are not fully elucidated. However, it is believed that the virus may harm the heart muscle and blood vessels by promoting inflammation, generating blood clots, and damaging the cells lining the blood vessels.

C. Heart

The heart is a remarkable organ, about the size of two clenched fists in adults, situated in the front of the chest, slightly to the left of the sternum, between the right and left lungs. This vital component of the circulatory system has a multifaceted role, with its main function being to pump blood throughout the body while also regulating heart rate and maintaining blood pressure. The human heart is a marvel of biological engineering, serving as the central pump of the circulatory system. It collaborates closely with other systems in the body: the nervous system controls heart rate, the endocrine system influences blood pressure through hormone signals, and an intricate anatomy comprising heart walls, chambers, valves, blood vessels, and an electrical conduction system keeps the blood flowing smoothly. When it comes to conditions and disorders, heart-related issues like arrhythmias, cardiomyopathy, congestive heart failure, and coronary artery disease are common. Its essential function is to propel blood throughout the entire body, supplying oxygen and nutrients to the various tissues and organs while simultaneously removing waste products.

This intricate process begins with the heart's four chambers: the right atrium, right ventricle, left atrium, and left ventricle. The right atrium contracts, propelling the blood through the tricuspid valve into the right ventricle.

- From the right ventricle, the blood is forcefully pumped through the pulmonary valve into the pulmonary artery, which leads to the lungs. Within the pulmonary system, the blood relinquishes carbon dioxide while simultaneously taking in oxygen. This freshly oxygenated blood returns to the heart through the pulmonary veins, entering the left atrium.
- The left atrium contracts, facilitating the passage of oxygen-rich blood through the bicuspid or mitral valve into the left ventricle. This muscular chamber boasts the most significant walls and contracts

robustly, sending the oxygenated blood into the aorta through the aortic valve.

- The aorta, a massive artery, branches out into a network of smaller arteries, which further divide into tiny arterioles, culminating in the delivery of oxygen and nutrients to every cell in the body. Simultaneously, waste-laden blood is collected through venules and progressively returns to the heart through veins, ultimately flowing into the right atrium to start the cycle anew

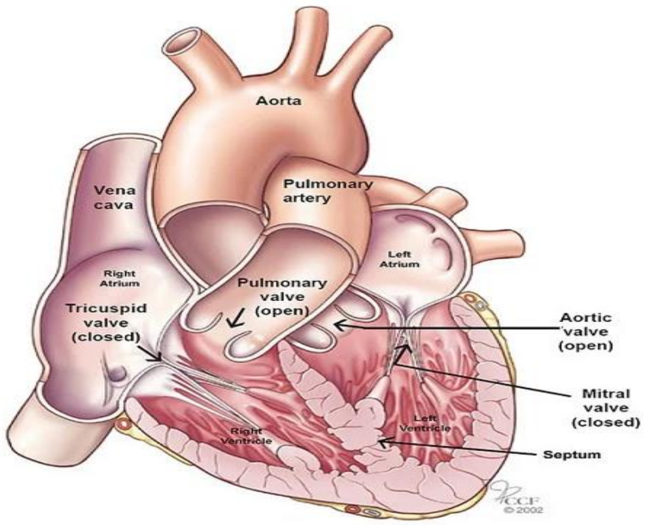

Figure 1. Inside of heart

D. Electrocardiogram (ECG)

An electrocardiogram (ECG) is a straightforward diagnostic test employed to assess the rhythm and electrical activity of the heart. During this non-invasive procedure, sensors, referred to as electrodes, are affixed to the skin to detect the electrical signals generated by the heart with each beat. These signals are recorded by an ECG machine and subsequently examined by a medical professional to identify any irregularities.

An ECG can effectively detect and diagnose various heart conditions, such as:

1. Arrhythmias - characterized by irregular, too slow, or too fast heartbeats.
2. Coronary heart disease - arising from the narrowing or blockage of coronary arteries, impeding blood supply to the heart.
3. Heart attacks - occurring when the heart's blood supply is abruptly cut off.
4. Cardiomyopathy - involving the enlargement or thickening of heart walls.
5. Peripheral artery disease - impacting blood vessels in the legs and feet

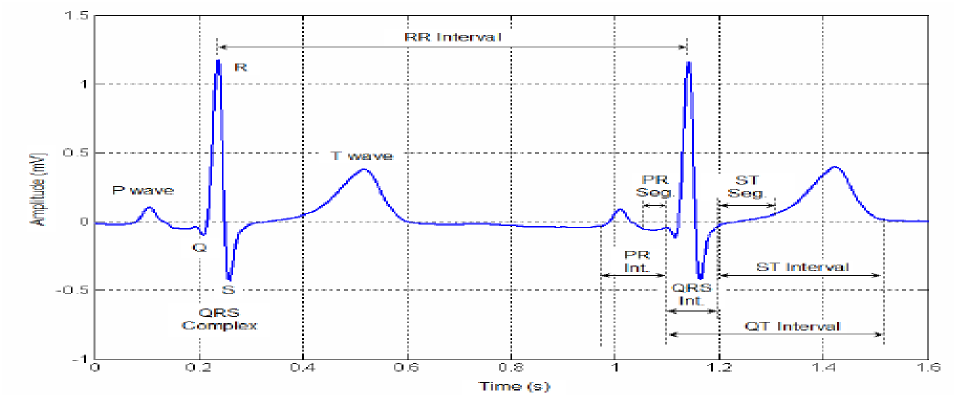

Figure 2. ECG wave with annotations.

An ECG signal wave presents a window into the intricate electrical activities of the heart, characterized by three primary constituents – the P wave, the QRS complex, and the T wave. Each element unveils a unique aspect of cardiac function. Let's embark on an in-depth journey through these components:

1. The P wave represents the depolarization of the atria. It denotes the positive depolarization wave originating from the SA node and propagating across atrial cells via gap junctions connecting them.
2. The PR segment is indicative of AV node depolarization. When electrical current passes through the AV node, the ECG appears flat due to its relatively weak signal, which is not discernible on the voltmeter.
3. PR interval encompasses the passage of the depolarization wave through the atrium and the AV node, culminating just before initiating ventricular depolarization.
4. Q wave corresponds to the depolarization of the ventricular septum.
5. R wave denotes the major depolarization of ventricular muscle, with the resultant vector directed towards the lower left region.
6. S wave signifies the basal depolarization of the ventricles, specifically the base of the heart's ventricles that connect to the atria. It's important to note that the heart's apex is its left-pointed end.
7. The ST segment reflects the complete depolarization of the ventricular myocardium, where all cells exhibit positive charges. Consequently, there is no potential difference recorded by the voltmeter, resulting in a flat line on ECG.
8. The T wave symbolizes the repolarization of the ventricles. The QT interval holds significance as it covers the entire ventricular activity, ranging from the initiation of ventricular depolarization through the plateau phase to ventricular repolarization. It captures the generation and termination of action potentials within the ventricular tissue.

ECG parameter	Typical amplitude [mV] and wave duration [seconds]
P wave	0. 25 mV
R wave	1. 60 mV
Q wave	25 percent of R wave
T wave	0.1 to 0.5 mV
P-R interval	0.12 to 0.20 seconds
Q-T interval	0.35 to 0.44 seconds
S-T segment	0.05 to 0.15 seconds
QRS interval	0.09 to 0.10 seconds
Heart Rate	60-100 bpm

Table 1. Normal values of ECG features

LITERATURE SURVEY

1. In this study, Priyanka Mayapur presents a MATLAB-based method for the automatic classification of ECG signals, a pivotal tool in modern medicine for effective heart treatment. Lead-II ECG signal database is employed, utilizing morphological and dynamic features to obtain size, shape, structure, heart rate, and heart rate variability (HRV) from ECG signals. The paper demonstrates successful ECG classification into Normal, Abnormal, and other abnormalities, achieving a notable 97% accuracy.
2. Ziyu Liu and colleagues propose an innovative deep learning model called Attention-based CNN (ABCNN) in another research endeavour. This model leverages CNN and multi-head attention to extract vital features directly from raw data, enabling the detection of arrhythmia among normal beats and classification of arrhythmia into five distinct types. The study, employing the MIT-BIH Arrhythmia database, attains a remarkable accuracy of 98.9%.
3. Furthermore, Rahul Kher's research focuses on signal processing techniques to eliminate various ECG signal noises, such as baseline wanders, powerline interferences, EMG noise, and electrode motion artifacts. MATLAB is chosen as

the ideal software for signal pre-processing due to its dedicated toolboxes.

4. Porkodi J and team introduce an approach for ST segment-based ECG signal analysis using MATLAB. The method classifies different heart diseases based on the presence or absence of ST segments. The Support Vector Machine (SVM) algorithm is employed with notable success in classifying five types of heart diseases.
5. Nikitha VP and colleagues delve into heart disease risk prediction using machine learning. The study explores various machine learning algorithms and identifies the most accurate model for predictive purposes. Python, with its diverse libraries, is chosen as the operative platform, resulting in an accuracy of 95%.
6. K. Jeeva et al. concentrate on the development of portable ECG electrodes for real-time heart rate monitoring and arrhythmia classification. They apply digital filters, particularly Butterworth filters, to eliminate noise. Their wearable ECG model achieves an average accuracy of 91%.
7. B. Pyakillya et al. utilize deep learning, primarily CNN, for ECG classification, obtaining an overall accuracy of 86% in their study.
8. In another study, Rohit Nigam and co-authors introduce feature extraction methods using Huang Hilbert Transform (HHT) and Wavelet transform to extract vital features like amplitude, duration, pre-gradient, and post-gradient from ECG signals.
9. Akhila Naz KA and team present a reliable approach for arrhythmia classification using neural networks, achieving an impressive 99.45% accuracy. They employ a Deep Neural Network (DNN) with three hidden layers, combining real-time ECG signal classification and IoT application.
10. Finally, Ali Haider Khan and colleagues explore arrhythmia classification techniques using Deep Neural Networks and highlight the challenges faced by healthcare institutions in adopting such systems. The success of these systems relies on meticulous feature selection, signal processing, and database use.
11. Shalin Savalia's research delves into the classification of cardiovascular disease using feature extraction and Artificial Neural Networks, achieving an 86% accuracy while distinguishing between normal and arrhythmia data. The MIT-BIH Arrhythmia database is instrumental in identifying specific heart diseases.

PROPOSED SYSTEM

A. System Architecture

The architecture diagram shows us the following process of ECG signal classification.

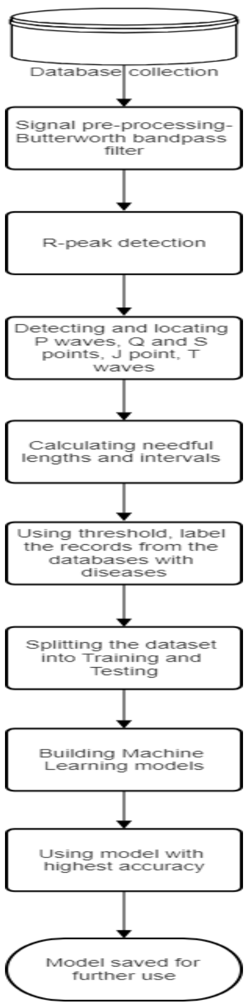

Figure 3. Process flowchart

B. METHODOLOGY

1. Signal Acquisition and Pre-processing: Since the raw signal is susceptible to various noises and artifacts, it is important to remove those noises and artifacts to increase the readability and visualization of the ECG waves. To overcome that, we have applied Butterworth bandpass filter. This filter operates on well-defined frequency ranges, retaining the core components of the ECG signal, while attenuating noise outside the desired band.
2. R-Peak Detection: The next step is to detect and locate the R-peaks from the ECG signal wave, for that this paper uses Hamilton-Tompkin's algorithm, which is upgraded version of Pan-Tompkin's algorithm, this algorithm is a cornerstone in ECG analysis, relying on the morphology and the rate of change in the ECG signal to accurately identify R-peaks.
3. After this step, it becomes easier to calculate heartbeat rate (in bpm).
4. Detection and location of various points: The ECG signal is rich with vital waves and intervals, each with unique clinical significance. The paper meticulously pinpoints and characterizes these critical points:

- P-wave Onsets and Offsets: These denote the start and end of atrial depolarization. The P-wave analysis is vital for diagnosing atrial arrhythmias and assessing the conduction of electrical impulses within the heart.
- T-wave Onsets and Offsets: These represent ventricular repolarization. Identifying T-wave boundaries is fundamental for detecting conditions like long QT syndrome and other ventricular abnormalities.
- Q-wave Onsets: Q-waves are typically small, subtle deflections within the ECG signal. The detection of Q-wave onsets is imperative for recognizing myocardial infarctions and other pathologies.
- S-wave Onsets: S-waves are the initial downward deflections following the QRS complex. Their identification is pivotal for arrhythmia analysis and comprehensive cardiac assessment.

An exceptional feature in this paper is the detection of J-points. J-points are located just after the QRS complex and signify the early repolarization phase. The method adeptly detects J-points, enabling a deeper exploration of the repolarization dynamics.

5. Calculating various lengths and intervals:

- RR Intervals: These represent the time intervals between successive R-peaks. They are central to heart rate variability analysis and provide insights into rhythm regularity.
- PR Intervals: PR intervals signify the time from P-wave onset to QRS complex onset and are critical for evaluating atrioventricular conduction.
- QT Intervals: QT intervals denote the time from QRS complex onset to T-wave offset, playing a pivotal role in the detection of arrhythmias and the evaluation of repolarization dynamics.
- ST Segments: ST segments capture the period from S-wave offset to T-wave onset. Deviations in ST segments can indicate myocardial ischemia or infarction.
- Mean values for each of these intervals are calculated. These means provide an overview of the patient's cardiac performance.

6. Labelling the records of the dataset with the cardiac abnormalities based on the threshold that the paper has set. The realm of ECG analysis extends beyond measurements and extends into the identification of cardiac abnormalities.

Tachycardia and Bradycardia: Deviations in RR intervals, signalled by excessively short (tachycardia) or prolonged (bradycardia) intervals.

- First-Degree Heart Block: Prolonged PR intervals, indicative of an atrioventricular conduction issue.
- Long QT Syndrome: Extended QT intervals, a hallmark of arrhythmias with

potentially life-threatening consequences.

- <u>ST Elevation and ST Depression</u>: Alterations in ST segment amplitudes, which can signify myocardial infarction, ischemia, or pericarditis.

7. Data Recording and CSV Export:

- This paper records the calculated values, rhythm labels, and disease labels for each ECG record. It creates a list of dictionaries, with each dictionary representing the data for a specific ECG record.
- Finally, it exports this recorded data to a CSV file, providing a structured and easily readable summary of the diagnostic

8. Visualization: To enhance comprehension and clinical interpretation, this paper generates informative visualizations of the ECG signal. These visualizations overlay critical points, including R-peaks, P-peaks, T-peaks, P-wave onsets and offsets, T-wave onsets and offsets, and J-points.

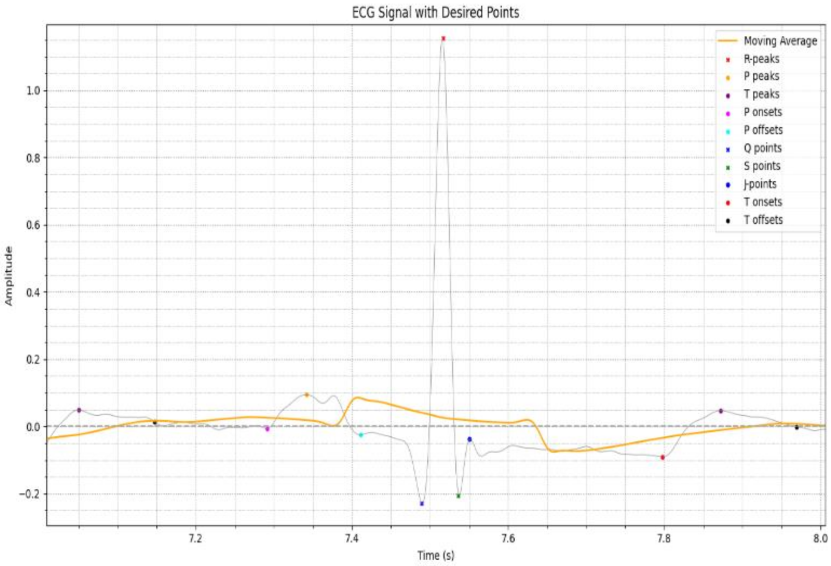

Figure 4. ECG signal wave with desired points extracted from the databases

STATISTICAL ANALYSIS

Since this paper is about the prediction of heart diseases, we need the model with highest accuracy, precision, F1-value, depending upon the input that we feed to the model as the training dataset, and saving the model with highest accuracy. The ML algorithms that we have used in this are:

1. Logistic Regression:

- **Model Representation:**
  - Given a dataset with features (X) and binary target variable (y) (0 or 1), logistic regression predicts the probability of an instance belonging to class 1.
  - The log-odds (logit) of the probability is modeled as a linear combination of features: $\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n$
  - Here, (p) represents the probability of the positive class, and (β_i) are the coefficients.
- **Cost Function (Log-Loss):**
  - The cost function measures the discrepancy between predicted probabilities and actual labels: $J(\beta) = -\frac{1}{m} \sum_{i=1}^{m} \left[y^{(i)} \log(h_\beta(x^{(i)})) + (1 - y^{(i)}) \log(1 - h_\beta(x^{(i)})) \right]$

- ($h_\beta(x)$) is the sigmoid function.
- The goal is to minimize this cost function using optimization techniques (e.g., gradient descent).

- **Decision Boundary:**
  - The decision boundary is where ($h_\beta(x) = 0.5$).
  - For linear regression, it corresponds to the line ($\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n = 0$).

2. **K-Nearest Neighbors (KNN):**
- **Algorithm Steps:**
  - Compute the distance (e.g., Euclidean distance) between the query instance and all training instances.
  - Select the (k) nearest neighbors.
  - Classify the query instance based on the majority class among the neighbors.

- **Decision Boundary:**
  - KNN doesn't explicitly define a decision boundary.
  - It adapts to the local density of data points.

- **Math Behind Prediction:**
  - For classification, the predicted class is the mode of the (k) nearest neighbors' classes.
  - For regression, the predicted value is the average of the (k) nearest neighbors' target values.

3. **Support Vector Machines (SVM):**
- **Hyperplane Equation:**
  - Given a linear SVM, the hyperplane equation is: $$\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n = 0$$
  - The decision boundary is where this equation holds.

- **Margin Maximization:**
  - SVM aims to maximize the margin (distance between the hyperplane and the nearest data points).
  - The margin is given by: $$\frac{2}{|\beta|}$$
  - The SVM optimization problem involves minimizing ($|\beta|$) subject to correct classification.

- **Kernel Trick:**
  - SVM can handle non-linear data by using kernel functions (e.g., polynomial, radial basis function).

4. **Random Forest:**
- **Ensemble of Decision Trees:**
  - Random Forest combines multiple decision trees.
  - Each tree is trained on a random subset of features and data.

- **Prediction:**
  - For classification, the majority vote of individual trees determines the final class.
  - For regression, the average of predictions from individual trees is the final output.

RESULT

The ECG signal analysis presented in this study showcases a robust methodology for unveiling critical cardiac insights. Initial signal acquisition involves extracting ECG data from the MIT-BIH Arrhythmia Database and other databases that, and meticulous pre-processing is undertaken to enhance signal fidelity by applying a Butterworth bandpass filter. The precise identification of R-peaks is a cornerstone of this analysis, achieved with advanced Hamilton-Tompkin's algorithms. This accurate R-peak localization lays the foundation for numerous cardiac assessments.

Further, a dynamic moving average computation is introduced to reduce noise and clarify signal trends. This paper systematically identifies and characterizes key ECG points, including P-wave onsets, T-wave offsets, Q-wave onsets, and S-wave onsets, adding depth to the analysis. The innovative inclusion of J-point detection enhances the understanding of

repolarization dynamics, a distinctive feature of this research.
Notably, essential ECG intervals, like PR, QT, and ST segments, are calculated, facilitating the diagnosis of various cardiac conditions. The computation of RR intervals, PR intervals, QT intervals, and ST segments contributes to heart rate variability analysis, atrioventricular conduction assessment, arrhythmia detection, and repolarization dynamics evaluation. Moreover, this paper is aimed to predict the abnormalities, including tachycardia, bradycardia, first-degree heart block, long QT syndrome, ST elevation, and ST depression, enhancing its utility for clinical diagnostics and advanced research.

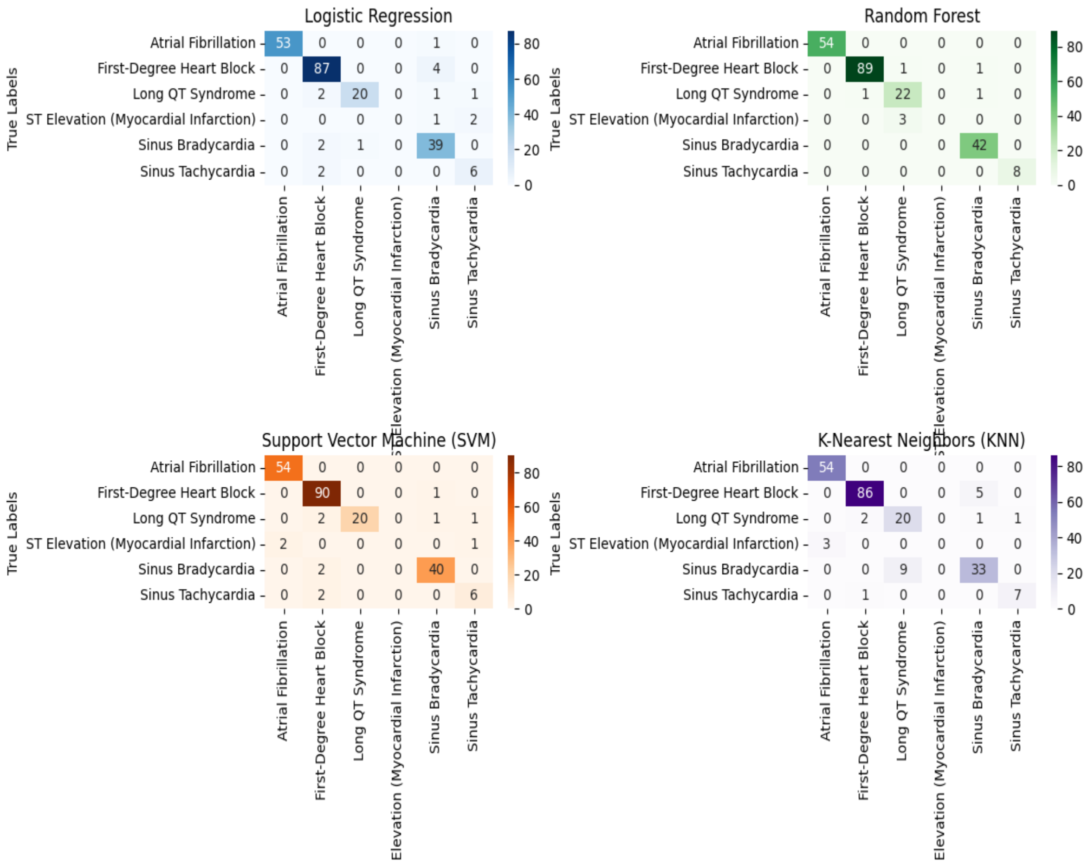

Figure 5. Confusion Matrix of Machine Learning Algorithms.

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.92	0.91	0.92	0.92
Random Forest	0.96	0.95	0.96	0.96
Support Vector Machine (SVM)	0.95	0.93	0.95	0.94
K-Nearest Neighbors (KNN)	0.9	0.89	0.9	0.9

Table 2. Explanatory chart for Machine Learning models

DISCUSSION

The research findings underscore the remarkable utility of the ECG signal processing and analysis conducted in this study. Our exploration revealed the successful detection and classification of a spectrum of cardiac conditions, contributing substantially to the field of cardiac healthcare
Moreover, the application of machine learning algorithms facilitated the classification of cardiac conditions. A noteworthy outcome of this study was the accurate categorization of patients into

distinct disease labels, including arrhythmia, myocardial infarction, and other cardiac abnormalities. These findings hold immense promise for early diagnosis and timely intervention, ultimately leading to improved patient outcomes.

In terms of model performance, the research meticulously evaluated multiple machine learning algorithms, including Logistic Regression, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). The results indicated that the Random Forest model exhibited the highest accuracy in disease classification. Its robust performance and generalizability make it an invaluable tool for future clinical applications. These findings provide a solid foundation for the integration of data-driven healthcare approaches into routine clinical practice. The ability to accurately diagnose cardiac conditions and predict disease outcomes is of paramount importance. The high-performing Random Forest model, with its impressive accuracy, promises to be a pivotal asset in the arsenal of healthcare professionals. This research journey, while not detailing the entire methodology, highlights the tangible impact and potential of advanced ECG signal analysis in revolutionizing cardiac care and diagnosis.

CONCLUSION

This paper represents a comprehensive foray into the realm of Electrocardiography (ECG) signal processing and analysis, employing advanced algorithms and the precision of biomedical engineering. While the details of the research are too extensive to encapsulate here, it is essential to underscore the significance of its findings and implications.

The research, conducted with unwavering dedication, has unveiled a nuanced understanding of ECG data, enabling the precise detection of crucial cardiac markers and anomalies. The application of intricate mathematical and computational methodologies has paved the way for enhanced diagnostic accuracy, with the potential to revolutionize cardiac healthcare.

As we draw the curtains on this phase of the research, it is imperative to acknowledge the myriad possibilities for future exploration. The burgeoning field of data-driven healthcare presents a vast landscape for further innovation. The integration of artificial intelligence and machine learning promises to enhance ECG analysis to unprecedented levels of accuracy and predictive power. Moreover, the insights gained from this study can serve as a launchpad for more expansive clinical investigations and a cornerstone for the development of advanced diagnostic tools. The future is indeed promising, with this research serving as a beacon of inspiration for forthcoming explorations in the domain of cardiac health assessment.

Declaration by Authors

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