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Application of Decision Tree Method in ECG Signal Classification for Heart Disorder Detection

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Abstract: The primary cause of death worldwide is Cardiovascular Disease or CVD. This group of illnesses targets the heart and blood vessels. One of the most common CVDs in Indonesia is Coronary Heart Disease (CHD). However, due to the high cost of drugs, lengthy treatment duration, and various supporting examinations required, treating CHD can be very expensive. An obstacle to treating heart disease in Indonesia is the insufficient number of cardiologists and experts experienced in interventional cardiology. Along with technological developments, the computer science community is encouraged to contribute to the medical field. For instance, using an electrocardiogram (ECG) can help prevent and minimize problems arising from heart disease. A medical test called an Electrocardiogram (ECG) uses a device that senses electrical impulses to monitor and record the cardiac electrical activity. The use of Artificial Intelligence (AI) in ECG is rapidly increasing and has shown to have great potential in improving the diagnosis and treatment of cardiac patients. AI has become a valuable tool in helping doctors diagnose, predict risk, and manage heart disease with greater accuracy, speed, and precision. The decision tree method is frequently used to make decisions and is one of the machine learning techniques utilized in this study. The decision tree method exhibited promising results, with an accuracy rate of 99% in identifying early-stage heart problems. This method has significant potential to assist doctors in identifying early-stage heart problems with high accuracy.

Keywords: Cardiovascular Disease, Coronary Heart Disease, Decision Tree, Electrocardiogram, Artificial Intelligence

INTRODUCTION

A significant cause of death worldwide, Cardiovascular Disease (CVD) claims the lives of 17.9 million people annually on average. Blood arteries and the heart are affected by a group of conditions known as cardiovascular disease (CVD). Heart conditions such as rheumatoid arthritis, cerebrovascular disease, and Coronary Heart Disease (CHD) are examples of CVD (World Health Organization, n.d). The death rate from heart disease in Indonesia reaches 650,000 people per year, based on data from the Indonesian Ministry of Health in 2023 (Prasetya Online, 2023). Heart disease affects not only older people but also the productive age group, so its mortality causes an economic and social burden on society (Rokom, 2023). Some lifestyle choices, such as smoking, being inactive, and being obese, can lead to heart disease (Gulati et al., 2020).

Every year, numerous individuals lose their lives or face permanent health conditions due to a failure to identify and respond appropriately to the symptoms of a heart attack. The main symptoms of a heart attack include chest tightness or pressure that radiates to the neck and arms, trouble breathing, and profuse perspiration (Abdo et al., 2020). In Indonesia, CHD remains one of the top-ranking cardiovascular diseases (Afifah et al., 2022). Preventing CHD is essential to undertake preventive measures through early detection (Rahayu et al., 2021). The Indonesian population, especially in rural areas, has low knowledge and awareness about heart disease (Sujarwoto, 2019). Indonesia is still lagging in equity and quality of health services, especially for heart disease. The inadequate number of cardiologists is a big obstacle in managing heart disease in Indonesia. In addition, another problem is the lack of experts experienced in cardiology interventions (Shanti, 2022).

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Along with technological developments, the computer science community is encouraged to contribute to the medical field. The computer science community designs and implements software to aid the analysis of bioelectric signals, which benefits the medical community. An Electrocardiogram (ECG) can help to prevent and minimize the problems that arise from heart disease. With an electrical impulse-detecting device, a medical test known as an ECG monitors and documents the cardiac electrical activity. It translates the electrical impulses into a graph display on a monitoring screen (Halodoc, 2022). In the medical field, especially for clinics, a standard ECG records the heart's electrical activity from 12 different viewpoints (Santamónica et al., 2024). ECG technology continues to develop rapidly. Some examples of ECG developments include Wearable ECG, 3-lead ECG, algorithms and Artificial Intelligence (AI), ECG with wireless capabilities, mobile ECG, and 3D ECG.

Artificial Intelligence (AI) in ECG is rapidly increasing and has a great potential to improve the diagnosis and treatment of cardiac patients. AI-powered ECG analysis can reduce the rate of misdiagnosis related to ECG interpretation, patient characterization, and treatment selection (Martínez-Sellés M & Marina-Breysse M, 2023). Several studies have already started to develop wireless ECG technologies for mobile use in medical settings. Through the development of this remote monitoring system, the expectation is that each patient can be monitored online and in real-time (Turnip et al., 2018; Turnip et al., 2018). The development of ECG Miner, a tool that converts several paper ECG records into digital format instantly. The straightforward interface enables researchers and cardiologists to utilize it with minimal training (Santamónica et al., 2024). ECG research aims to remove ECG noise by presenting a technique that combines optimizing particle swarms, the transform of wavelet, and feature extraction of ECG (Wijaya et al., 2019 & Azzouz et al., 2024). Analysis of 12-lead ECG with CNN (Convolutional Neural Network) was able to detect Mitral valve prolapse (MVP), which is at high risk of ventricular arrhythmia, death, and or fibrosis (Tison et al., 2023). There are also generalized ECG-AI studies to predict the likelihood of experiencing heart failure in the upcoming decade (Butler et al., 2023). ECG is also used to detect arrhythmias in cats. Arrhythmic disease is more common in older male cats (Szlosek et al., 2024).

METHOD

This research uses a decision tree method. The approach of decision trees is a machine learning technique frequently applied in determining a classification. In the PhysioNet/CinC Challenge seminar for short-term ECG signals, this method was used to detect ECG signals with classifications Normal, Atrial Fibrillation (AF), and Others. The results showed a score of "Normal" of 0.93, "AF" of 0.86, "Others" of 0.76, and a final score of 0.86 on a scale of 0-1 (Bin et al., 2017). Within the same seminar, another study used an ensemble decision tree to detect ECG Artefacts. The data employed for this research consisted of 16-lead ECG data with a recording interval of 60 seconds. This dataset was then organized into "minority" or "majority" groups and then analyzed with an accuracy rate of 99.85% (Moeyersons et al., 2017). This method can identify factors influencing the decision and group them in an organized tree structure. This method is helpful because it can handle diverse and unstructured data well. Decision trees can present an easy-to-understand visualization of the decision-making process. This method is easy to understand and interpret, allowing doctors and medical experts to comprehend how ECG data is classified. Furthermore, this approach is applied to detect heart abnormalities. This analysis can potentially help the medical community diagnose heart disease early on to reduce the rate of heart disease.

The tools and materials used in data acquisition are electrodes, data cable, AD8232 sensor board, ESP-32 MCU node, SD card, Raspberry Pi, Bluetooth, and wifi. Application of a 3-lead ECG involves placing electrodes on the subject's chest according to their designated colors. The red electrode was placed next to the right shoulder under the collarbone, the yellow electrode was positioned adjacent to the left collarbone next to the left shoulder, and the green electrode was attached towards the base of the left rib cage, just below the pectoral muscle, as shown in Fig. 1.

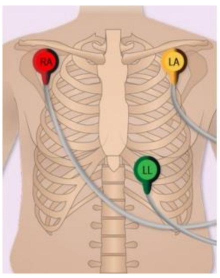

Fig. 1 ECG lead placement position

This research took place at Universitas Prima Indonesia and involved 30 male students between the ages of 18 and 22. The data collection process consisted of experiments conducted in three different situations: sitting, walking, and running. Data was acquired for 9 minutes per subject, divided into three categories: sitting, walking, and running, with each category being 3 minutes long. Electrodes were attached directly to the surface of the

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subject's chest to make contact with the chest muscle tissue. During relaxed sitting, the subject was asked to breathe normally while the data signal was recorded using a portable ECG device. The recorded ECG data was pre-processed to remove noise and artifacts and improve the quality. Finally, significant features, such as the PQRST wave, were extracted from the processed data.

The decision tree converts table data to a tree model. Simplified rules will be produced by the tree model to make it easier to understand and implement (Basuki et al., 2003). The decision tree will select the best features to divide the data and create decision rules at each node. The resulting decision tree serves as a predictive model. The ECG data will be filtered and normalized to ensure consistency, and then the tree's root will be computed. The root will originate from selected characteristics by computing the gain value for each attribute. The attribute with the highest gain value will serve as the initial root. Initially, the entropy value is calculated before computing the gain value for the attribute. Mathematically can be formulated with:

$$\mathrm{Entropy(s)} = \sum_{i=1}^{n} - \mathrm{pi} * \mathrm{log2pi} \qquad (1)$$

S represents the collection of cases, A denotes the characteristic, n signifies the number of partitions within S, and pi indicates the ratio of Si to S. The decision tree picks the feature that splits the data best (highest gain) as its root. This "gain" is calculated using the following equation:

$$\mathrm{Gain(S, A)} = \mathrm{Entropy(S)} - \sum_{i=1}^{n} - \frac{|S_i|}{|S|} * \mathrm{Entropy(Si)} \qquad (2)$$

S represents the collection of instances, A signifies the attribute, n denotes the number of partitions within attribute A, |Si| indicates the number of cases in the i-th partition, and |S| is the total count of cases in S (Larose, 2008).

The Decision Tree method is used to classify data based on specific conditions. This method continues until all data in a branch has the same class, the amount of data in a branch is too small, and further data separation using features is unable. The Decision Tree analyzes new data and selects the path that is most relevant to the data. The method will follow that path until it reaches the final node, where the prediction/classification results are displayed. Before applying this method, heart-rate signals are collected first from subjects through electrodes attached to the chest while they are sitting, walking, and running. The collecting data will transferred to the Raspberry Pi system via Bluetooth and ESP32, which works as an intermediary. The system processes the data using Python with two main principles: filtration and extraction. The data is then processed using the decision tree method, which produces four categories: abnormal, normal, potential arrhythmia, and high potential arrhythmia. The collected data will be sent to the cloud system or web server via a WiFi connection, where it can be accessed by the user, as shown in Fig. 2.

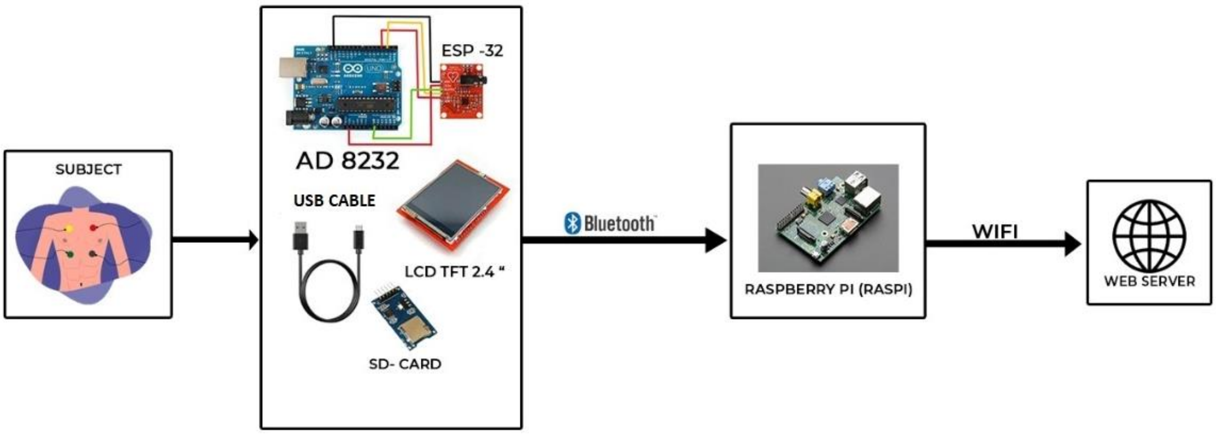

Fig. 2 Block Diagram

RESULT

An ECG or electrocardiogram is a commonly used diagnostic tool to detect various heart problems such as heart failure, arrhythmias, and myocardial infarction. It measures the electrical impulses generated by the heart to help doctors determine the patient's heart rate and rhythm. Decision tree analysis is a data analysis method that can be used to improve the accuracy and efficiency of heart disease diagnosis. Decision tree methods can reduce errors

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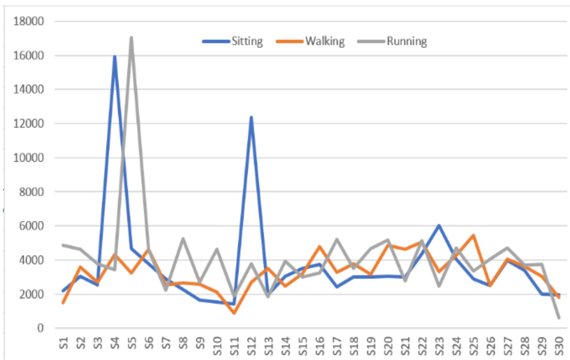
that may arise during visual observation of ECG data, thus improving the accuracy of diagnosis and patient outcomes. Each research subject produces a unique wave pattern with specific characteristics that distinguish it from others. Healthcare professionals use amplitude or wave height of ECG data to analyze heart rhythms, detect possible arrhythmias, and evaluate heart health. This amplitude indicates the repolarization and depolarization of the myocardium.

The averaged data of the extracted ECG signals were grouped and visually displayed according to the established experimental scenario. Fig. 3 depicts the activities of sitting (shown in blue), walking (shown in red), and running (shown in gray). Fig. 3 (a) shows the RR graph depicting the RR interval, the distance between two R wave peaks on the ECG measured in units of time (s/ms). The Normal RR interval ranges from 600 - 1200 ms. Fig. 3 (b) shows a PR graph illustrating the PR Interval. The PR interval represents the duration from the beginning of the P wave to the onset of the QRS complex on an ECG. PR interval signifies the duration required for an electrical signal to travel from the top chambers (atria) to the bottom chambers (ventricles). The Normal PR interval ranges from 120-200 ms. Fig. 3 (c) QS graph shows QS waves on the ECG, which signifies a lack of Normal electrical activity in the inferior ventricles of the heart during depolarization. Fig. 3 (d) The ST graph shows the segment of ECG recording known as the ST segment. This segment represents the time between the S wave (when the lower heart chambers contract) and the beginning of the T wave (when these chambers start to relax). It reflects the duration during which the ventricles undergo contraction (depolarization) and then begin the process of relaxing again (repolarization). A Normal ST segment length is between 5 and 150ms. Fig. 3 (e) QT graph shows the QT interval, which spans from the initiation of the Q wave to the conclusion of the T wave, signifies the length of time it takes for the ventricles to undergo depolarization and repolarization. Fig. 3 (f) QTC graph shows the corrected QT interval. Bazett's formula is a popular way to adjust the QT interval on an ECG based on heart rate. For adult men, the normal range for QTC is typically between 350 to 450 ms, while for adult women, it generally falls within 360 to 460 ms. Fig. 3 (g) HR graph shows the heart rate. HR is heartbeats per minute.



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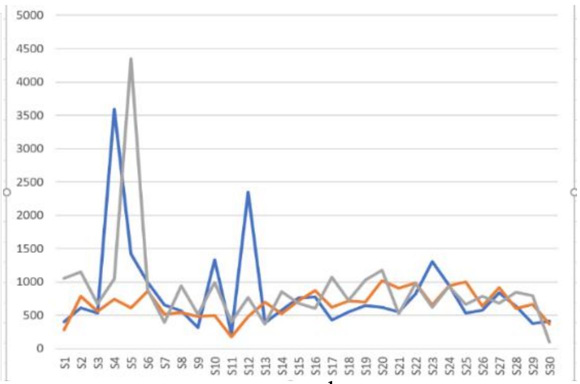
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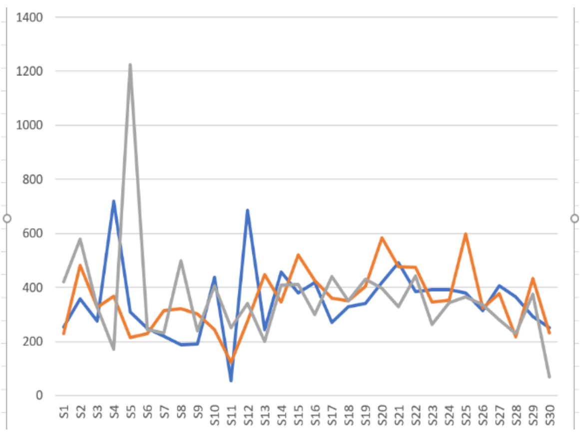
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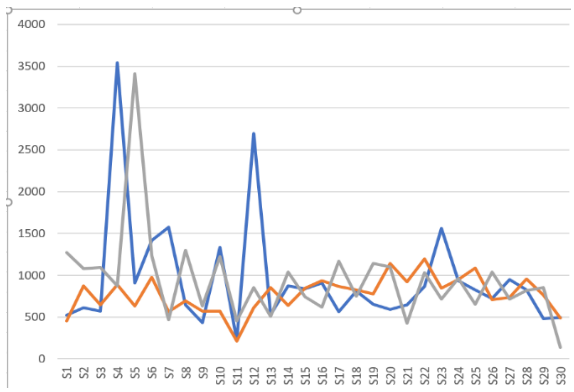
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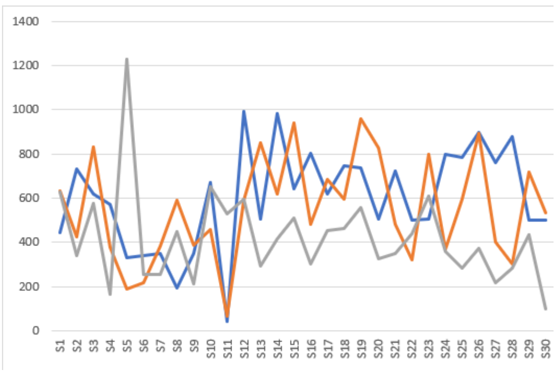

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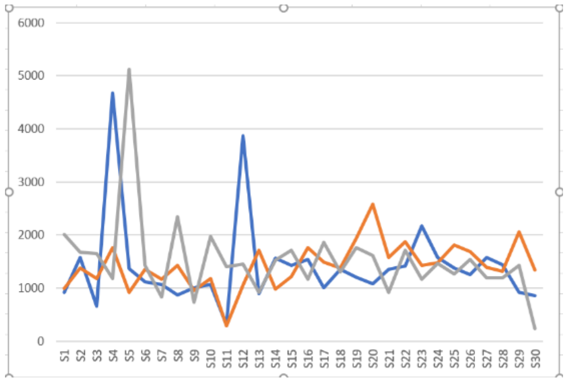

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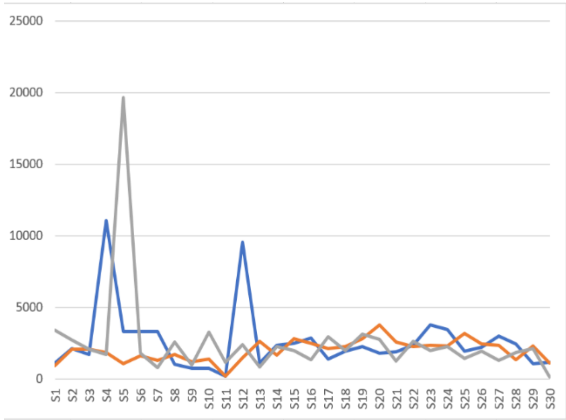

g.

Fig. 3 Visualization of average extracted features in sitting (blue), walking (red), and running (gray) conditions: a) RR b) PR c) QS d) ST e) QT f) HR g) QTC

DISCUSSIONS

In this section, the visualization shown in Fig. 3 becomes the basis for assigning input classes to the classifier using the decision tree method. By applying the decision rules that have been validated on the tree, a decision tree structure is created and utilized in the classification process to forecast the class or target value of the data. In this study, there are 4th classes, namely abnormal (<1618.15), normal (1618.15 - 2579.73), potential arrhythmia (2579.74 - 3541.33), and highly potential arrhythmia (3541.34 - 4502.93). The assignment of class value boundaries is considered based on the density of the test data involved. Do not forget that the decision tree makes predictions based on the bulk of classes found in the leaf nodes. Therefore, the prediction results may vary depending on the effectiveness of the splitting rules in the tree and the balance of the class distribution in the training data. Building a decision tree model requires careful consideration of pertinent splitting attributes and data processing to provide the best possible outcomes.

A scatter plot is a graph often used in statistics and data analysis to illustrate and evaluate the correlation between two numerical variables. It consists of several points located on cartesian coordinates, with each point serving as a representation of one data point or observation. On the graph, each point's position on the horizontal line reflects the value of the independent variable (generally on the X-axis), and the value of the dependent variable is represented by the vertical position (generally on the Y-axis). Scatter plots are suitable for recognizing the potential connection between 2 variables, such as positive, negative, or no clear relationship (uncorrelated) (RevoU, 2023). In Fig. 4, there are 4 data points, namely, "Abnormal" (blue color), "Normal" (red color), "Potential Arrhythmia" (yellow color), and "Highly Potential Arrhythmia" (purple color). Fig. 4(a) shows a negative correlation where the ST variable increases while the HR variable decreases. Fig. 4(b) shows no correlation between PR and QS variables where the data points are scattered randomly. Fig. 4(c) shows that the data points gather around a straight line and ascend from left to right, indicating a positive correlation between the QT and ST wave variables. Fig. 4(d) shows no correlation between the QS and QT variables where the data points are randomly scattered.

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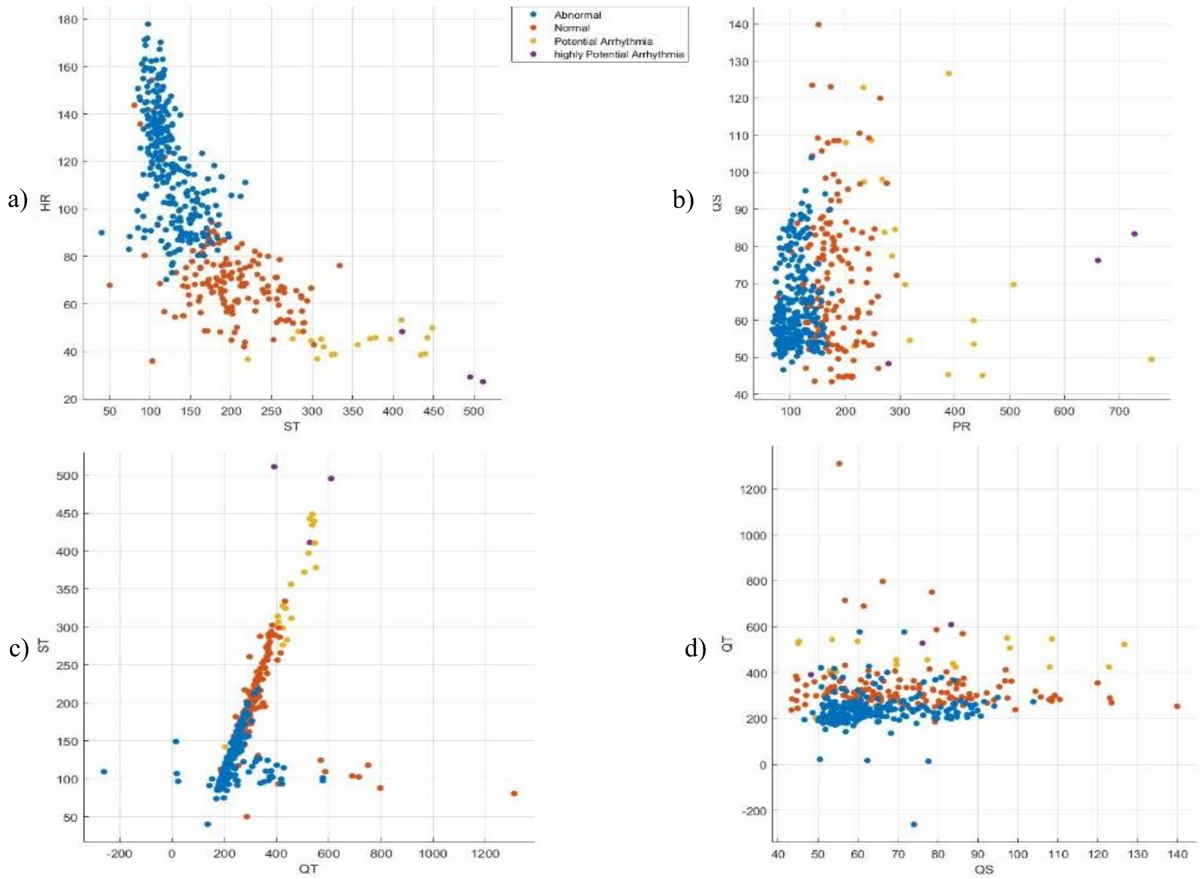

Fig. 4 Scatter Plot a) ST, b) PR, c) QT, d) QS

To assess the performance of a decision tree classification model, we compare the actual value with the predicted value. In machine learning, we use a performance measurement tool called a Confusion Matrix for two or multi-class classification. A Confusion Matrix is a table with four varied categories that show the contrast between the true and predicted values in classification problems. The Confusion Matrix comprises four expressions that signify the outcomes of the classification process: TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) (Anggreany, 2020). Fig. 5 displays the true class on the vertical axis (Y-axis) and the model's predicted class on the horizontal axis (X-axis). The higher the value of TP, the more intense the blue color, and the higher the value of FN, the more intense the red color. An ideal classifier would produce a confusion matrix where only the elements on the diagonal have values, which means that all test samples from all four classes or groups are correctly classified. In Fig. 5 (a), the first row of the first column shows a value of 285, while the other three columns have no values, which means the decision tree successfully classified all 285 Abnormal test samples correctly. In the second row, the second column shows a value of 151, and the third column has a value of 1. Thus, the decision tree did not successfully classify all Normal test samples 151 test samples were correctly predicted in the Normal class, and 1 test sample was incorrectly predicted as potential arrhythmia. Fig. 5 (b) displays the FNR (False Negative Rates) and TPR (True Positive Rates). TPR represents the percentage of observations accurately categorized according to the True class. FNR reflects the percentage of instances misclassified according to the true class. Fig. 5(c) shows the FDR (False Discovery Rates) and PPV (Positive Predictive Values). According to Fig. 5, the decision tree classification model achieved 99% accuracy, 99% precision, 99% recall, and 99% F1 score. The 99% accuracy result shows that the classification model exhibits a notable degree of accuracy in classifying data correctly. The precision result of 99% indicates that the classification model has a high level of precision in making Positive predictions. The recall result of 99% shows that the classification model has achieved a high recall of all positive cases. The F1 score finding of 99% shows that the classification model has a remarkable balance between precision and recall.

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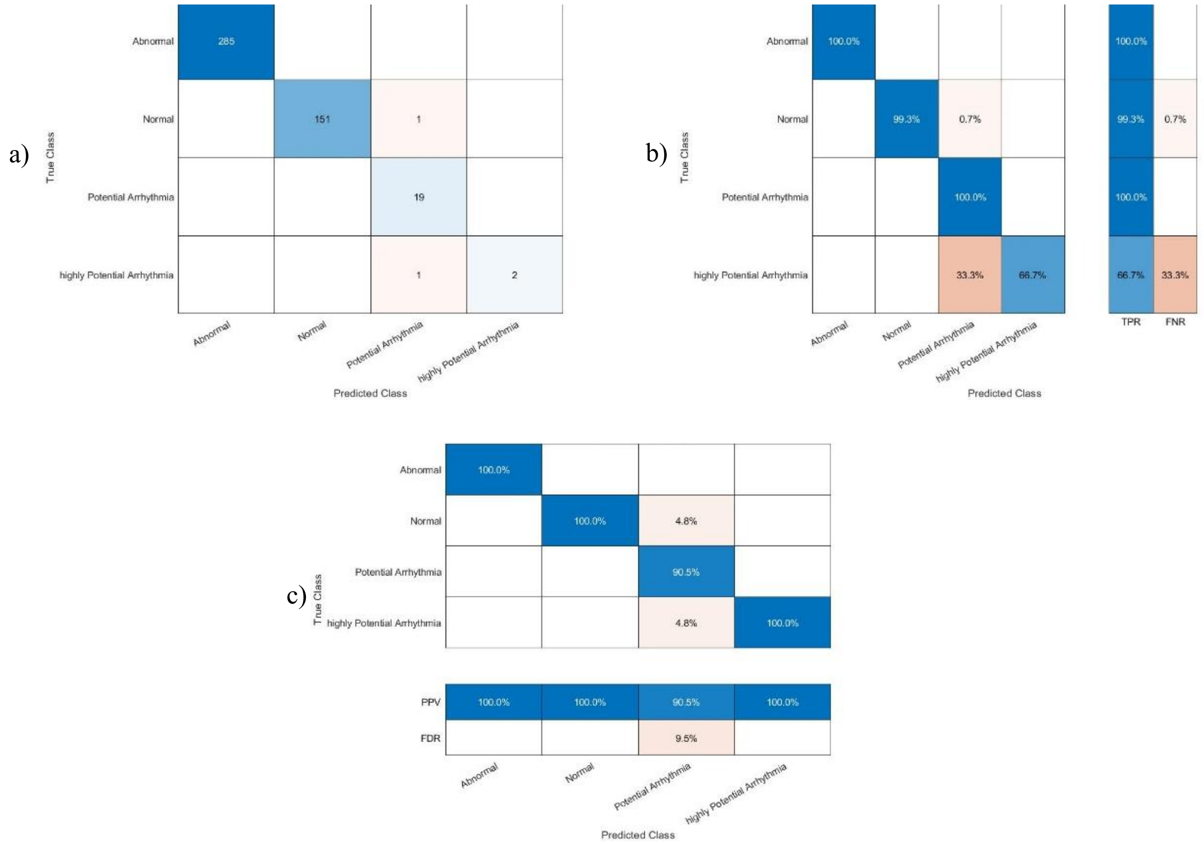
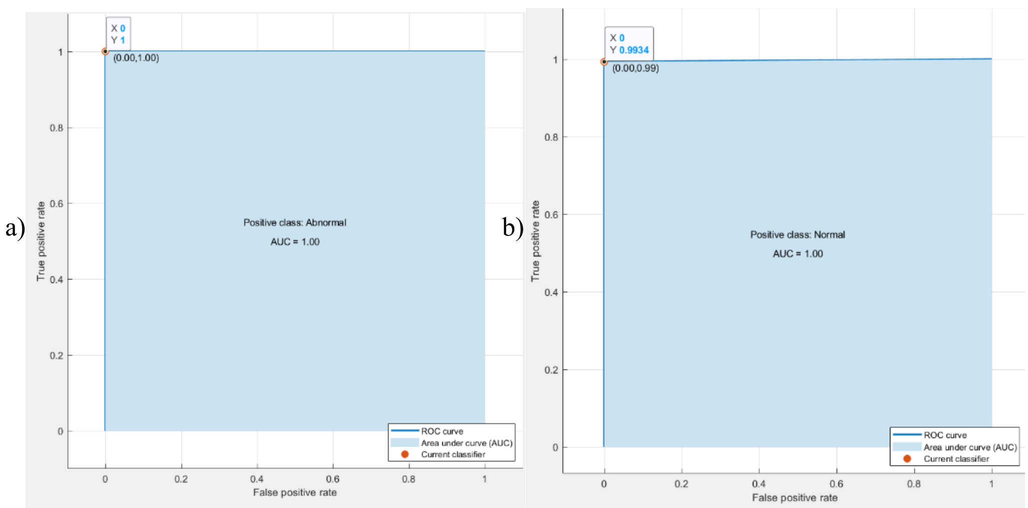


Fig. 5 a) Number of Observations b) TPR & FNR c) PPV & FDR

The performance of a classification model can effectively evaluated using a Receiver Operating Characteristic (ROC). The curve depicts the connection of TPR and FPR at different thresholds of classification score values. Each point on the ROC curve represents the correlation of TPR and FPR corresponding to a certain threshold in the classification score. Area under an ROC curve (AUC) is a metric that measures the overall classification performance, considering all possible threshold values. A model's AUC score goes from 0 to 1, with higher scores signifying better classification ability (MathWorks, n.d.). Figs. 6 (a), 6 (b), and 6 (c) show AUC = 1 for the abnormal, normal, and potential arrhythmia classes. It means that the decision tree classification model successfully classified all observations in the three classes correctly. Fig. 6 (d) shows the AUC value = 0.83 for the highly potential arrhythmia class. This means that the decision tree classification model has not succeeded in classifying all observations in the class correctly, but it is close enough.



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c) d)

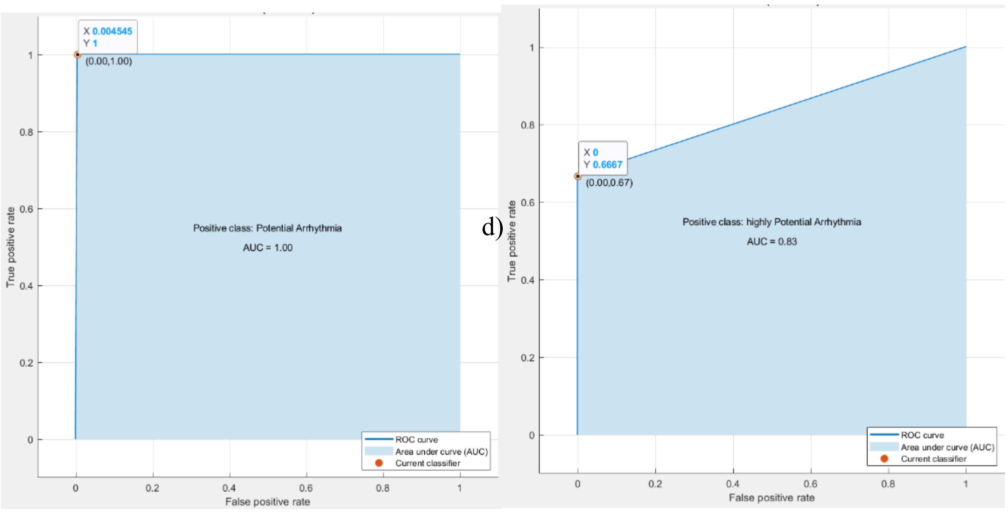

Fig.6 a) Data results using the ROC graph show the average positive data "Abnormal" b) Data results using the ROC graph show the average positive data "Normal" c) Data results using the ROC graph show the average positive data "Potential Arrhythmia" d) Data results using the ROC graph show the average positive data "Highly Potential Arrhythmia"

CONCLUSION

The decision tree method shows promising results in identifying heart abnormalities at an early stage. This method gets an accuracy rate of 99%, 99% precision, a recall of 99%, and an F1 score of 99% with a very high accuracy rate, which means that the model is quite good at classifying data. Overall, these results show that the decision tree method has great potential as an initial screening tool to detect cardiac abnormalities with exceptional accuracy. The decision tree method has great potential to assist doctors in identifying early-stage heart problems. With early detection, patients can receive appropriate treatment and increase their chances of recovery.

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