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PREDICTIVE MODELING OF CARDIAC ABNORMALITIES

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Abstract: Electrical signals in the heart are recorded by the electrocardiogram (ECG). The electrocardiogram is a diagnostic tool for heart diseases such as heart arrhythmias, sleep apnea, and myocardial infarction. To prioritize the detection of abnormalities in ECG data, this research presents a technology identified using machine learning algorithms. The final model that emerges is a method defined by regular heart rate analysis. The model, which is expected to reduce power consumption by more than 50%, is used in ARM Cortex M4-based embedded devices. The system is well-prepared for clinical use due to its real-time adaptation, single processing, reduced complexity and interpretation. It is an Internet of Things (IoT)-enabled wearable edge sensor that provides the necessary sensitivity and accuracy by consuming very little power.

***Index Terms* - Electrical signals; ARM Cortex M4; real-time flexibility; Single functionality; Internet of Things; Irregular heartbeat.**

I. INTRODUCTION

Respiratory sinus arrhythmia is an example of cardiac arrhythmia, normal, changes in heart rate that are generally not harmful to human health. On the other hand, some of the other types of arrhythmia may indicate a dangerous problem that could lead to stroke or shock death. Continuous self-management of electrocardiogram (ECG) abnormal data using Internet of Things (IoT)-enabled wearable devices can reduce risks associated with cardiovascular diseases. Range and individual differences affect the quality of data interpretation, and continuous monitoring of clinical-level ECG signals is not yet possible. To ensure the correct detection, dynamic features must be extracted from the ECG signal. It is not practical to keep them under constant observation.

Even though long-term data is available, doctors struggle to manually evaluate large amounts of data. If we decide to send all data to the cloud server in real time, the wearable device will need more power and the battery life of the sensor will be shorter. The system automatically detects abnormalities in the ECG and separates them into normal and abnormal. This frees up resources on the edge device because only random hits need to be given to the cloud server. The second class, with cardiologist-level accuracy and more advanced techniques, can be integrated into the cloud platform for sharing across multiple classes of abnormal devices. There are many ways to identify irregular heartbeats, including machine learning techniques. The power and footprint of the wearable platform is directly related to its complexity.

Additionally, complex data analysis requires cloud services that also support communication overhead and significant memory usage. Prevention, diagnosis and treatment of diseases. This decision opens a window to the future of clinical medicine by combining the power of data science, machine learning and clinical experience. It is important to evaluate a variety of patient information, including medical history and demographic characteristics. Provide early diagnosis and prevention using advanced algorithms and computational techniques to discover patterns, trends, and risk factors associated with different heart diseases. Prognostic models have important applications for cardiology. If doctors can know for sure when heart disease will occur, they can reduce the risk by intervening before heart disease occurs.

II. LITERATURE SURVEY

Deepu John, S. Gawsalyan, B. Cardiff, and K. K. Nundy and teams [1] discussed a rule mining strategy for instantaneous ECG anomaly detection in IoT edge sensors. Their plan will include the use of biased artificial neural networks (ANNs), whose content is derived from electrocardiographic heartbeat sequences. The main goal is to achieve target precision and accuracy with minimum runtime complexity. The algorithm tries to find the balance where the code of nodes can improve overall understanding, while single nodes can improve accuracy. This approach is done by using real content analysis to implement algorithms, thereby reducing overall energy consumption. The technology concept is particularly suitable for medical applications, especially in the context of wearable edge sensors supporting the Internet of Things. Its good definition, low complexity and adaptability make it a good solution for ECG abnormality detection. Leveraging mining rules and artificial neural network techniques, this approach can provide accurate and useful results in the context of IoT edge sensors. Overall, this paper presents a promising approach that meets the critical need for real-time ECG abnormality detection with IoT edge sensors as well as clinical and practical application technology.

Ogunpola A, Saeed F, Basurra S and team [2] focused on cardiovascular diseases, which is a major challenge in global health and shows the urgent need to improve more accurate and efficient detection methods. Many studies have provided important information in this area, but there is still a need to develop predictive models and resolve inconsistencies in current detection methods. For example, some previous studies did not account for the problem of inconsistent data; this can lead to poor predictions, especially when the data contains fewer learning units. The main goal of this research is to detect heart disease, specifically myocardial infarction, early using machine learning. It addresses the issue of data inequity by processing the best data to identify effective strategies. Seven machine learning and deep learning algorithms were used to improve the accuracy of predicting heart disease. This study sheds light on the development of myocardial infarction prediction models by investigating different factors and their performances. The results of the study demonstrate the effectiveness of the carefully evaluated XGBoost model for cardiovascular diseases. This optimization results in good results: 98.50% accuracy, 99.14% precision, 98.29% recall, and 98.71% F1 efficiency. This optimization significantly increases diagnostic accuracy for heart disease.

Olatunji, Aishat and Abdul-Ykeen and team [3] discuss the healthcare system that uses large amounts of patient information to provide insights into healthcare facilities. Gain clinical information through screening to make informed decisions. Decision-making information helps improve the organization, management and evaluation of patient information to achieve better outcomes. Technology and analytics help identify cardiovascular health issues by providing information to drive better outcomes. Heart disease is the leading cause of death in developing countries. Research shows that machine learning can help improve health in heart disease. This research article addresses the need for better machine learning (ML) models for early prediction of cardiovascular disease. This article focuses on machine learning such as logistic regression (LR), neural networks (NN), random forest classifiers (RF), and decision trees (DT) to help classify heart disease in patients. They also include machine learning data to improve the accuracy of the algorithms.

Edward Vigmond and Gernot Plank [4] focused on modeling the heart, which has become a powerful tool to help understand heart functionality through both normal research and medical development. Cardiac electrophysiology modeling has evolved remarkably over the last 50 years, with the most recent advance being the integration of mechanical systems into the model. This article will provide an overview of the physical systems to be modeled, the equations that govern them, and the basic assumptions that simplify them. Mathematical strategies for solving these problems are discussed. With today's electronics and technology, it is now possible to create a personalized, detailed electromechanical heart model.

Humayun, Humayun, AI, Gaffarzadegan S and team [5] also stated that predicting heart disease is a very difficult task in medicine and accurate prediction is important to decide on patient treatment in the future. Nearly 30 million people worldwide die from heart failure and various heart diseases. Machine learning are technologies that can now help understand the mind. Many researchers have developed methods to predict heart disease using a variety of methods, but accurate prediction of heart disease remains difficult. Cardiac index and age of the heart are two important indicators that show the true health of the heart. In this article, we propose to use IoT and machine learning techniques to predict heart disease. We initially collected data from various sensors such as sunroom BP for heart rate, max30100 for blood oxygen saturation, EEG for PT and QR segments. Powerful training model architecture. Through a comprehensive analysis, various machine learning (ML) and deep learning techniques were evaluated with existing applications. Recurrent Neural Network (RNN), SVM (Support Vector Machine), Naive Bayes (NB), Random Forest (RF), etc. It achieves better detection and classification accuracy than machine learning (ML) methods such as.

Rina S. Patil, Tripti Arjariya, & Mohit Gangwar [6] discuss cardiac auscultation, a widely used, noninvasive, and cost-effective method for early diagnosis of heart disease. Although machine learning-based systems can help evaluate patients effectively, the performance of these systems is affected by many factors such as the stethoscope/sensor, environment, and the process of recording information. This article explores the negative effects of heart rate variability and develops strategies to solve this problem. Methods: We propose a novel convolutional neural network (CNN) technique consisting of temporal convolution (tConv) units that simulate finite impulse response (FIR) filters. Filter coefficients can be changed via backpropagation and placed at the end of the network as a learned filter bank. Results: In case of multiple registrants, the recommended method for obtaining the best highest score in the case of heart sounds cannot be seen (binary division of work). We used sensitivity, specificity, F-1 score, and Macc (mean of sensitivity and specificity) as performance measures. Our system achieved up to 11.84% relative improvement in MACc compared to the state system.

H. A. Poonja, M. Soleman Ali Shah [7] believes that the most common cause of death worldwide is heart disease. It is important to evaluate and predict heart disease. This new method is to identify abnormalities in ECG signals and classify heart diseases (17 groups) based on 1000 ECG signal segments from 45 patients in the MIT-BIH Arrhythmia Database. The proposed method uses two methods, one of which uses traditional machine learning algorithm, which is SVM (Support Vector Machine), and the deep learning method uses CNN (Convolutional Neural Network) based architecture (ALEXNET). Spectral energy density was determined using the Welch method and discrete Fourier transform. Data are normalized and scaled to unity standard deviation. Among the testing methods, CNN classification accuracy is 87-90% and SVM classification accuracy is 70-76%. According to data, this is the easiest way to use deep learning with up to 90% accuracy. Deep learning techniques increase accuracy and can be used in clinical settings.

Shadman Nashif, Dr. Rakib Raihan and team [8] focused on cardiovascular disease, which is the most common cause of death in developing, underdeveloped and developing countries in the last few years. Early detection of heart disease and ongoing care from doctors can reduce death rates. However, it is not possible to diagnose all heart diseases and since it requires more expertise, time and expertise, patients consult doctors 24 hours a day. In this study, a preliminary design of cloud-based heart disease prediction is proposed to detect possible heart disease using machine learning. to achieve this to increase to increase to increase to increase to increase to increase to increase to increase to increase to sneeze The proposed algorithm has been validated by two widely used open source repositories, where 10-fold cross-validation was used to verify cardiac diagnostic performance. The accuracy of the SVM algorithm is 97.53%, and its sensitivity and specificity are 97.50% and 94.94%, respectively. In addition, we designed and prepared an instant patient monitoring system using Arduino, which has the ability to instantly know some indicators such as body temperature, blood pressure, humidity and heart rate, so that the environment of cardiac patients can be monitored by their caregivers/physicians. . . The built-in system can send the recorded data to the central server and update it every 10 seconds. So doctors can use the app to see real-time measurement data of the patient and start creating real-time videos when medicine is needed urgently. Another important feature of the system is that the doctor is immediately informed via GSM technology when the patient's time measurement exceeds the threshold value.

III. PROBLEM IDENTIFICATION

Continuous patient care is necessary to ensure the best possible patient outcomes, timely intervention, and early detection of serious health problems. However, many obstacles must be overcome to ensure consistency and ongoing care. Continuous monitoring produces a wealth of data, including physical parameters such as blood pressure, oxygen saturation and heart rate. Clinicians can become overwhelmed by managing and analyzing this data in real time; this can lead to data overload and the potential for important signals to be lost in the noise. Routine care is often associated with bed rest, which limits patients' comfort and mobility. This restriction increases the risk of complications such as heartburn and muscle weakness and may hinder patient satisfaction and recovery efforts. "Standard Diabetes Testing" uses electrocardiogram (ECG) signals to meet the needs of technology to distinguish heart rhythms and abnormalities.

i. EXISTING SYSTEM

Continuous monitoring now uses a variety of technologies and methods to track patient vital signs and health indicators. Hospitals and other medical facilities often use bedside monitors to constantly monitor vital signs such as heart rate, blood pressure, lung respiration, and blood oxygen saturation. Oftentimes, cables and sensors are used to connect these monitors to patients, allowing doctors to access real-time information. Telemetry systems can monitor patients' vital signs wirelessly and provide greater mobility and flexibility compared to bedside monitors. Although continuous monitoring has improved patient care and outcomes, efforts continue to address issues such as fatigue, coordination, privacy concerns, and usage restrictions.

ii. PROPOSED SYSTEM

The technology concept consists of tools that can identify abnormal ECG heartbeats and classify them into abnormal and abnormal heartbeats using low complexity techniques. This frees up resources on the edge device because only garbage needs to be sent to the cloud server. It includes developing better analytics, using sensors to improve patient comfort, and placing greater emphasis on patient engagement and self-care.

IV. METHODOLOGY

i. ARCHITECTURE DIAGRAM

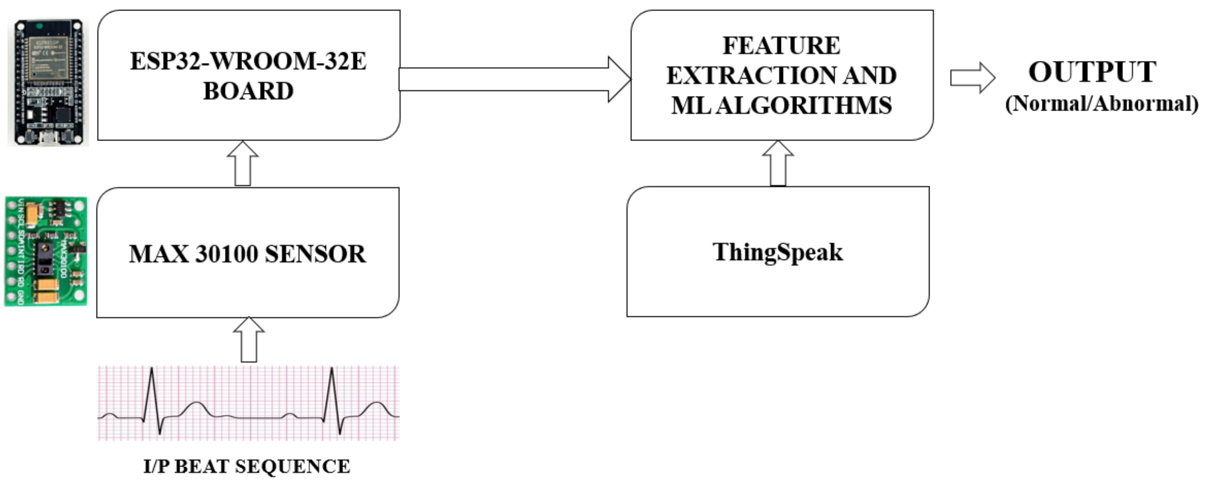

Figure 4.1 Architecture diagram of model for predicting cardiac abnormalities

1. **SENSORS**: Sensors are rod-like electrodes are used to monitor electrical signals from the heart. Computers then analyze data from these sensors to identify patterns that indicate abnormalities in the heart and distinguish heart rhythms.
2. **ESP32 BOARD**: The ESP32 board is a microcomputer commonly found in electronics to diagnose cardiac issues using ECG signals. By using special programs and connecting to an ECG sensor, the ESP32 can instantly analyze ECG data to diagnose heart disease without the need for traditional ECG analysis.
3. **ThingSpeak:** ThingSpeak is an online tool used to collect, measure and visualize physiological data, including ECG signals, to diagnose sleep apnea. Instead of needing traditional electrocardiogram data, researchers use ThingSpeak to stream data from medical devices or wearables, allowing heartbeats to be monitored and analyzed.

ii. ALGORITHM USED

1. **DECISION TREE ALGORITHM**: Decision tree algorithm is the most popular machine learning method for regression and classification applications. It is a useful tool for data analysis and predictive modelling, as it is very simple and straightforward to use. The decision tree algorithm represents the data as a tree; each node represents a decision based on a specific value, each branch represents a decision, and each leaf represents a final choice or prediction. Depending on conditions such as data gain or Gini impurity, this algorithm determines which of these is best for the data segment. The goal is to identify features that optimize the end result. It is repeated by dividing the data into subsets based on selected features until certain limits are met, such as the maximum height of the tree, the minimum number of samples per leaf, or until further improvements in impurity reduction are achieved. When the tree reaches maturity, each leaf is assigned a continuous value for the regression function or a list for the classification function. The class majority in the affected leaf or the average of the training samples forms the basis for these predictions.

Algorithm 1: Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
DecisionTree = DecisionTreeClassifier(criterion="entropy",random_state=2,max_depth=5)
DecisionTree.fit(Xtrain,Ytrain)
predicted_values = DecisionTree.predict(Xtest)
x = metrics.accuracy_score(Ytest, predicted_values)
acc.append(x)
model.append('Decision Tree')
print("DecisionTrees's Accuracy is: ", x*100)
print(classification_report(Ytest,predicted_values))
```

2. **NAÏVE BAYES ALGORITHM**: Naive Bayes method is based on Bayes theorem and assumes that the features are independent. Naive Bayes is particularly suitable for text classification and other problems with high-dimensional data because it is simple yet powerful and effective. Includes theories of independence, modeling, and classification.

Algorithm 2: Gaussian Naïve Bayes

```
from sklearn.naive_bayes import GaussianNB
NaiveBayes = GaussianNB()
NaiveBayes.fit(Xtrain,Ytrain)
predicted_values = NaiveBayes.predict(Xtest)
x = metrics.accuracy_score(Ytest, predicted_values)
acc.append(x)
model.append('Naive Bayes')
print("Naive Bayes's Accuracy is: ", x)
print(classification_report(Ytest,predicted_values))
```

3. **SUPPORT VECTOR MACHINE ALGORITHM**: As a supervised learning technology, the support vector machine (SVM) algorithm is used in regression and classification problems. The purpose of this method is to find the best hyperplane in different areas to separate the points into different groups. SVM easily processes linear and nonlinear datasets by using various kernel functions to render the input data in a higher level space. Maintaining separation between groups, essentially creating a decision boundary, is his main idea.

Algorithm 3: Support Vector Machine (SVM)

```
from sklearn.svm import SVC
from sklearn.preprocessing import MinMaxScaler
norm = MinMaxScaler().fit(Xtrain)
norm = MinMaxScaler().fit(Xtrain)
X_train_norm = norm.transform(Xtrain)
X_test_norm = norm.transform(Xtest
SVM = SVC(kernel='poly', degree=3, C=1)
SVM.fit(X_train_norm,Ytrain)
predicted_values = SVM.predict(X_test_norm)
x = metrics.accuracy_score(Ytest, predicted_values)
acc.append(x)
model.append('SVM')
print("SVM's Accuracy is: ", x)
print(classification_report(Ytest,predicted_values))
```

4. **RANDOM FOREST ALGORITHM**: It behaves like a community of experts and each expert uses a decision tree to choose the answer. In order take a decision, the algorithm consults all experts or trees and chooses the most frequent answer in classification problems, or averages its predictions in regression problems. To ensure variety, each expert teaches using slightly different questions and information. With his intelligence, Orman is able to produce reliable and clear answers without extreme flexibility (or getting stuck in a single thought).

Algorithm 4: Random Forest

```
from sklearn.ensemble import RandomForestClassifier
RF = RandomForestClassifier(n_estimators=20, random_state=0)
RF.fit(Xtrain,Ytrain)
predicted_values = RF.predict(Xtest)
x = metrics.accuracy_score(Ytest, predicted_values)
acc.append(x)
model.append('RF')
print("RF's Accuracy is: ", x)
print(classification_report(Ytest,predicted_values))
```

V. DATA FLOW DIAGRAM

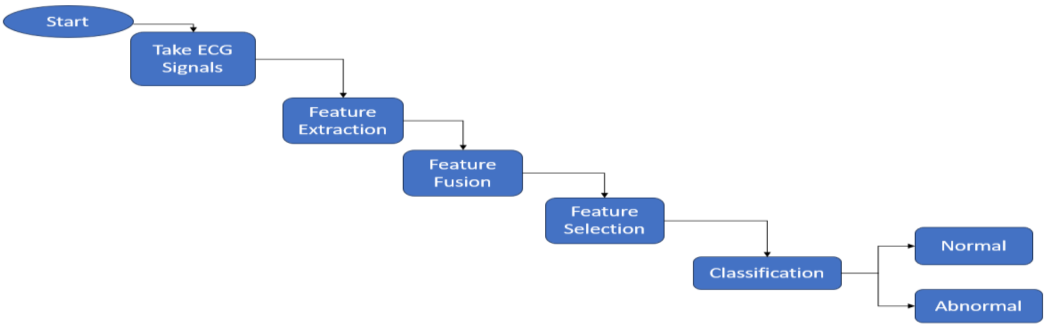

Figure 5.1 Data flow diagram of a predictive model for identifying cardiac abnormalities.

1. **FEATURE EXTRACTION**: The feature extraction process is to transform raw data into a collection of features that can capture the underlying trends of the data. This process is important to reduce the rest of the profile, collect key points, and prepare for processing with machine learning or further analysis. Feature extraction methods vary depending on the specific problem domain and data type.
2. **FEATURE FUSION**: To create a representation that contains additional information or integration, information from different sources or models is combined in a process called feature fusion, also called feature fusion or combination. Using multiple input methods, these methods aim to improve the robustness, discrimination, and capability of machine learning models. Feature fusion methods vary depending on the equipment and features.
3. **CUSTOM SELECTION**: Select a combination of key features in the initialization process to enhance interpretation, minimize redundancy, and improve model performance. This process is called feature selection. Model selection can simplify the model, reduce computational complexity, and improve overall resource efficiency by focusing on the most important data and eliminating unnecessary features that are essential or repetitive.

VI. RESULT

The results of heart function tests may vary depending on the specific equipment used and the quality of the data. The graph below shows the results obtained from the ECG sensor and the BPM values shown in the graphical manner.

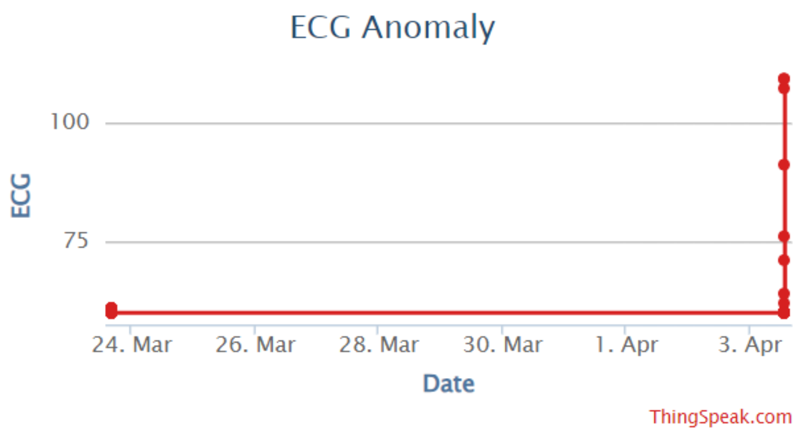

Figure 6.1 ECG readings from ThingSpeak.

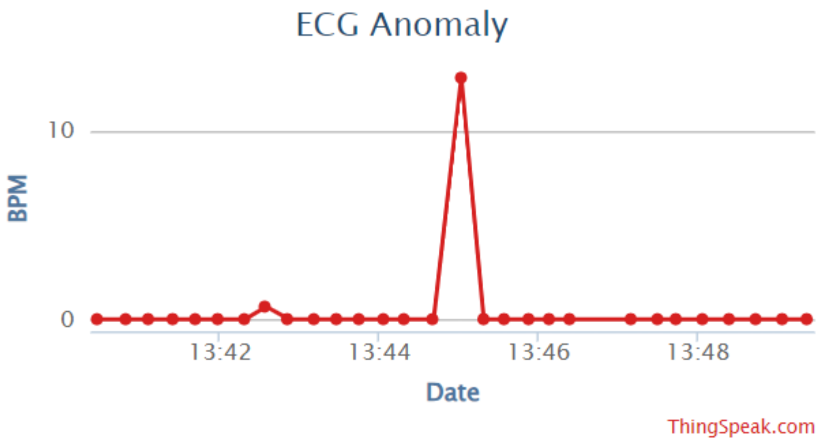

Figure 6.2 BPM readings from ThingSpeak.

The figure below shows the actual comparison results of data run by machine learning algorithms such as decision tree algorithm, naive Bayes algorithm, support vector machine algorithm and random forest algorithm. As can be seen from the figure, the accuracy of decision tree and random forest algorithms is 100%, while the accuracy of Naive Bayes and SVM is 94.67% and 98.67%, respectively.

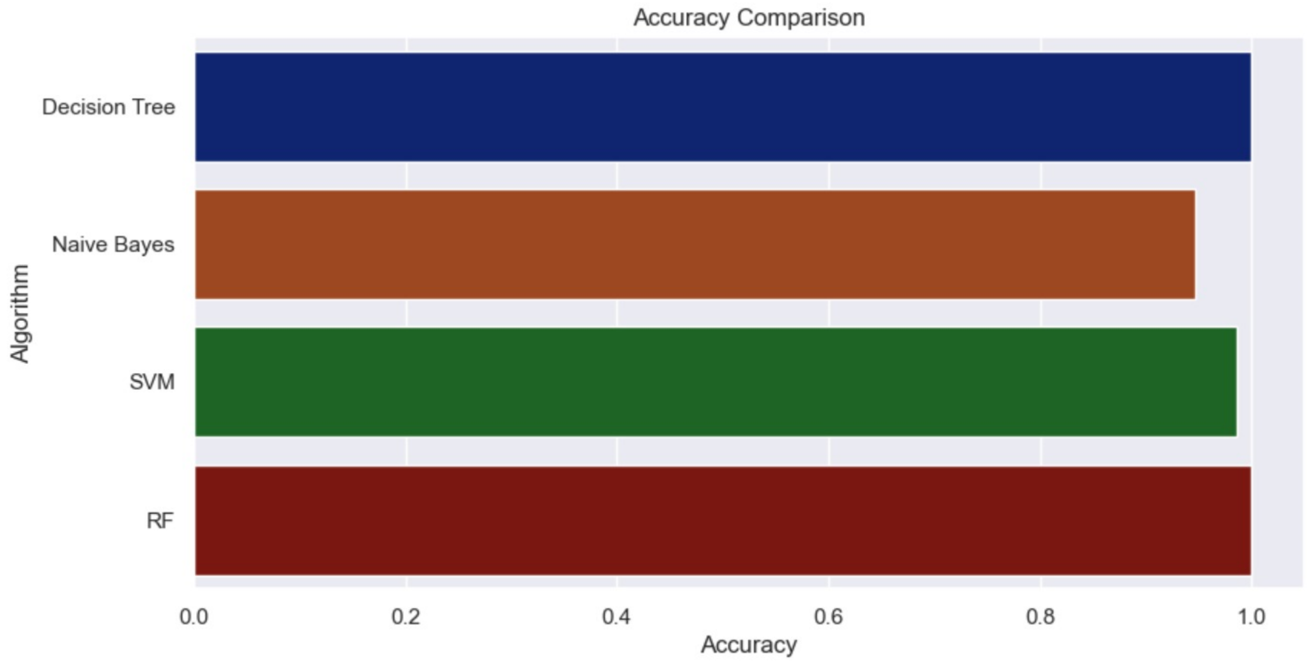

Figure 6.3 Accuracy Comparison between different machine learning algorithms

VII. CONCLUSION

In summary, ECG abnormality detection shows great potential in improving the issues related to heart. By leveraging ML Algorithms and signal processing technology, we have created a powerful system that can identify abnormalities in the ECG recording. Many milestones were reached throughout the project. First, we successfully processed and processed different ECG datasets, ensuring the data used to train and evaluate the model is excellent. Secondly, using state-of-the-art machine learning algorithms, we can learn and extract important features from ECG signals, allowing us to identify normal and abnormal heart rate.

VIII. FUTURE ENHANCEMENT

Future developments include better analytics, usage of smaller sensors to increase patient comfort, improved cybersecurity measures, and importantly, patient engagement and self-care.

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