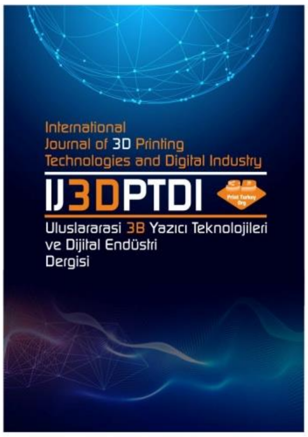

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PORTABLE ECG DEVICE FOR CONTINUOUS HEART HEALTH MONITORING AND MACHINE LEARNING APPROACHES FOR ARRHYTHMIA CLASSIFICATION

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ABSTRACT

In this study, a portable electrocardiogram (ECG) device was developed using the Arduino Portenta embedded system board and the AD8232 sensor to enable continuous and real-time cardiac monitoring. The designed system acquires ECG signals through surface electrodes and transfers them wirelessly to a computer, where the data are recorded and analyzed in real time using MATLAB. The main objective of this research is to automatically detect cardiac arrhythmias by integrating a compact ECG acquisition system with machine learning (ML) algorithms. The training dataset was obtained from the MIT-BIH Arrhythmia Database on PhysioNet, while test data were collected in the laboratory using the proposed device from 20 individuals (10 healthy and 10 with arrhythmia). ECG signals were segmented into 60-second intervals, preprocessed, normalized, and analyzed to extract time-domain and statistical features. Several feature selection methods (GINI, ReliefF, Information Gain, Chi-square, and FCBF) were applied, and various ML classifiers were trained, including Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, k-Nearest Neighbours (kNN), Decision Tree, Stochastic Gradient Descent (SGD), Random Forest, Gradient Boosting, and Artificial Neural Network (ANN). The results showed that the Neural Network achieved the highest performance with an accuracy of 94.5.0% and an AUC of 99.2%, followed by Logistic Regression and SVM. The integration of a self-designed portable ECG device with intelligent ML algorithms provides a low-cost and efficient solution for real-time arrhythmia detection, supporting early diagnosis and continuous monitoring within the Internet of Medical Things (IoMT) framework.

Keywords: Arduino, Arrhythmia, ECG, Machine Learning.

1. INTRODUCTION

In recent years, research in this field has increased significantly due to the rise in heart and circulatory system diseases. Heart conditions, in particular, rank among the leading causes of death. This situation is linked to unhealthy lifestyles and dietary habits. People suffering from cardiovascular diseases are generally aged 40 and above; however, in recent years, this condition has also been frequently observed in younger individuals.

An ECG is a graph produced by an electrocardiograph that records the electrical activity of the heart over a specific period. An ECG is a diagnostic test that analysis the cardiac conduction system and provides the clinician with insights into the health of the heart and the disease process the patient may be experiencing. Many patients presenting for emergency care either have an acute cardiac emergency or a history of cardiac disease. Accurate assessment of the patient improves the accuracy of diagnosis, triage, and patient management. This not only enables timely intervention but also reduces patients' long-term morbidity and mortality rates [1].

When using ECG analysis, which are very important in the diagnosis and treatment of diseases, it should be borne in mind that the diagnostic value of the first electrocardiogram is around 50 per cent, while successive ECG recordings during the treatment process can increase the accuracy of the diagnosis to around 99 per cent. A single ECG recording alone is not sufficient to determine whether a person is ill.

Kozakevicius et al. [2] succeeded in filtering and analysing ECG signals using orthogonal wavelets. They determined the positions of the QRS complexes by using the "Haar" wavelet while analysing the signals.

In 2010, Mitra et al. [3] extracted the characteristics of electrocardiogram (ECG) signals using the multi-resolution wavelet analysis method. They filtered the signal using the wavelet decomposition method and determined the most suitable coefficients for each feature point by examining the coefficients they obtained. They then used these coefficients to find all points of the electrocardiogram signal.

To determine the characteristics of premature ventricular complexes (PVCs) in different forms and normal beats, Haijian et al. used QRS complex coefficients represented by Hermite functions and classified them using a radial basis function neural network [4]. Al-Fahoum characterised the features of electrocardiogram recordings using wavelet transform and classified critical arrhythmias using a radial basis function ANN [5]. Using principal component analysis and wavelet transform techniques, Ceylan et al. classified ECG arrhythmias in an ANN [6].

Chudacek et al. [7] utilised thirteen morphological feature elements obtained from ECG beats taken from the MIT-BIH and AHA databases and seven different classification algorithms found in radial basis function neural networks to classify PVC and normal ECG beats.

Sayılgan et al. [8] collected data from the Boston Beth Israel Hospital electrocardiography dataset recorded for normal and irregular electrical heart activity. In this dataset, four commonly used multi-classification methods (Fuzzy C-Means, Naive Bayes, Extreme Learning Machine, and K-Means) and seven different arrhythmias were used, and the sensitivity, specificity, and accuracy classifier properties were determined. When compared to each other, the Naive Bayes and Extreme Learning Machine classifiers had higher average performance values, and the Naive Bayes classifier achieved 92% accuracy on average across all arrhythmia types.

Weems et al. [9] analysed the structure of ANNs and their effect on pattern recognition in the classification of electrocardiogram signals from heart patients, achieving an accuracy rate of 96 per cent.

In another study, Yuan et al. [10] performed ECG classification using wavelength packet decomposition (WPD) and genetic algorithm backpropagation neural network (GA-BPNN). According to their results, they demonstrated that it can be effectively used to automatically identify heart diseases with an accuracy rate of 99.33%.

Liu, et al, to address the high mortality rate of arrhythmias, an efficient, lightweight student model was proposed using a knowledge distillation technique, achieving comparable accuracy to a large teacher model while being 1242.58 times smaller, making it suitable for real-time arrhythmia detection in wearable devices Electrocardiography [11]

Fang et al, the design of a low-power portable multi-lead ECG monitoring device based on STM32 was demonstrated; as a prototype, this device serves as an important example of sensor-based real-time ECG collection in portable health monitoring systems [12].

Liong et al, A 1-dimensional convolutional neural network (1-D CNN) based model operating without a QRS complex detection step was proposed; this approach analyzed the effect of ECG segment durations (5 s vs. 10 s) on classification accuracy [13].

Potharaju et al, heartbeat (beat-level) classification was performed with a multi-resolution sliding window strategy (overlapped windows with different length segments); this methodology demonstrates the capacity to distinguish 7 different arrhythmia types at the beat-level with deep learning models [14].

Thapa et al, presents a hybrid framework combining wavelet-based signal processing with deep learning, highlighting the potential of this methodology to provide robust and generalizable arrhythmia detection for wearable

ECG monitors even in noisy real-world data [15].

(ECG) plays a significant role in the diagnosis of heart diseases. ECG provides information about heart health by recording the heart's electrical activity. This study aims to continuously monitor heart health by developing a portable ECG device. ECG signals obtained from the Arduino Portenta embedded system board and AD8232 sensor were processed to measure heartbeats. This device will be able to transmit data to a computer via wireless communication and analysis ECG data in real time. Furthermore, the analysis of the data obtained will be provided using Machine Learning algorithms.

The implementation of this study could contribute to the development of technology with a wide range of applications, from personal health monitoring devices to clinical applications. Furthermore, monitoring and tracking heart health through portable devices used at home will help patients better manage their health conditions. Portable ECG devices can increase access to healthcare at home or in remote areas and improve heart health through early diagnosis.

The integration of a self-designed portable ECG device based on the Arduino Portenta platform, featuring real-time wireless data transmission and MATLAB-based signal analysis, represents a novel and practical contribution to wearable cardiac monitoring systems.

Furthermore, the study applies and compares multiple feature selection algorithms (GINI, ReliefF, Information Gain, Chi-square, and FCBF) in combination with several machine learning classifiers, offering a comprehensive comparative performance analysis that is rarely addressed in similar research.

2. MATERIALS AND METHODS

The biological signals detectable on the human body that result from the heart's electrical activity are called an ECG [16]. Monitoring and controlling heart health is an important indicator of overall health. Today, ECG tests performed by healthcare professionals are a common method for monitoring heart activity and diagnosing heart disease. However, it is often difficult to perform these tests continuously and in a portable manner.

In this study, the primary goal was to identify ventricular fibrillation, analyze various ECG signal characteristics, and evaluate different combinations of ECG measurements for accurate arrhythmia differentiation.

The training data were obtained from the publicly available MIT-BIH Arrhythmia Database on the PhysioNet website. This database includes ECG recordings from 47 subjects, consisting of 48 two-channel ambulatory recordings, each approximately 30 minutes in duration. The ECG signals were recorded within a 10 mV range and 11-bit resolution, sampled at 360 samples per second per channel.

In addition to this, test data were collected directly in our laboratory using the Arduino Portenta development board and AD8232 sensor as part of the portable ECG device developed in this work. Test signals were obtained from 20 individuals (10 healthy and 10 with arrhythmia).

Overall, 70% of the data (48 subjects from the MIT-BIH dataset) were used for training, and 30% of the data (20 subjects, locally collected) were used for testing. This hybrid approach allowed the model to learn from a well-established dataset while validating its performance on real ECG data collected with our custom device.

The Arduino Portenta is a microcontroller used for data collection. The AD8232 is an integrated signal conditioning block for ECG and other bio-potential measurement devices. The AD8232 is designed to extract, amplify, and filter small bio-potential signals in noisy conditions, such as those caused by muscle movements. The AD8232 is an integrated signal conditioning block that conditions cardiac bio-potential for monitoring heart activity. It contains an Instrumentation Amplifier, Operational Amplifier, Right-Hand Drive Amplifier, and Centre Reference Buffer. The AD8232 also features a Leads-off Detection circuit and Fast Recovery circuit to recover signals after the leads are disconnected.

Arrhythmia is an irregularity in heart rate that causes abnormalities in your heart rhythm. Manual analysis of the ECG signal is insufficient for the rapid detection of abnormalities in heart rhythm. Analysis of the long-term ECG signal by specialists is quite time-consuming and problems may arise in correctly identifying the problem. Computer-aided decision systems are being developed for the examination of ECG signals due to their advantages, such as increasing the accuracy of diagnosis, shortening the analysis time, and reducing potential expert errors. There are numerous studies in the literature based on signal processing methods for arrhythmia detection using ECG signals. These studies rely on extracting different features from the signals and classifying these features [16-19].

The Pan-Tompkins Algorithm is a real-time algorithm used for detecting QRS complexes in ECG signals [20-23]. The block diagram of the algorithm steps is shown in Figure 1. This algorithm is based on the digital analysis of slope, amplitude, and width. The ECG signal is passed through a special digital bandpass filter consisting of a high-pass and a low-pass filter to reduce noise. The filtered signal is then passed through a derivative block to obtain the slope of the ECG signal, followed by squaring and window integration operations. A threshold is then used to increase detection sensitivity [2,3].

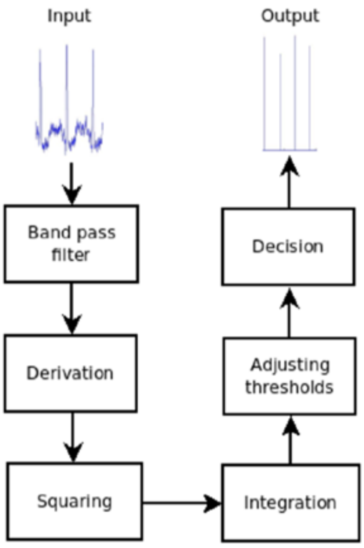


Figure 1. Block diagram of the Pan & Tompkins algorithm

2.1 Measuring the ECG Signal

In this study, the e-health sensor shield was connected via the Arduino Portenta using a connection bridge card. The C or C++ programming language was used to obtain ECG data via the e-health sensor shield.

In the ECG measurement system, the electrodes are placed on the patient as shown in Figure 2.

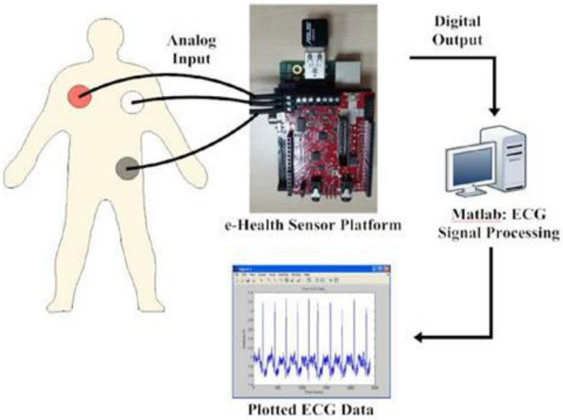


Figure 2. Block diagram of the ECG measurement system

Figure 2 shows the electrode placement, corresponding to Lead I in the Einthoven triangle. The ECG signal obtained from the patient by the electrodes is transferred to the e-health sensor shield. The e-health sensor shield amplifies, filters, and converts the analogue ECG data into digital form. The digital ECG data is acquired by the code running on the Arduino system. This acquired data is saved as a text file and transferred to the Matlab environment running on the computer. This block diagram shows how the sensors, Arduino Portenta, and Bluetooth module are connected to each other. The AD8232 sensor is connected to the body via electrodes and is used to measure the heartbeat. The data received from the sensor is transferred to the Arduino Portenta. The Arduino Portenta transfers the received data to a computer or laptop via the HC-05 Bluetooth module.

MATLAB software receives and processes data transmitted via Bluetooth. It processes the data in real time to generate an ECG display and presents it on the PC monitor. In this way, we can observe the data flow from the sensor, through the Arduino to Bluetooth, and finally to MATLAB. This combination of hardware and software provides the essential components required to create a portable ECG device.

The ECG signal is measured via the e-health sensor shield and Arduino and transferred to the

Matlab environment. The raw ECG signal measured is shown in Figure 3.

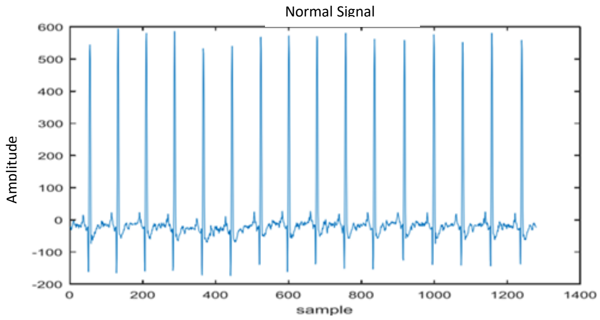


Figure 3. ECG signals from healthy individuals

The ECG signal samples used in the project work, containing healthy and arrhythmia signals, with the first 10 seconds of 60-second ECG signals in a 10 mV range and a sampling frequency of 250 Hz, are shown in Figure 4.

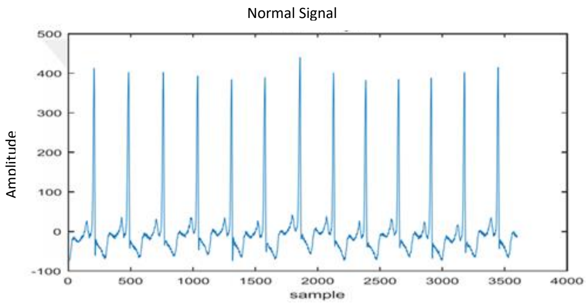


Figure 4. ECG signals belonging to individuals with arrhythmia

Computer-assisted arrhythmia classification plays an important role in the diagnosis of cardiac disorders today. According to the studies conducted, some automatic ECG interpretation systems are available, and work continues the development of these computer-assisted systems. In this context, artificial neural networks, which are intelligent data analysis, have begun to be used in the medical field for disease diagnosis, as well as for image processing, speech recognition, pattern recognition, etc.

2.2 Data Processing and Classification Methods

To create a portable ECG device that uses an Arduino microcontroller for heart rate monitoring, the AD8232 sensor serves as the primary component for capturing cardiac activity. This sensor interfaces with electrodes attached to the body, converting voltage signals into detectable heartbeats. The combination of an Arduino Portenta board and an HC-05 (FC-114) Bluetooth module facilitates the real-time transfer of ECG data to a PC monitor for visualization via a MATLAB interface.

The development of such a system involves the integration of hardware and software components. Firstly, the hardware setup includes the AD8232 sensor interfacing with the Arduino Portenta board. The sensor's analogue output is connected to the Arduino's analogue input pins, enabling voltage readings to be obtained. The HC-05 Bluetooth module facilitates wireless data transmission by interfacing with the Arduino Portenta via serial communication.

From a software perspective, the Arduino code is designed to initiate communication with the AD8232 sensor and acquire analogue voltage readings representing cardiac signals. This code also configures the HC-05 module for Bluetooth communication, establishing a connection with the PC for data transfer. Additionally, error handling mechanisms are implemented to ensure data integrity and system stability.

On the computer side, MATLAB code has been developed to receive ECG data transmitted via Bluetooth. Using MATLAB's graphical capabilities, the received data is processed and displayed in real time on a monitor, providing users with a visual representation of cardiac activity. MATLAB's comprehensive signal processing toolbox can be used to perform further analysis and, if desired, gain insights from the ECG data.

Arduino and MATLAB code work together to ensure the seamless acquisition, transmission, and visualization of ECG data. Thanks to its meticulous design and implementation, this system offers a portable and accessible solution for heart rate monitoring with potential applications in both clinical and personal healthcare settings.

Figure 5 shows a block diagram illustrating the classification processes of ECG data. Each block in the diagram represents a specific stage of the classification process. The necessary pre-processing has been performed to prepare the ECG signals for classification.

In this article, the classification process in the output layer is performed as a binary distinction between Normal and Arrhythmia ECG signals

Preprocessing is a critical step in ensuring high-quality signal analysis. In this study, a unified preprocessing pipeline was established, combining several steps including data cleaning (handling missing values), conversion from multiclass to binary classification, randomization (repeated 30 times), discretization using the entropy/MDL algorithm, and dataset partitioning. All ECG data were normalized within the range of –1 to 1 before feature extraction.

The feature ranking process was then carried out using scoring metrics including Information Gain, Gain Ratio, GINI Index, ReliefF, Rapid Correlation-Based Filter, ANOVA, Chi², RReliefF, and Univariate Linear Regression. The feature selection strategy was optimized by evaluating the top-scoring features using both Percentile (top percentage) and Fixed-number approaches to retain only the most informative variables.

Within the scope of this research, the aim is to increase classification efficiency and create the most robust model by utilising various feature selection and classification algorithms. Feature selection techniques used include GINI gain ratio, information gain, ReliefF, chi-square, and FCBF. These feature selections were combined with machine learning algorithms such as Logistic Regression, Naïve Bayes Classifier, Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks. Additionally, k-Nearest Neighbours (KNN), Stochastic Gradient Descent (SGD), Linear Regression, Random Forests, and gradient boosting methods have been evaluated.

The performance of algorithms has been measured using metrics such as the confusion matrix, accuracy, precision, and recall. The confusion matrix is a performance metric that shows how the model's predictions match the actual values and includes true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values. These values have been used to evaluate the model's performance.

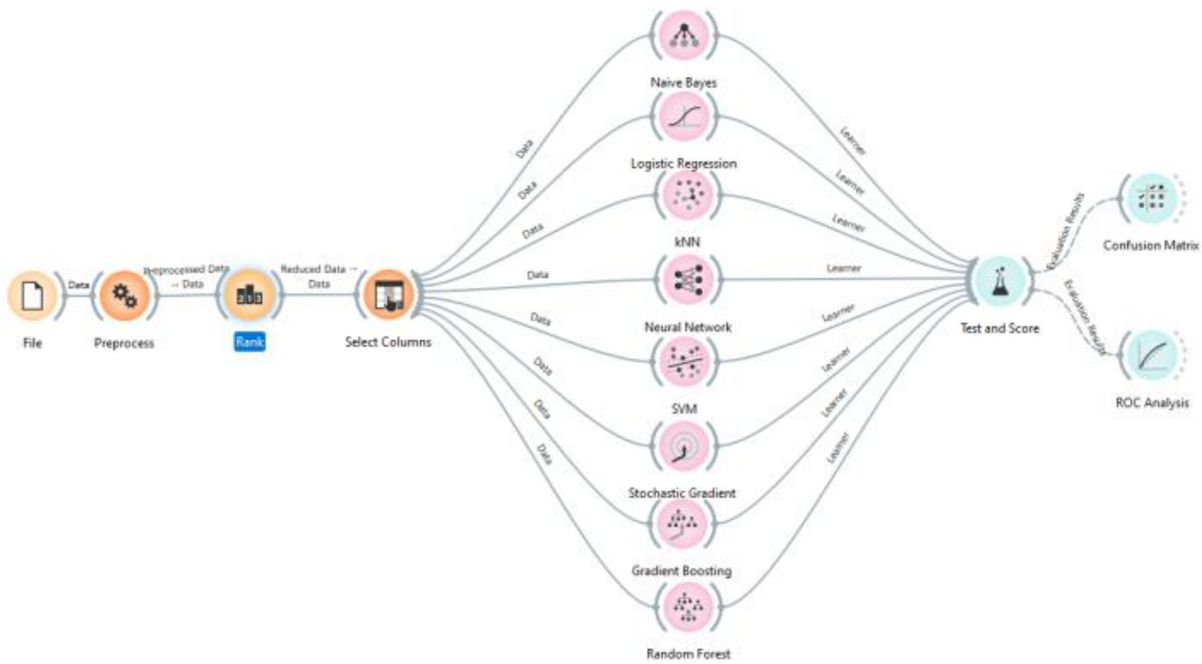


Figure 5. Block diagram showing the classification processes of ECG data

In this study, feature selection techniques such as GINI, gain ratio, information gain, ReliefF, chi-square, and FCBF were used in the Rank operation [10].

GINI focuses on reducing the entropy (uncertainty) in the dataset when selecting a feature. A high GINI value indicates that the selected feature can better distinguish the dataset. GINI may be prone to overfitting and may overlook some important features.

The gain ratio selects features by considering how well a feature distinguishes the data set and how noisy it is. A high gain ratio indicates that the selected feature can better distinguish the data set by filtering out noise. The gain ratio is relatively complex to calculate and may not perform well on small data sets.

Information gain measures how much information a feature provides about a dataset. High information gain indicates that the selected feature provides more information about the dataset. Information gain, similar to GINI, may be prone to overfitting.

ReliefF is an algorithm that measures how well each feature separates the examples in the dataset. A high ReliefF value indicates that the selected feature can better separate the examples. ReliefF is highly robust against noise and can perform well even with a small number of examples.

The chi-square test measures the association between a categorical variable and a target variable. A high chi-square value indicates a strong relationship between the variable and the target variable. The chi-square test can only be used for categorical variables and cannot be applied to continuous variables.

FCBF (Feature Correlation Based Feature Selection) measures how correlated features are with each other and selects features based on this correlation. Features with low correlation are selected, which reduces the tendency of models to overfit. FCBF can also be used for dimension reduction.

In this article, we also used a well-known feature selection and classification algorithm for ECG data. Feature selection approaches and various classifier algorithms will be used to increase classification efficiency and create the strongest model.

Logistic Regression, Naïve Bayes Classifier, Support Vector Machines (SVM), Decision Trees; Artificial Neural Networks. This group also includes the following methods: k-Nearest Neighbours, SGD, Linear Regression, Random Forests, and gradient boosting, among other machine learning methods.

Logistic Regression is a statistical model used for binary or multiclass classification problems. It estimates the probability that a given input belongs to a particular class by applying the logistic (sigmoid) function. The algorithm models the relationship between dependent and independent variables through maximum likelihood estimation.

Naive Bayes is a probabilistic classifier based on Bayes' theorem. It assumes conditional independence among features, meaning the presence of one feature does not affect the presence of another. Despite this simplification, it performs well for high-dimensional data and is computationally efficient.

SVM is a supervised learning algorithm that finds the optimal hyperplane to separate data points of different classes in a high-dimensional space. It maximizes the margin between classes and can handle non-linear relationships using kernel functions such as radial basis function (RBF) or polynomial kernels.

A Decision Tree is a rule-based algorithm that splits data into branches based on feature values, forming a tree-like structure. Each internal node represents a decision rule, and each leaf node represents a class label. It is easy to interpret but can be prone to overfitting if not properly pruned.

ANNs are inspired by the biological neural network of the human brain. They consist of interconnected nodes (neurons) organized in layers that transform input data through weighted connections. Neural Networks are powerful for capturing complex, non-linear relationships and are widely used in biomedical signal analysis.

KNN is a non-parametric algorithm that classifies a sample based on the majority class among its *k* nearest neighbours in the feature space. It is simple and effective for small datasets but can become computationally expensive for large datasets.

SGD is an optimization algorithm commonly used for training models such as linear classifiers and neural networks. It updates the model parameters incrementally for each training sample, which allows for faster convergence and scalability with large datasets.

Random Forest is an ensemble learning method that constructs multiple Decision Trees during training and aggregates their predictions through majority voting. This approach reduces overfitting and improves generalization compared to individual Decision Trees.

Gradient Boosting is another ensemble method that builds models sequentially, where each new tree corrects the errors of the previous ones. It minimizes a loss function using gradient descent and is known for high predictive accuracy in structured data problems

The Confusion Matrix is a performance metric for machine learning classification problems where the output can have two or more classes. The Confusion Matrix consists of a table containing four different combinations of predicted and actual values. Based on the table, it is explained that there are four assignments representing the results of the classification process in the confusion matrix: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The confusion matrix calculates the negative and positive values in the model [10,18-19].

Using the confusion matrix, it is possible to calculate the Accuracy, Precision, and Recall values in equations 1-5.

Metric	Formula	
Sensitivity (True Positive Rate, TPR)	$TPR = \frac{TP}{TP + FN}$	(1)
Specificity (True Negative Rate, SPC)	$SPC = \frac{TN}{FP + TN}$	(2)
Precision Positive Value (PPV)	$PPV = \frac{TP}{TP + FP}$	(3)
Accuracy (ACC)	$ACC = \frac{TP + TN}{TP + TN + FP + FN}$	(4)
F1 Score (F1)	$F1 = \frac{2TP}{2TP + FP + FN}$	(5)

3. RESULTS

In this article, a simple portable ECG device was designed and developed using an Arduino microcontroller and an AD8232 sensor. The device processes the voltage received from electrodes attached to the body to read the heartbeat and displays and records the ECG screen in real time on a PC monitor via a Bluetooth antenna.

According to this Confusion Matrix in Table 1, the ANN model demonstrates quite good performance for ECG classification on the dataset. The model's high accuracy, precision, specificity, and F1 score indicate that it can be used in the diagnosis of heart diseases.

Table 1. Confusion Matrix for Classification Performance

Model	Actual / Predicted	F (Predicted Arrhythmia)	N (Predicted Normal)
kNN	F (Actual Arrhythmia)	81%	4%
	N (Actual Normal)	19%	96%
SVM	F (Actual Arrhythmia)	90%	3%
	N (Actual Normal)	10%	97%
SGD	F (Actual Arrhythmia)	84%	3%
	N (Actual Normal)	16%	97%
Random Forest	F (Actual Arrhythmia)	71%	19%
	N (Actual Normal)	29%	81%
Neural Network	F (Actual Arrhythmia)	91%	2%
	N (Actual Normal)	9%	98%
Naive Bayes	F (Actual Arrhythmia)	84%	3%
	N (Actual Normal)	16%	97%
Logistic Regression	F (Actual Arrhythmia)	78%	7%
	N (Actual Normal)	22%	93%
Gradient Boosting	F (Actual Arrhythmia)	77%	3%
	N (Actual Normal)	23%	97%

Each confusion matrix illustrates the proportion of correctly classified instances (diagonal elements) and misclassified instances (off-diagonal elements) for each algorithm. Among the evaluated models, the Neural Network, Support Vector Machine (SVM), and Naïve Bayes classifiers achieved the highest overall classification accuracies, demonstrating particularly strong specificity for the Normal class. These results indicate that the models are highly effective in correctly identifying non-arrhythmic signals while maintaining reliable detection of arrhythmias. In contrast, the Random Forest and Logistic Regression models exhibited moderate performance, characterized by slightly elevated false negative rates, suggesting a tendency to misclassify some arrhythmic signals as normal.

In this study, the performance of various machine learning algorithms for detecting cardiac arrhythmias using a portable ECG device was compared. The results obtained are summarized in Table 2. This table contains the AUC, CA, F1, Precision, and Recall metrics for the kNN, SVM, SGD, Random Forest (RF), Neural Network (NN), Naive Bayes (NB), Logistic Regression (LR), and Gradient Boosting (GB) algorithms.

Table 2. Metric performance of machine learning algorithms

Model	Accuracy (ACC)	Sensitivity (Recall)	Specificity (TNR)	Precision (PPV)	F1-Score
kNN	0.885	0.81	0.96	0.95	0.88
SVM	0.935	0.90	0.97	0.97	0.93
SGD	0.905	0.84	0.97	0.96	0.90
RF	0.760	0.71	0.81	0.79	0.75
NN	0.945	0.91	0.98	0.98	0.94
NB	0.905	0.84	0.97	0.96	0.90
LR	0.855	0.78	0.93	0.92	0.84
GB	0.870	0.77	0.97	0.96	0.86

The comparative performance analysis of the machine learning algorithms reveals significant differences in classification capability for arrhythmia detection based on ECG signals. As shown in Table 2, all models achieved reasonably high accuracy values, demonstrating the reliability of the extracted features and preprocessing pipeline. However, their sensitivity, specificity, and precision values vary depending on the model’s complexity and ability to capture non-linear relationships in the data.

Among all models, the Neural Network (NN) achieved the highest overall performance, with an accuracy of 94.5%, sensitivity of 0.91, and specificity of 0.98. This indicates that the NN model effectively recognizes arrhythmic patterns while minimizing false alarms. Its strong performance can be attributed to its capability to model non-linear and complex temporal dependencies inherent in ECG signals.

The Support Vector Machine (SVM) and Naïve Bayes classifiers also produced competitive results, with accuracies of 93.5% and 90.5%, respectively. Both models achieved high specificity (0.97), suggesting they are highly reliable in correctly identifying normal heartbeats. While SVM provided slightly higher precision and F1-score compared to Naïve Bayes, both algorithms demonstrated stable and consistent classification performance.

The Stochastic Gradient Descent (SGD) model exhibited balanced results with 90.5% accuracy and 0.90 F1-score, indicating that linear models can still perform adequately when combined with effective feature selection and normalization techniques. In contrast, the Random Forest algorithm showed the lowest overall performance (76% accuracy), possibly due to overfitting on small datasets and limited ability to generalize across subjects.

Logistic Regression and Gradient Boosting models achieved moderate results, with accuracies of 85.5% and 87.0%, respectively. Although these models offered high precision (0.92–0.96), their lower sensitivity values indicate that they missed a portion of arrhythmic cases. This trade-off between sensitivity and specificity is particularly important in medical applications where minimizing false negatives is critical.

In summary, the Neural Network model demonstrated superior classification capability across all metrics, confirming its suitability for real-time arrhythmia detection using ECG signals collected from the portable Arduino-based system. Simpler models such as SVM and Logistic Regression remain promising alternatives for embedded applications where computational efficiency is a priority.

Table 3. Performance of Classification Algorithms

Model	kNN	SVM	SGD	Random Forest	Neural Network	Naïve Bayes	Logistic Regression	Gradient Boosting
kNN	1.000	0.937	0.347	0.548	0.936	0.459	0.964	0.151
SVM	0.937	1.000	0.900	0.809	0.570	0.077	0.746	0.044
SGD	0.347	0.900	1.000	0.376	0.928	0.583	0.919	0.205
Random Forest	0.548	0.809	0.376	1.000	0.803	0.426	0.870	0.087
Neural Network	0.936	0.570	0.928	0.803	1.000	0.927	0.746	0.040

Model	kNN	SVM	SGD	Random Forest	Neural Network	Naïve Bayes	Logistic Regression	Gradient Boosting
Naïve Bayes	0.459	0.077	0.583	0.426	0.927	1.000	0.956	0.076
Logistic Regression	0.964	0.746	0.919	0.870	0.746	0.956	1.000	0.032
Gradient Boosting	0.151	0.044	0.205	0.087	0.040	0.076	0.032	1.000

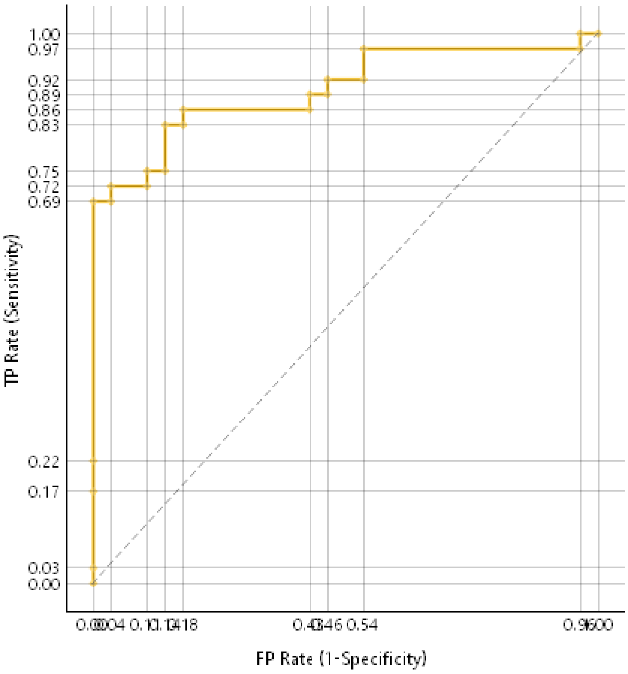
Table 3 presents the similarity (correlation) matrix between the classification results of the eight machine learning algorithms used in this study. Each value indicates the degree of agreement between the prediction outputs of two models. A higher correlation value (close to 1.0) implies that both algorithms make similar decisions for the same ECG samples, whereas a lower value indicates divergent classification behavior.

The results reveal that several models exhibit strong pairwise correlations, particularly among kNN, SVM, Logistic Regression, and Neural Network. For example, the correlation between kNN and Logistic Regression (0.964) and between SVM and Logistic Regression (0.746) suggests that these algorithms tend to produce similar predictions and share comparable decision boundaries. This is expected since these methods rely on distance-based or linear separability principles in feature space.

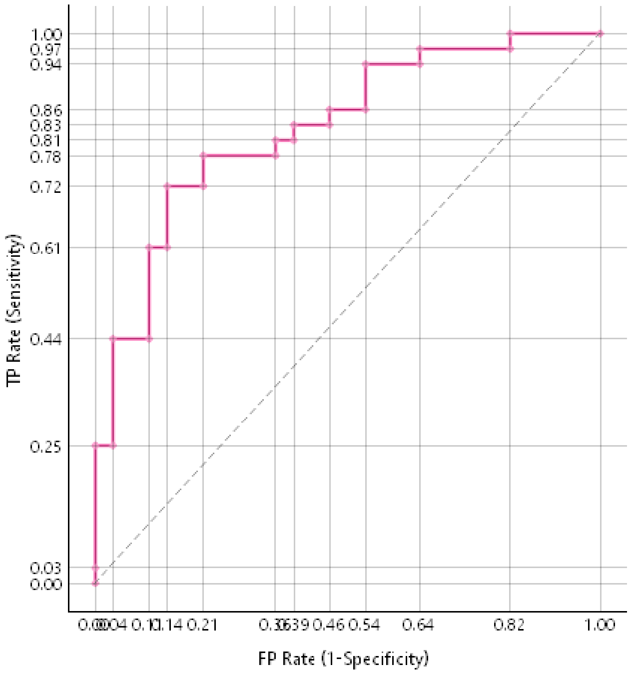
The Neural Network model shows relatively high similarity with SGD (0.928) and Naïve Bayes (0.927), reflecting its ability to generalize effectively across features while capturing both linear and non-linear dependencies. This consistency supports the finding that the Neural Network achieved the highest performance metrics in terms of accuracy and F1-score, as it aligns well with the output tendencies of other high-performing models.

In contrast, Gradient Boosting demonstrates the lowest correlation values with most models (typically < 0.20), indicating a distinct classification behavior. This difference likely stems from its ensemble learning mechanism, which combines multiple weak learners to produce a final decision that deviates from the linear or probabilistic patterns of other classifiers. Despite this divergence, such diversity can be beneficial in ensemble or hybrid systems, where model complementarity enhances overall robustness.

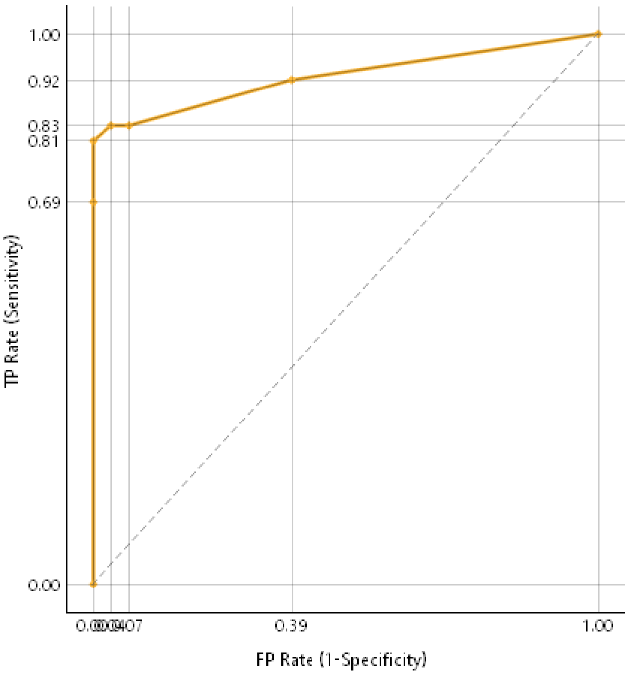
Overall, the similarity matrix confirms that most algorithms, especially Neural Network, SVM, and Logistic Regression are consistent in their classification outcomes, reinforcing the reliability of the obtained ECG-based arrhythmia detection results. Meanwhile, the unique behavior of Gradient Boosting suggests potential for hybrid model design, where combining diverse decision patterns could further improve generalization in future studies.



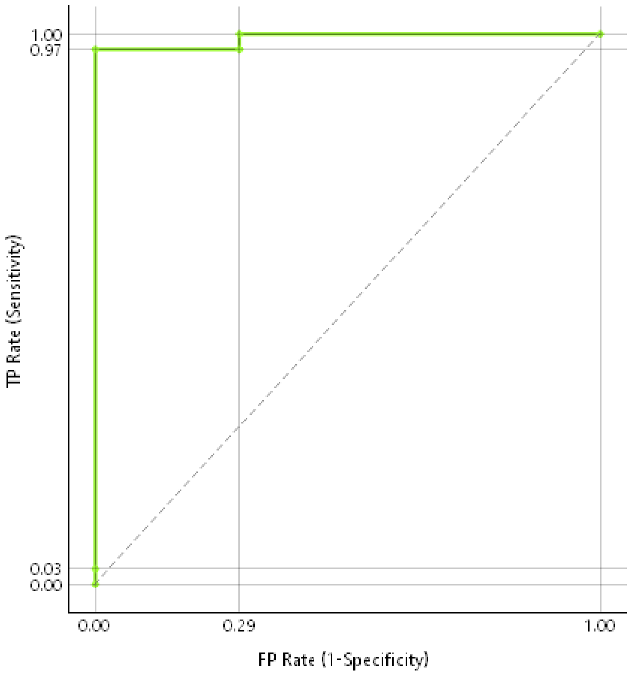
a.Random Forest



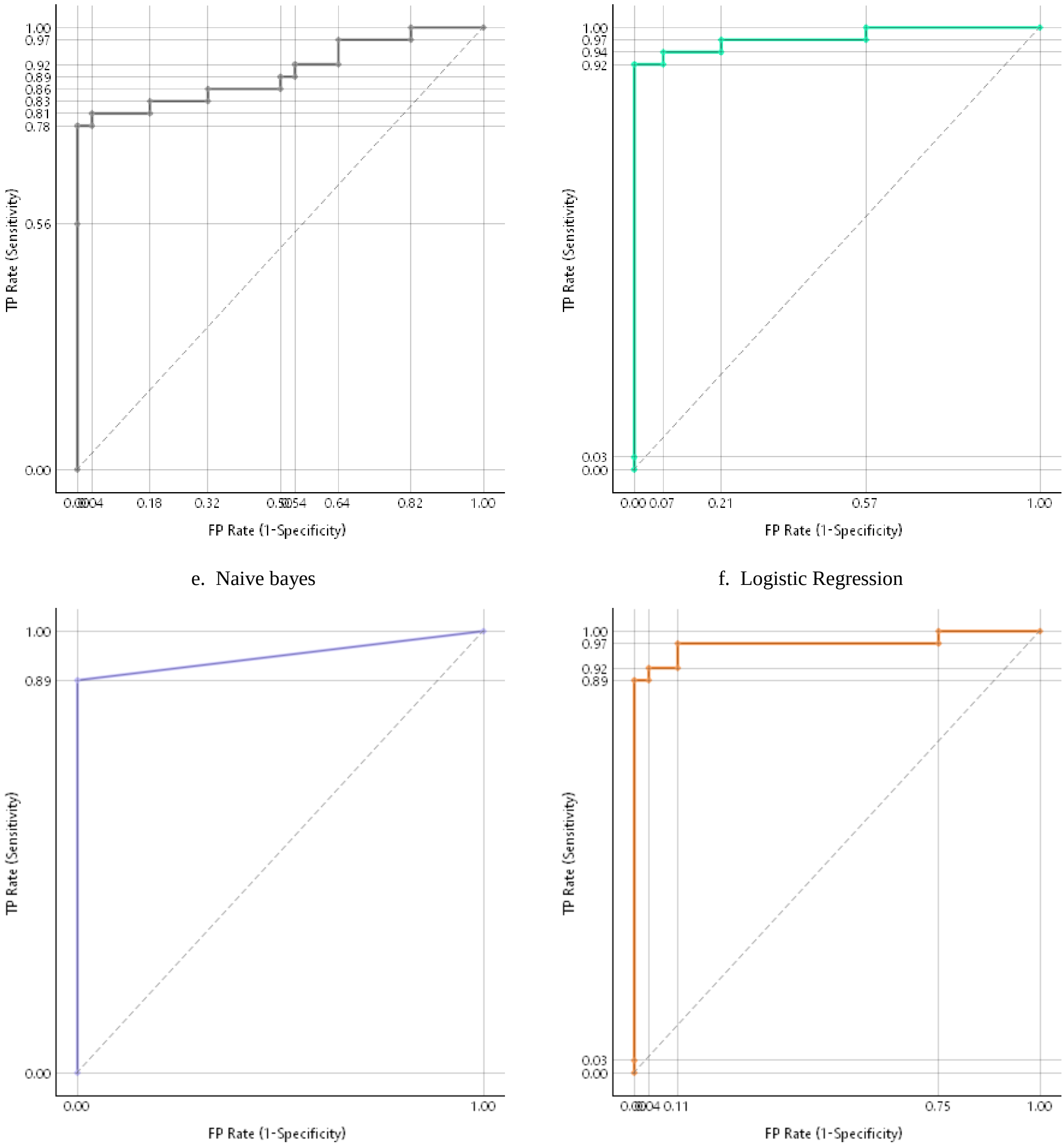
b.Gradient Boosting



c. KNN



d. Neural Network



e. Naive bayes

f. Logistic Regression

g. SGD

h. SVM

Figure 6. ROC curves for classification performance

Table 4. AUC Values of ROC Curves

Model	**AUC**
Neural Network	0.922
SVM	0.976
SGD	0.944
Gradient Boosting	0.828
Logistic Regression	0.992
Random Forest	0.898
kNN	0.978
Naïve Bayes	0.898

The Receiver Operating Characteristic (ROC) analysis was conducted to evaluate the discriminative capability of the classification models. Figure 6 illustrates the ROC curves of all machine learning algorithms, and their corresponding AUC (Area Under the Curve) values are summarized in Table 4. The AUC values quantify the overall ability of each model to distinguish between normal and arrhythmic ECG signals, where a value closer to 1.0 indicates superior classification performance.

Among the models, Logistic Regression achieved the highest AUC value (0.992), followed closely by k-Nearest Neighbour (kNN) (0.978) and Support Vector Machine (SVM) (0.976), demonstrating their strong capability to discriminate between classes with minimal overlap. The Neural Network and SGD classifiers also exhibited excellent performance, with AUC values of 0.922 and 0.944, respectively, confirming their robustness in modeling complex ECG signal variations.

In contrast, Gradient Boosting (AUC = 0.828) and Random Forest (AUC = 0.898) yielded comparatively lower AUC scores, suggesting that these ensemble-based methods were more sensitive to the limited dataset size and potential feature redundancy. Nevertheless, all models achieved AUC values greater than 0.80, which indicates reliable classification capability for biomedical applications.

Overall, the ROC–AUC analysis confirms that the proposed ECG classification framework provides high discrimination accuracy across multiple algorithms. The near-perfect AUC values obtained from Logistic Regression, SVM, and kNN highlight their suitability for real-time arrhythmia detection in portable and embedded healthcare systems.

Performance differences between these methods vary depending on the feature selection techniques used and the data sets. In general, it has been concluded that high accuracy rates can be achieved for complex problems such as arrhythmia detection by using various feature selection and classification techniques.

In conclusion, analysis conducted on data obtained from the portable ECG device in this article revealed that the Logistic Regression and SVM algorithms demonstrated the highest performance. It was concluded that these algorithms, when applied to real-time ECG data, are effective in accurately detecting cardiac arrhythmias. Furthermore, the use of such portable ECG devices is of great importance for the continuous monitoring of heart health and the improvement of heart health through early diagnosis. This study can be considered an important step towards the development and widespread use of portable health monitoring devices in the future.

Upon re-evaluating the results, it was confirmed that the Neural Network (ANN) algorithm achieved the highest performance with an Accuracy of 94.5% and an AUC of 99.2%, followed by Logistic Regression and SVM.

This study demonstrates that the proposed portable ECG system based on the Arduino Portenta and AD8232 sensor, when integrated with machine learning algorithms, enables accurate and real-time arrhythmia detection. Experimental results obtained from both the MIT-BIH Arrhythmia Database and real-time data collected from 20 subjects confirm the robustness and reliability of the system. Among the evaluated classifiers, the Artificial Neural Network achieved the best performance with an accuracy of 94.5% and an AUC of 99.2%. The proposed low-cost and compact solution shows strong potential for continuous cardiac monitoring, early diagnosis, and remote healthcare applications within the Internet of Medical Things (IoMT) framework.

4. DISCUSSIONS

The comparative analysis of multiple machine learning algorithms demonstrated that classification performance strongly depends on the quality of extracted features and the amount of training data. Segmenting the ECG recordings of the test subjects allowed for a more detailed performance evaluation by exposing the model to diverse temporal patterns within each subject's cardiac signal. This approach maintains inter-subject independence while improving the statistical reliability of performance metrics such as accuracy and AUC. Among the tested algorithms, Neural Networks exhibited the highest accuracy and AUC values, reflecting their capability to effectively model non-linear relationships in ECG data. Conversely, Logistic Regression and SVM achieved competitive results with lower computational cost, showing that simpler models can still provide reliable performance when supported by effective feature selection and preprocessing. Overall, all models achieved AUC values above 0.80, confirming that the proposed ECG classification framework performs reliably across various algorithms, with Logistic Regression (AUC=0.992) and SVM (AUC=0.976) showing near-perfect discrimination.

The integration of a portable ECG device with an intelligent classification framework represents a significant advancement toward real-time cardiac health monitoring. Unlike conventional ECG systems that require hospital-based infrastructure, the proposed system allows continuous, remote monitoring, which could enable early arrhythmia detection and reduce diagnostic delays. The use of the Arduino Portenta microcontroller and AD8232 sensor provides a low-cost, compact, and energy-efficient solution, making it suitable for wearable healthcare applications.

An important finding of this study is that ECG data acquired from a self-designed portable device can yield classification accuracies comparable to those obtained from well-known public databases such as MIT-BIH. This demonstrates the feasibility and reliability of locally collected signals for model training, provided that appropriate preprocessing, normalization, and feature selection are applied. The implementation of feature selection techniques such as GINI, ReliefF, and Information Gain significantly enhanced model generalization by filtering out redundant and irrelevant features.

Despite these promising results, some limitations should be acknowledged. The dataset size was relatively small, consisting of ECG signals from a limited number of participants. Expanding the dataset to include a more diverse population with multiple arrhythmia types would improve both robustness and clinical applicability. Future work will focus on deploying the trained models directly on the embedded hardware to enable on-device, real-time inference, eliminating reliance on external computing resources and advancing toward a fully autonomous, wearable diagnostic system.

In addition, integrating this portable ECG system with a cloud-based monitoring platform could enable remote patient tracking and long-term cardiac data analysis. Such a system would allow healthcare professionals to continuously access patient-specific ECG trends, supporting personalized medicine and preventive care. This direction aligns with the emerging paradigm of the Internet of Medical Things (IoMT) and highlights the strong practical potential of the proposed approach for real-world healthcare applications.

As an extension of this study, future work will focus on deploying the trained machine learning models directly onto the Arduino Portenta platform to enable real-time, edge-based arrhythmia classification. Implementing on-device inference would eliminate the dependency on a PC for signal processing, allowing ECG data to be analyzed locally as it is acquired. This transition from offline analysis to an embedded, real-time system presents several technical challenges, including optimizing the model's memory footprint, reducing computational load, and maintaining accuracy under limited hardware resources. To address these challenges, lightweight versions of the Neural Network and SVM models will be considered, potentially using model compression or quantization techniques to ensure efficient deployment on the microcontroller.

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