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Efficient ECG Classification Based on Machine Learning and Feature Selection Algorithm for IoT-5G Enabled Health Monitoring Systems

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Abstract: With the rise of the Internet of Things (IoT) and Fifth Generation (5G) networks, real-time health monitoring has become more efficient, enabling continuous tracking of cardiac health. Electrocardiograms (ECG) are essential for diagnosing cardiovascular diseases, but classifying ECG signals presents challenges due to their high-dimensional features. Standard machine learning classifiers often struggle to achieve high accuracy, and IoT devices face resource constraints that hinder real-time processing. This paper introduces a novel methodology that combines Particle Swarm Optimization (PSO)-based feature selection with machine learning classifiers, such as K-Nearest Neighbors (KNN), Random Forest (RF), Decision Trees (DT), and Support Vector Machines (SVM). The proposed method uses the accuracy of the machine learning classifiers as the fitness function in the PSO algorithm. This ensures that the selected features are optimal and well-suited for the classifier, improving both classification accuracy and computational efficiency. The approach was validated using the MIT-BIH Arrhythmia dataset, achieving 98% accuracy with PSO-SVM and 84% without PSO-based feature selection. The dimensionality of the ECG dataset is reduced from 4000 features to 888, improving classification accuracy and computational efficiency. These results outperform current machine learning and deep learning methods, demonstrating the effectiveness of the proposed approach for arrhythmia detection. This research provides a scalable solution for IoT-enabled, 5G-powered health monitoring systems, enhancing both classification performance and real-time processing in resource-constrained environments.

Keywords: Arrhythmia detection, Machine learning classifier, Feature selection, IoT-5G, Healthcare systems, ECG classification.

1. Introduction

Cardiovascular diseases are the most common cause of death worldwide, resulting in millions of deaths annually [1]. Early identification and continuous monitoring of the condition of the heart, such as arrhythmias, are very critical in further improving the outcomes for patients and lessening the burden on healthcare systems [2, 3]. Electrocardiogram (ECG) monitoring is a very critical tool in capturing the electrical activity of the heart for the early detection of life-threatening conditions [4].

In recent years, the Internet of Things (IoT) has increased drastically and revolutionized health care by allowing real-time and remote monitoring and also enabling the continuous collection of physiological data from patients even outside clinical settings [5-6]. This paradigm shift toward IoT-enabled health monitoring offers enhanced patient mobility, timely interventions, and a drastic reduction in healthcare costs [7]. With the increasing application of IoT devices, the rapid growth of ECG data has brought about the challenge of how efficiently analyzing and classifying the data in real time [8].

The high-dimensional nature of ECG signals combined with large volumes of data strains traditional machine learning models that have to make a tradeoff between good classification accuracy and computational efficiency. The commonly used classifiers, such as K-nearest neighbor (KNN), random forest (RF), decision tree (DT), and support vector machine (SVM), usually suffer from reduced accuracy or slower processing times when applied to large datasets. This is particularly critical in IoT-enabled systems, given that computational resources are generally constrained and fast, accurate decision-making is critical for early medical intervention [9].

Despite the advancements in machine learning, traditional feature selection methods, such as Mutual Information [10] and Chi-Square [11], often fail to address the unique challenges posed by high-dimensional ECG data, especially in real-time applications. These methods rely on statistical measures to rank features independently of the classifier, neglecting important feature interactions and the classifier's specific requirements for optimal performance. As a result, static methods may select suboptimal features that degrade classification accuracy. In contrast, metaheuristic feature selection algorithms, like Particle Swarm Optimization (PSO), typically use default fitness functions that do not account for the classifier's accuracy [12-13]. This approach leads to ineffective feature selection, as it does not adapt the feature set to the classifier's specific needs.

To address these challenges, this study introduces a novel approach that combines PSO with machine learning classifiers to achieve dynamic feature selection and dimensionality reduction. Unlike traditional filter-based methods and traditional metaheuristic feature selection, the proposed PSO-based feature selection process is adaptive, dynamically adjusting to the classifier's specific needs. The PSO fitness function evaluates the classifier's accuracy and optimizes the selection of features, ensuring that only the most relevant and effective features are chosen. This dynamic selection process enhances the classification performance while reducing the dimensionality of the ECG dataset to low dimensions, thus improving computational efficiency without sacrificing diagnostic accuracy. The proposed method is particularly well-suited for IoT-enabled and Fifth Generation (5G)-powered healthcare systems, where real-time, resource-efficient decision-making is essential. By improving both the speed and accuracy of ECG classification, the proposed solution offers a scalable and effective framework for timely arrhythmia detection and real-time cardiac health monitoring.

The main key contributions of this study are:

- The study utilizes PSO to enhance the feature selection process, achieving dimensionality reduction of the ECG dataset from 4000 features to 888. This reduction ensures that only the most vital features necessary for identifying various arrhythmias are retained. As a result, the approach improves computational efficiency, reduces processing time, and enhances classification accuracy.
- The proposed framework is optimized to work in IoT and 5G integrated health monitoring areas, as highlighted in Fig. 1. They discuss the computational complexity for real-time processing on these devices and show the suitability of such a system for remote health monitoring.
- When using the SVM, the system provides a maximum accuracy of 98% when integrating PSO with machine learning classifiers. This result shows that the proposed framework outperforms the existing approaches and ensures accurate and efficient diagnosis of arrhythmias in IoT-integrated healthcare systems.

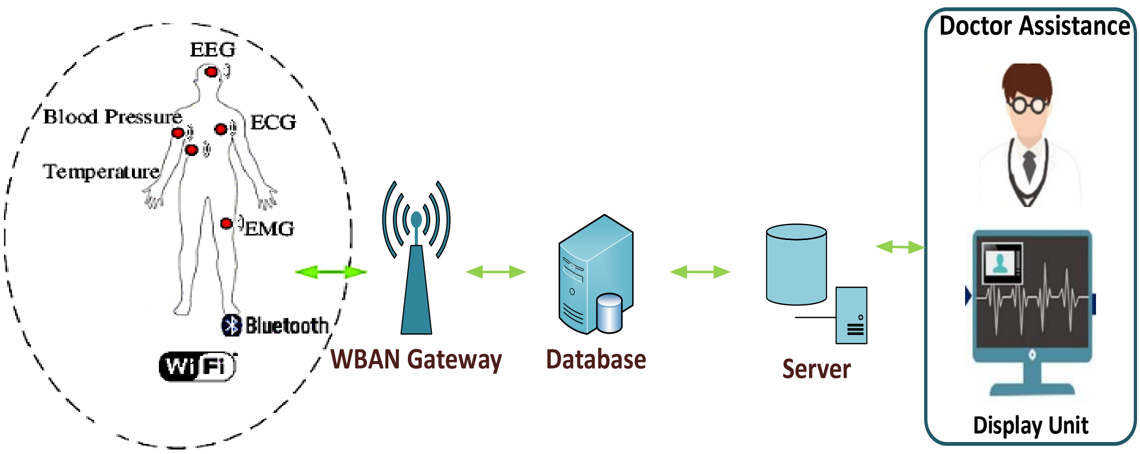

Figure. 1 Overview of IoT-assisted ECG monitoring framework

The flow of this proposed work is constructed as follows: Section 2 includes earlier research on medical prediction and classification. Section 3 discusses the Methodology, PSO-based feature selection, and machine-learning classifier. Section 4 presents the outcomes and discusses Efficient ECG Classification. Finally, section 5 concludes the paper.

2. Related works

Artificial intelligence (AI) is important for medical prediction and classification in clinical settings. This technology largely assists medical personnel in dealing with data in clinical practice. All these strategies can improve the timely identification and diagnosis of diseases. Metaheuristic feature selection algorithms were applied with both deep learning and machine learning techniques. For instance, Rangappa et al. [14] have proposed a hybrid approach that uses the new feature selection called infinite feature selection with RF for earlier arrhythmia detection based on ECG signal. The proposed approach was tested on the MIT-BIH Arrhythmia dataset and achieved an accuracy of 94.32% with feature selection and 93.29% without feature selection. However, the proposed feature selection method improved classifier accuracy by only 1.03%. In general, the accuracy that was achieved is moderate and needs improvement. Al-Shammary et al. [15] have proposed a novel approach that utilized the PSO as feature selection and the Kullback-Leibler classifier (KLC) as classifier to classify the ECG signal. Their approach integrates feature optimization and probabilistic classification to handle the complex and noisy nature of ECG data. The use of PSO for selecting optimal features and KL divergence for assessing distributional differences results in an accuracy rate exceeding 86.67% on the MIT-BIH arrhythmia dataset. However, the proposed approach has low rate of accuracy and need more improvement. Baños et al. [16] proposed a computational model called Hybrid-PSO-CNN, which integrates PSO with Convolutional Neural Networks (CNN) to classify cardiac arrhythmias. The model automatically optimizes CNN hyperparameters, achieving 97% accuracy during testing on the arrhythmia dataset. This approach reduced the time spent on manual hyperparameter selection and lowered computational costs. However, H-PSO-CNN model is that it is currently restricted to a four-dimensional PSO population, limiting its ability to fully optimize additional hyperparameters for more complex classification tasks.

Soman and Sarath. [17] have introduced a novel strategy that used the Sparrow Search Algorithm (SSA) feature selection with Deep CNN for arrhythmia classification. The authors have employed many steps in the suggested approach, beginning with preprocessing, feature extraction then feature selection, and finally classifiers (such as CNN, CNN-SVM). On the MIT-BIH arrhythmia dataset, the hybrid approach that utilized the Deep-CNN with SSA achieved moderate accuracy. However, the suggested approach has a low rate of accuracy compared with recent studies and needs improvement in accuracy.

Dhiah et al. [18] have proposed a novel classifier called Chi-square distance supported by feature selection based on PSO to select optimal features from the ECG signal. The authors also used the other machine learning classifier with the proposed classifier (Chi-square distance). The proposed approach achieved a notable accuracy of 98%. Nevertheless, the other standard classifiers such as RF and DT with PSO-based feature selection achieved an accuracy of 93% and 91% respectively. In [19], the study proposed a novel method that enhances PSO by using Hellinger distance (HD) for clustering the dataset into highly similar and harmonious groups. This clustering technique aims to improve the feature selection process, which is critical for disease detection, especially in complex medical datasets like the MIT-BIH Arrhythmia dataset. The authors apply this improved PSO method in conjunction with traditional machine learning algorithms such as KNN, DT, SVM, RF, Minkowski, and NB. The results demonstrate significant improvements in classification accuracy, with the Minkowski classifier achieving the highest accuracy of 97.5%. However, the proposed approach needs testing to optimize the size of cluster size and this increases the complexity and computational. Additionally, the proposed approach with some standard classifiers such as KNN, RF, DT, and SVM achieved low accuracy. Hassaballah et al. [20] presented new is metaheuristic optimization (MHO) is called Marine Predator Algorithm (MPA) with machine learning classifier namely: SVM, RF, GBDT, and KNN to classify the ECG signals. The authors also used the parameters optimization to find optimal parameter for the classifiers. The suggested approach testing on the divers' datasets, such as MIT-BIH Arrhythmia dataset and achieved high accuracy up to more 99%. However, the proposed approach depending on the parameter's optimization process and also the proposed approach achieved moderate accuracy of 96.44% in KNN classifier.

Unlike previous studies that used Metaheuristic algorithms like PSO for feature selection without

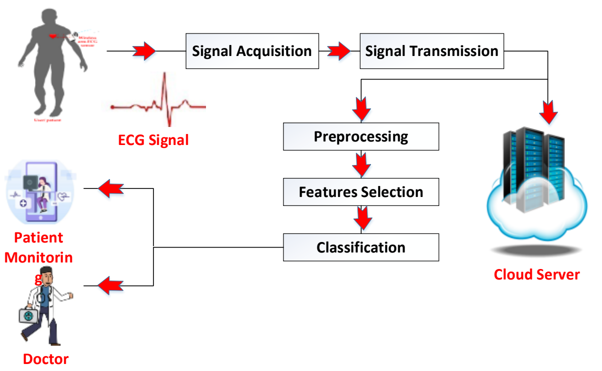

Figure. 2 Proposed workflow of ECG arrhythmia healthcare system's early diagnosis and classification

considering classifier accuracy, this study uniquely incorporates the classifier's accuracy as the fitness function. This allows for the selection of the most effective feature subset tailored to each classifier, thereby enhancing performance and improving ECG signal classification accuracy. Previous approaches focused on optimizing feature selection, but did not account for classifier accuracy, a crucial factor for achieving high performance in practical applications.

3. Methodology

The smart healthcare system has several sub-parts, discussed below: health record sensors for pulse records, electrodes for heartbeat records, data analysis of heartbeat records, a system mainly designed for pulse measuring, and a pulse measuring system in healthcare practice. This paper presents an early diagnosis and categorization model of ECG arrhythmia for healthcare. It has three primary stages: preprocessing, feature selection, and classification. The detection or classification process is one aspect of the system; hence, the main areas of this research are presented in the classification, as indicated below in Fig. 2.

3.1 Description of dataset

The MIT-BIH Arrhythmia Dataset (https://www.physionet.org/content/mitdb/1.0.0/) includes 48 thirty-minute parts of two-channel ambulatory ECG from 47 individuals investigated in the BIH Arrhythmia Laboratory through 1975-1979. The MIT-BIH dataset is widely used in research and diagnostics worldwide. Any gains in forecasting its utilization will, therefore, be of great value to several clinics and hospitals in the improvement of ECG monitoring and detection. This data set is crude and rudimentary because the researchers require compiling and purifying it before evaluating it. This has resulted in unfair assessment, as the researchers with variably ranked status and characteristics may employ a number of components. The collected MIT-BIH arrhythmia dataset was obtained from the MIT-BIH Arrhythmia dataset. The recording was digitized at thirty samples of 360 samples per second, so thirty samples were obtained for each ten seconds. The segments were defined as such because there appear to be no recurring statuses, meaning that each segment is uniquely labelled and categorized with regard to signal cycles. Records were grouped into five classes per class 100, as shown below in Table 1.

3.2 Preprocessing dataset

At the first preprocessing stage, the signal undergoes scaling to conform to the range of 0–1. The mathematical expression for the min-max scaler is

$$S_i = \frac{X_i - min(X_i)}{max(X_i) - min(X_i)} \quad (1)$$

In this respect, $\boldsymbol{S_i}$ represents the normalized signal, which is the output after scaling the raw input signal. $\boldsymbol{X_i}$ represents the raw signal, which is the signal free from noise before the preprocessing step.

Table 1. Details of classes in the dataset

Class	Description	Included beats	Number of extracted records
N	Non-ectopic beats	Regular beats, left bundle branch block, right bundle branch block, nodal (junctional) escape beat, and atrial escape beat	**100**
S	Supraventricular ectopic beats	Aberrated atrial premature beat, supraventricular premature beat, atrial premature beat, and nodal (junctional) premature beat	**100**
V	Ventricular ectopic beats	Ventricular escape beat and premature ventricular contraction	**100**
F	Fusion beats	Fusion of ventricular and normal beat	**100**
Q	Unknown beats	Paced beat, unclassified beat, and fusion of paced and normal beats	**100**

$\boldsymbol{max}(\boldsymbol{X_i})$ and $\boldsymbol{min}(\boldsymbol{X_i})$ refer to the minimum and maximum values of the raw signal. The purpose of this normalization process is to scale the signal within the range of 0 to 1. This scaling step improves the accuracy and efficiency of the classification process by eliminating large differences in the values of the data [21]. The normalization is performed by calculating the minimum and maximum values of the raw signal $\boldsymbol{X_i}$, then adjusting all the values of the signal to fall within the normalized range. During the preprocessing, challenges arose in selecting an optimal normalization range. Negative ranges were found to produce suboptimal results, and data overlap within the dataset created further complications. Despite these challenges, this preprocessing step is essential for preparing the data for the next stages of analysis and classification.

3.3 PSO-based feature selection

Feature selection is performed before the classifying and can be considered an important prerequisite. In other words, the primary goal is to remove all the unrelated characteristics and choose some of the set as crucial features. This can reduce the number of dimensions in the classification problem while maintaining the same classification accuracy.

The conventional term used for any of the constituents of the swarm in PSO is a particle [22]. Every particle denoted by $\boldsymbol{P_i}$ (where $\boldsymbol{i}$ takes values in the range $(\boldsymbol{1}, \boldsymbol{K})$), is associated with a position $\boldsymbol{L_i(t)}$in a multi-dimensional search space mentioned as $\boldsymbol{t}$. These particles have $\boldsymbol{V_i(t)}$ velocity and possess information about their best position found so far or "pbest". The variable "gbest" represents the position of the best-found particle till now. Eqs. (2) and (3) are used to update the positions and velocities of all the particles within the various population.

$$L_i(t+1) = L_i(t) + V_i(t) \tag{2}$$

$$V_i(t+1) = wL(t) + C_1R_1\ (pbest - L_i) + C_2R_2(\ gbest - L_i) \tag{3}$$

The inertia weight $\boldsymbol{w}$, which controls the balance between exploration and exploitation, is set to 0.5 in this study, whereas its default value is typically within the range of [0.1 1.0]. The acceleration coefficients $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$, which influence the attraction towards the personal best and global best positions, are set to 2, as is standard in PSO. The random values $\boldsymbol{R_1}$ and $\boldsymbol{R_2}$, which introduce randomness into the search process, are set to 0.5 in this study, though they are typically random values between 0 and 1.

The fitness function $\boldsymbol{f(x)}$ in this study is the accuracy of the machine learning classifier after selecting a subset of features using PSO. The fitness function is given by Eq. (4).

$$f(x) = Accuracy(Classifier(X)) \tag{4}$$

Where $\boldsymbol{x}$ represents the selected features, and the accuracy measures the performance of the classifier using that feature subset. This approach contrasts with previous studies, as it directly optimizes feature selection based on the classifier's performance.

3.4 Classifiers

The supervised machine learning classifiers used for diagnosing rhythm disorders, which were tuned by the developed artificial intelligence PSO algorithm, are support vector machines, random forests, gradient-boosting decision trees, and K-nearest neighbors.

3.4.1. Support vector machine

The experiences of the SVM in practical application and practical guidance provide a useful reference for improving efficiency and increasing efficiency by a large margin [23]. SVM operates by mapping the input data into a high-dimensional feature space and determining the optimal hyperplane that divides the data into distinct classes. Its goal is to divide the training vectors into clusters to find a maximum margin hyperplane.

In SVM, each data point $\boldsymbol{X_i}$ from the training set is associated with a label $\boldsymbol{y_i} \in \{+\boldsymbol{1}, -\boldsymbol{1}\}$, where $+\boldsymbol{1}$ represents one class and $-\boldsymbol{1}$ represents the other class. The hyperplane that separates the classes is defined by the Eq. (5).

$$w \cdot z_i + b = 0 \tag{5}$$

Here, $\boldsymbol{w}$ is the weight vector, $\boldsymbol{z}_i$ represents the feature vector for the input $\boldsymbol{X_i}$, and $\boldsymbol{b}$ is the bias term. The actual classification of the input $\boldsymbol{X_i}$ is done by calculating the output function $\boldsymbol{f(x_i)}$ is given by the Eq. (6).

$$f(x_i) = sign(w \cdot z_i + b) = \begin{cases} 1, & if x_i = 1 \\ -1, & if x_i = -1 \end{cases} \tag{6}$$

SVM classifier aims to find a hyperplane that maximizes the margin between the two classes, while minimizing the classification error. For a linearly separable case, the condition given by Eq. (7).

$$\begin{cases} (w \cdot z_i + b) \geq 1, & if x_i = 1 \\ (w \cdot z_i + b) \leq -1, & if x_i = -1,' \\ \quad where\, i = 1, \ldots, l \end{cases} \tag{7}$$

holds true for all training samples $\boldsymbol{X_i}$. In cases where the data is not linearly separable, SVM allows for a soft margin classification by introducing slack variables $\tilde{\boldsymbol{\xi}}_{\boldsymbol{i}}$, which measure the degree of violation for each sample. The optimization problem is given by Eq. (8).

$$\begin{aligned} &min \frac{1}{2} w \cdot w + C \sum_{i=1}^{l} \tilde{\xi}_i, \\ &subject\, to\, y_i(w \cdot z_i + b) \geq \\ &1 - \xi_i, \, where\, \xi_i \geq 0, i, \ldots, l. \end{aligned} \tag{8}$$

Here, $\boldsymbol{C}$ is a regularization parameter that controls the trade-off between maximizing the margin and minimizing the classification error.

3.4.2. Gradient boosting decision tree

In decision trees, every node is termed as internal if it contains a particular input type. This is done by labeling the arcs that stem from the node representing the defined feature by each one of the feature values that it might assume. Any tree leaf can be described as having probability distribution concerning a range of types. In gradient boosting, the most basic concept behind the decision tree is to combine several fragile base classifiers into a single strong [24]. Unlike other methods of calculating examples to boost positive and negative weight, GBDT makes the algorithm globally converge by maintaining the negative gradient direction. The weak learner applies a test function to the fault at each splitting node. The weights $\boldsymbol{w_i^j}$ and residuals $\boldsymbol{r_i^j}$ are updated iteratively, as described in Eq. (9). This equation minimizes the weighted sum of squared errors, optimizing the model by adjusting the predictions from each weak learner. Specifically, the weights are updated based on the gradients, and the error correction is applied to the residuals, improving the model's performance with each iteration. The equation for updating the weights and residuals is given by Eq. (9).

$$\begin{aligned} &\epsilon(\tau) = \sum_{i:k(\mathrm{x}_i)<\tau} w_i^j \big(r_i^j - \\ &\eta^l\big)^2 \sum_{i:\kappa(\mathrm{x}_i)\geq\tau} w_i^j \big(r_i^j - \eta^r\big)^2 \end{aligned} \tag{9}$$

Next, Eq. (10) defines the update rules for the weights $\boldsymbol{w_i^j}$ and residuals $\boldsymbol{r_i^j}$.

$$\begin{aligned} &w_i^j = \exp\left(-y_i f_j(\mathrm{x}_i)\right), \\ &r_i^j = g(\mathrm{x}_i)/w_i^j = \\ &-y_i \exp\left(-y_i f_j(\mathrm{x}_i)\right)/w_i^j = -y_i \end{aligned} \tag{10}$$

In these equations, $\boldsymbol{y_i}$ represents the true label, $\boldsymbol{f_j(\mathbf{x}_i)}$ is the prediction of the $\boldsymbol{j}$-th tree for the $\boldsymbol{i}$-th sample, and $\boldsymbol{g(\mathbf{x}_i)}$ is the gradient at $\boldsymbol{x_i}$. The weights $\boldsymbol{w_i^j}$ and residuals $\boldsymbol{r_i^j}$ are updated during each iteration to minimize the residual errors, ultimately enhancing the accuracy of the model.

3.4.3. Random forests

RF is most similar to the Bayesian method and is used to find an ensemble using several hierarchical tree structure predictors. The basic concept of RF is that several learning tree models can make a combined performance greater than an individual decision tree, if errors are independent.

In this context, instead of a single tree being constructed, we build multiple trees, each based upon values of independently and randomly distributed vectors that correspond to the entire forest. Combining several random decision trees, the RF is an ensemble classifier. A single classification output from these decision trees is generated and the values are summed up to give the final classifier outcome [25]. The RF, once set, runs at a very high speed due to the simple computation task needed to perform its functions. At the same time, it has a high level of obviousness, which allows its use to incorporate existing knowledge. Appropriate randomness means that we can obtain accurate regressors and classifiers. In addition, some research shows that random inputs generate better results in terms of classification [26].

3.4.4. K-Nearest neighbor

KNN is one of the simplest and most essential categories of machine learning that uses supervised learning. It belongs to the category of non-parametric, which implies that the basic data do not have to be assumed to be classified. It provides the likeness of the new class with existing examples and assigns the new class the closest related feasible category. The estimations obtained using the KNN technique are influenced by local noise and are generally less than satisfactory [27]. A higher choice of k makes the classification boundaryless complex, while a small choice of k makes the boundary complex. As for the strengths of KNN, its disadvantage is that KNN is an algorithm with no training process required.

3.5 Evaluation metrics

In this study, the given ECG heartbeat was categorized using ML techniques such as DT as a classifier with PSO feature selection, RF, KNN, and SVM. Before employing methods from the ML sphere, the paragraph briefly describes many measures, including the confusion matrix, recall, the F1-score, and accuracy.

- **Confusion matrix:** A confusion matrix is an illustration of the algorithm's input and output. Confusion matrix is an effective way to represent error in prediction. The proportion of true negatives to the total number of true negatives and false positives defines the specificity of a test. For instance, based on [28], they explained that a matrix is made of the column expected class instances and row actual class instances. It is also possible to add more measurements of the analysis, such as F1 score, accuracy, or even recall, to the same confusion matrix.
- **Precision:** a measure of the accuracy of a model, which is an evaluation of the correctness of predictions against the total number of predictions made. It means that TP is divided by TP and FP (if positive predictions = TP + FP). Specificity is measured mathematically by dividing TP by the overall number of TP and FP. It is computed as the ratio between true positive predictions that were made by the model and all the positive predictions that the model made, as given by Eq. (12) [29].

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

- Recall: the specificity or the true positive (TP) rate is another key performance indicator [30]. It measures how many of all actual positive cases were successfully classified by the model as such. This measure offers an indication of the model's failure to capture all the positive samples. In other words, recall can be defined mathematically as the fraction of actual positive instances that the model has correctly identified, and it is measured as a true positive out of total true positives plus false negatives, as given by Eq. (12).

$$Recall = \frac{TP}{TP+FN} \tag{12}$$

- **F1-score:** Described as the average of precision and recall with the ratio 2:1, F1 – the F1-score is considered accurate when performing the comparison of classifiers, especially when working with an unbalanced database. This metric is quite helpful since it will give both the number of prediction errors and the kind of errors made by the model [31]. It is commonly used as a reliable measure of the accuracy of classifiers. The F1 score is defined mathematically in the formula below by Eq. (13).

$$F1 - score = 2\,\frac{Recall \times Precision}{Recall + Precision} \tag{13}$$

- **Accuracy:** Accuracy enjoys a wide application in the assessment of performance because it is easy to comprehend. That is the percentage of true positives divided by the total count of the instances. This measure speaks for the general performance of a model as the name, confusion matrix, suggests [32]. The formula for accuracy is defined by Eq. (14).

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{14}$$

4. Results analysis and discussion

For the practical part that covers elementary programming concepts, Python 3.12 was used because of its versatility and because it is widely used for general programming. This aspect of Python makes it possible to design various applications across the desktop to web applications. Visual Studio Code was the primary IDE with better UI, improved output viewing, and tailored data manipulation actions.

Table 2. Details of the implementation environment.

Components	Specifications
Processor	6th Generation Intel® Core™ i7
RAM	16 GB
Editor	Visual Studio Code
Programming language	Python 3.12
Operating system	Windows 10 Pro

Table 3. Evaluation of the machine learning classifiers without feature selection.

Classifier / Metrics	DT	SVM	RF	KNN
Accuracy	81	84	83	84
F1-score	88.05	89.87	89.44	90.12
Precision	87.6	88.75	90	91.25
Recall	87.5	91.03	88.89	89.02

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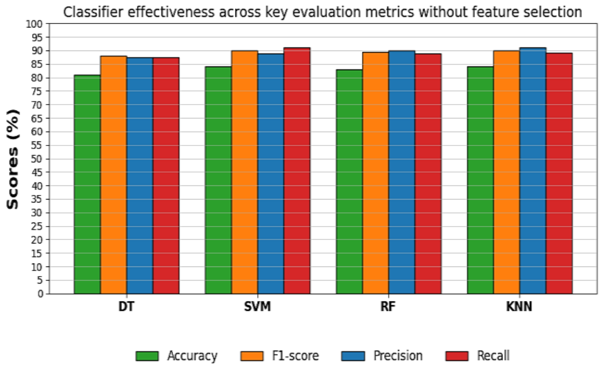

Figure. 3 Classifier effectiveness across key evaluation

The system configuration is described in Table 2, which contains detailed specifications of the chosen equipment.In the next section, we shall evaluate and describe the experimental outcomes performed on the MIT-BIH arrhythmia signal database. There will be a key emphasis on comparing and contrasting our classifier with other classifiers, as well as comparing feature selection techniques with no feature selection at all.

4.1 Performance of machine learning classifiers without feature selection

The performance of the classifiers that do not make use of feature selection was used for comparison. The classifiers used in the current study were KNN, RF, SVM, and DT. For evaluation, F1-score, recall, precision, and accuracy measures were used in order to determine the efficiency of the methods depending on the data size. Using the MIT-BIH arrhythmia dataset and without employing feature selection, the evaluation results of the proposed method are shown in Table 3 below.

The results show that, without feature selection, RF and KNN have relatively higher accuracy, precision, recall, and F1-score than the DT and SVM models. Both RF and KNN score consistently and marginally higher than the other classifiers, and the features in each have to do with RF being an ensemble technique and KNN being capable of handling non-linear relationships. Hence, DT and SVM exhibit slightly lower classification accuracy, which again proves that all classifiers classified these MIT-BIH arrhythmia samples with reasonable features within the MIT-BIH arrhythmia dataset are already rich in information, as illustrated in Fig. 3. An even higher performance might be achieved by adding feature selection to the current solution in order to filter out noise.

Fig. 4 shows the confusion matrices of four machine learning models (DT, SVM, RF, and KNN) concerning the classification of Arrhythmia and Healthy cases without the elimination of features. DT and SVM performed almost equally for both accuracy and Misclassification Rates, with slight variations, for 70-71 Arrhythmia and 11-13 healthy datasets.

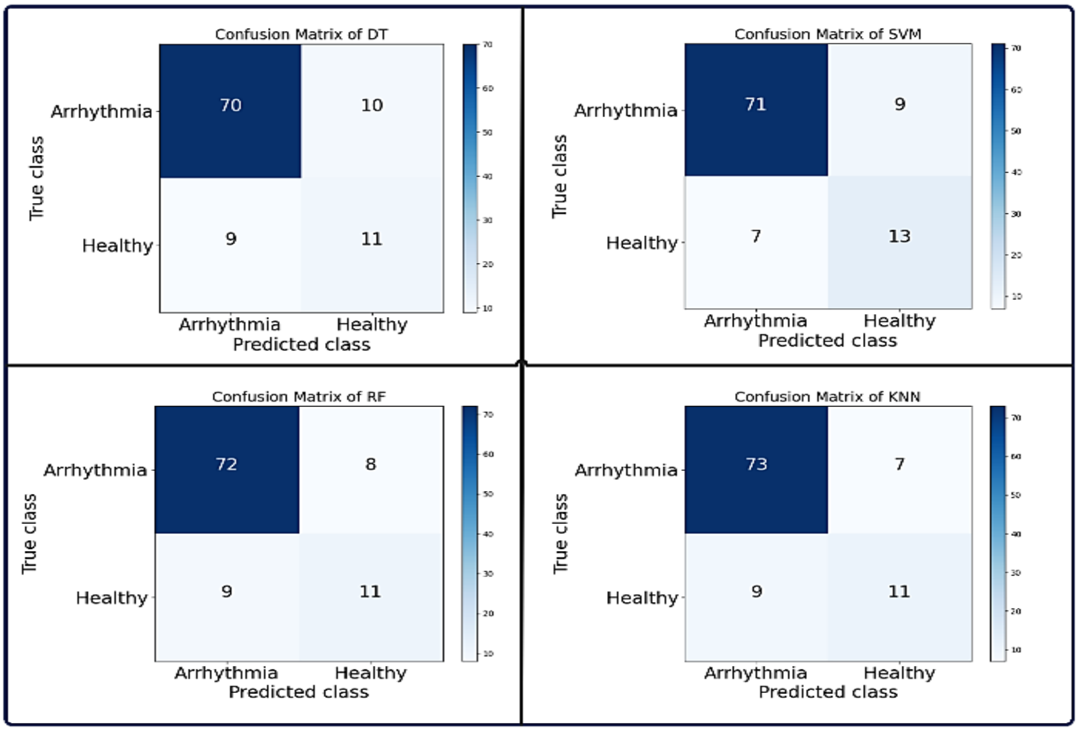

Figure. 4 Confusion matrix of the machine learning classifiers without using any feature selection

Table 4. Evaluation of the classifiers with feature selection.

Classifier / Metrics	DT	SVM	RF	KNN
Accuracy	95	98	97	97
F1-score	96.86	98.77	98.14	98.11
Precision	96.25	100	98.75	97.5
Recall	97.47	97.56	97.53	98.73

Figure. 5 Classifier effectiveness across key evaluation metrics with PSO feature selection.

RF was slightly better at the identification of Arrhythmia with 72 cases, while the best accuracy was scored by KNN, which correctly classified 73 cases of Arrhythmia. While, on average, KNN gave the best results, all the classifiers were wrong in some cases, thus increasing the potential for the best results.

4.2 Performance of machine learning classifiers with feature selection

The performance of the proposed approach was evaluated using various machine-learning classifiers, with feature selection implemented through PSO. Notably, rather than using a large set of 4000 features, as in many traditional methods, the PSO method effectively selected only 888 features. This reduction in the number of features enabled a more efficient and targeted learning process, contributing to the classifiers' improved accuracy. Table 4 summarizes the evaluation metrics for DT, SVM, RF, and KNN. The results indicate that SVM outperformed the other classifiers with the highest accuracy of 98%, the highest precision of 100%, and a robust F1-score of 98.77%, reflecting its ability to balance precision and recall effectively. RF and KNN both achieved high accuracies of 97%, with KNN showing the highest recall at 98.73%, making it highly effective in detecting all relevant instances. These findings demonstrate that the combination of PSO for feature selection and machine learning classifiers is highly effective, with SVM emerging as the most robust and reliable model in terms of overall performance. The precision of SVM and the recall of KNN further underscore the flexibility of the proposed approach to optimize results across different performance metrics.

The evaluation of four ML algorithms, namely DT, SVM, RF, and KNN, was performed with the help of feature selection in terms of Accuracy, F1-score, Precision, and Recall, as shown in Fig. 5. All models show the tool's very high efficacy in all categories, with results ranging from 96 to 99 percent in many instances. This indicates that the integration of feature selection enhanced the reliability and consistency of classification performance. With the classifiers, the differences in scores are small, meaning that all models under consideration are almost equally good. The increase in all the measures further affirms the effectiveness of feature selection in improving model genericity and classification.

The feature selection solution results in confusion matrices of four machine-learning models, which include DT, SVM, RF, and KNN. The proposed DT model achieved 77 correct classifications for the Arrhythmia and 18 for the Healthy class, whereas it misclassified 3 Arrhythmia and 2 Healthy samples. SVM achieved a perfect result in the classification of Arrhythmia cases – 80 correct classifications out of 2 Healthy cases misclassified. RF also performed well in identifying all arrhythmia; only 1 arrhythmia was mistaken as healthy, and only 2 healthy cases were misclassified as arrhythmia.

KNN also gave good results, with 78 samples correctly classified as arrhythmia and 19 as healthy, with two arrhythmias and one healthy misclassified sample. Collectively, feature selection led to a qualitative enhancement of all models in terms of TPR and minimized misclassifications, as illustrated in Fig. 6. The performances for SVM were the best across the board, especially for perfect classification of the Arrhythmia cases and moderation in correctly sorting between Arrhythmia and Healthy cases, as was evident with KNN. These results imply that a proper selection of the features significantly improves the quality and stability of the model.

4.3 Comparison proposed approach with similar works

The proposed approach is compared with recent studies that used different feature selection algorithms with machine and deep learning classifiers on the MIT-BIH Arrhythmia dataset. Table 5 provides a detailed comparison, highlighting differences in feature selection techniques, classifiers, and achieved accuracy.

Table 5. Comparison of the methodology defined in this study with recent studies based on the MIT-BIH arrhythmia dataset

Ref.	Year	Feature selection technique	Fitness Function	Classifier	Accuracy	F1-score	Sensitivity	Specificity
[15]	2024	PSO	Accuracy of KLC	KLC	86.67	86.5	86.67	73.17
[16]	2023	PSO	Accuracy of CNN	CNN	97	85.6	92.6	N/A
[17]	2024	SSA	Optimal Food in the search procedure	Deep CNN	94.8	N/A	96.5	93
[18]	2024	PSO	Accuracy of Chi-square	KNN	96	96.06	96	86.95
				RF	93	92.89	93	78.57
				SVM	95	94.92	95	85.71
				NB	82	83.26	82	54.54
				DT	91	91.11	91	68.75
				Chi-square classifier	98	98.03	98	90.90
[19]	2024	PSO	Default fitness function	KNN	90.0	87.05	84.63	N/A
				RF	90.0	87.46	81.81	N/A
				SVM	72.5	42.02	50.0	N/A
				NB	95.0	94.38	96.55	N/A
				DT	92.5	90.40	89.18	N/A
				Minkowski classifier	97.5	96.87	95.45	N/A
[20]	2024	MPA	Accuracy of (KNN, GBDT, SVM, RF)	KNN	96.44	92.73	92.55	**97.73**
				RF	**99.67**	**99.34**	**99.27**	**99.8**
				GBDT	**99.61**	**99.23**	**99.15**	**99.77**
				SVM	**99.48**	**98.97**	**98.90**	99.68
Proposed		**PSO**	Accuracy of (DT, SVM, RF, KNN)	**DT**	**95**	**96.86**	**97.47**	**85.71**
				RF	97	98.14	97.53	94.73
				KNN	**97**	**98.11**	**98.73**	90.47
				SVM	98	98.77	97.56	**100**

The proposed method in this study outperforms several recent approaches that utilized PSO and other feature selection techniques on the MIT-BIH Arrhythmia dataset. Compared to studies such as [15], [16], and [17], which achieved accuracies ranging from 86.67% to 97%, the proposed approach achieves up to 98% accuracy across multiple metrics and classifiers. Additionally, the proposed method demonstrates superior performance in F1-score, sensitivity, and specificity, especially with the SVM classifier, which achieves 100% specificity.

Reference [20] achieves remarkable results in some classifiers, particularly with RF (99.67% accuracy, 99.34% F1-score, and 99.8% specificity) and SVM (99.48% accuracy and 98.97% F1-score). However, the proposed method excels in others, such as KNN, where it achieves higher sensitivity (98.73% compared to 92.55%) and F1-score (98.11% compared to 92.73%). This comparison highlights how the proposed approach balances high performance across multiple classifiers and metrics, showcasing its robustness and adaptability.

This consistent improvement in performance highlights the effectiveness of using accuracy as the fitness function in PSO for feature selection, optimizing the feature set for each classifier. The high accuracy achieved in this study can be attributed to using the fitness function based on the machine learning classifier’s accuracy, as opposed to other methods that used Chi-square, KLC, or other generic fitness functions. This approach selects the most effective features tailored to each classifier, which results in notable accuracy improvements for each classifier. By focusing on optimizing feature sets specific to the classifiers' needs, the proposed method maximizes the performance of the classifiers on the dataset.

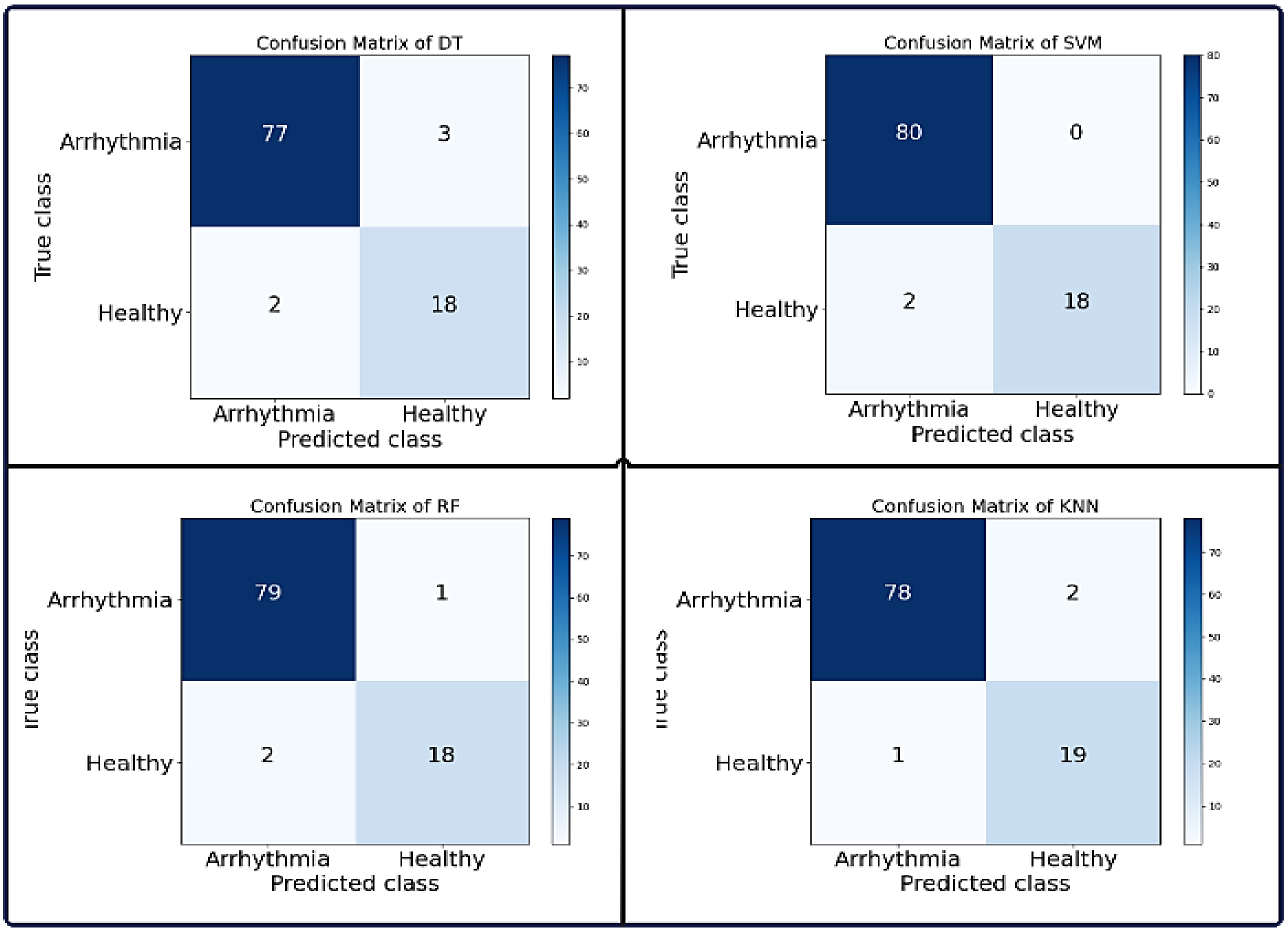

Figure. 6 Confusion matrix of the machine learning classifiers with PSO feature selection.

5. Conclusion

The paper presented a practical framework for ECG classification in IoT-enabled 5G-driven health monitoring systems for classifying ECG signals effectively by reducing high-dimensional data and overcoming the challenges related to the computational power of resource-constrained environments. The proposed approach combined PSO feature selection with the machine learning classifiers for utmost performance, where a maximum accuracy of 98% was achieved by SVM, thus outperforming state-of-the-art methods. Thus, feature selection has reduced the dimensionality of ECG data and enhanced computational efficiency without compromising the feasibility of the framework for real-time IoT and 5G applications. The findings proved that the utilization of PSO for feature selection significantly enhances the performance of the classifier based on different performance metrics such as accuracy, precision, recall, and F1-score. This underlines the robustness of the proposed framework in terms of removing noise and focusing the attention to the most salient features in the realization of valid and reliable arrhythmia classification. The review further brings to light the potential of traditional machine learning classifiers, such as KNN, RF, to match results using effective feature selection methods. Therefore, the scalability and practicality of the proposed framework provide a potentially effective solution for its real implementation in IoT-based healthcare systems, mainly for remote cardiac health monitoring. The future directions include scaling up this methodology to more medical data, advanced optimization techniques, and the use of edge computing for further relevance in shifting healthcare environments.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Mustafa and Ali; methodology, Ali; Software, Safa; validation, Waleed, Ali; formal analysis, Mustafa; investigation, Ali; resources, Mustafa; data curation, Ali and Safa; writing—original draft preparation, Ali; writing—review and editing, Waleed; visualization, Safa;

supervision, Ali; project administration, Mustafa, and Ali; funding acquisition, Ali". All authors have read and approved the final manuscript.

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