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Research Article

Arrhythmia Classification Using Wearable Sensor: Machine Learning Approach

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ABSTRACT

Heart rate variability holds significant importance in assessing cardiac health. Monitoring heart rate offers essential information regarding cardiovascular well-being, physical fitness, stress responses, and various health conditions. Additionally, categorizing heart rate patterns into normal, tachycardia, or bradycardia can support the early detection of arrhythmias. Utilizing real-time data for analysis yields more accurate and practical observations compared to relying solely on previously collected datasets. In this paper propose an interface for capturing the real heart rate data (bmp) from heart rate sensor & build machine learning model for analysis of data.SVM, Random Forest, KNN and logistic regression classifier used for classification of different types of arrhythmias. Logistic regression and random forest provides high accuracy as compared to SVM and KNN with accuracy rate 99.00% and 99.20%.Random Forest excels due to its ensemble learning capability and ability to handle non-linearity, resulting in superior performance. Similarly, Logistic Regression, being well-suited for both binary and multiclass classification, outperforms SVM and KNN.

Keywords: Anonymization techniques. ML model security. Data protection. Privacy of electronic healthcare system. Differential Privacy.

INTRODUCTION

Heart rate (HR) denotes the count of heartbeats occurring over a defined period, typically recorded in beats per minute (bpm). It often differs from person to person, influenced by various factors such as age, physical activity, gender and overall fitness. Resting heart rate reflects the heart's efficiency in circulating blood and serves as an indicator of a person's fundamental fitness level [1]. Heart rate is regarded as one of the key vital signs, serving as a reliable indicator of an individual's overall health condition. As a result, continuous heart rate monitoring is essential in critical care environments such as intensive care units (ICUs), post-anesthesia care units, telemetry wards, and emergency rooms, where patients' conditions may quickly worsen [2][3].

Many methods are there to measure heart rate, the most noninvasive is an Electrocardiogram (ECG) and the rest are by using a heartbeat sensor. Heart rate sensor is an easy way to monitor heart rate. Sensors come in various shapes and sizes and provide a quick way to measure the heartbeat. Availability of these sensors are in Smartphone, wrist watches, chest strap, ring finger etc. Measured in beats per minute (bpm), heart rate represents the count of cardiac contractions over a 60-second period. As per the American Heart Association, for adults; the normal resting heart rate typically ranges from 60 to 100 beats per minute (bpm). In tachycardia the heart rate exceeds 100 bpm in a resting state. In bradycardia, the heart rate is below 60 beats per minute (bpm). [4].

In this paper the heartbeat data is collected from a heart rate sensor in BPM and stored in time series format using a wi-fi module microcontroller. The collected heart rate data(BPM) is processed using various machine learning methods to classify it into different arrhythmia categories, specifically bradycardia, tachycardia, and normal heart rhythms. The models are trained on heart rate data to monitor heart rate on real-time series data. SVM, KNN, random forest and logistic regression these classifiers are used and calculate the accuracy of classification. Random forest and logistic regression demonstrate superior performance over SVM and KNN due to ensemble learning capability and Capability to manage non-linearity of the data.

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Recent advancements in wearable sensor technologies have made it possible to continuously monitor heart rate extends, allowing for real-time detection of anomalies. Despite these accurately classifying heart rate patterns remains challenging due to factors like individual variability in heart rhythms, sensor noise, and the similarity in characteristics across different cardiac conditions. Machine learning (ML) techniques have proven to be effective in analyzing ECG signals and identifying abnormal heart rate patterns with high accuracy.

OBJECTIVES

The objective of this study is to develop a real-time arrhythmia detection framework by collecting heart rate data through a heart rate sensor and transmitting it wirelessly to a centralized system via a Wi-Fi communication interface.

The acquired heart rate values are then analyzed and categorized into normal rhythm, bradycardia and tachycardia conditions by using machine learning module. This research aims to enable timely detection and classification of abnormal heart rate patterns, supporting early diagnosis and continuous monitoring of cardiac health using an integrated hardware-software approach.

RELATED WORK

The Continuous heart monitoring is important for the early detection of cardiac arrhythmia and suitable treatment for patients. Cañón-Clavijo et al. build an IoT system to monitor ECG and provide alert for arrhythmia. Arrhythmia classification accuracy is provided using KNN, CNN and random forest classifier [5]. to overcome the minority class performances of existing dataset a lightweight Transformer combined with CNN model build with high accuracy of classification suggested inref[6]. Machine learning (ML) and deep learning techniques provides better approach for the classification of arrhythmia along with limitation of computational time, performance on redundant dataset, Al-Shammary et al. [7] emphasized Chi-square distance-based feature selection To enhance the efficiency of classifiers in different type of arrhythmia with classification accuracy 98%. Mohamed Hammad et al[8] proposed a model Deep Convolution Neural Network(CNN) model with SVM classifier on PTB-XL dataset that leads to 99.20% accuracy.

The photoplethysmogram (PPG) signal is also used by researchers as it provides a non-invasive, inexpensive, and an efficient channel for gathering information on cardiac performance. Qasem Qananwah [9] used PPG signal from database PhysioNet Challenge 2015 to classify different types cardiac arrhythmias basically tachycardia, ventricular tachycardia ,bradycardia, and ventricular flutter/fibrillation using Support Vector Machines (SVM), Decision Trees (DT), K-Nearest Neighbors (KNNs), and Ensembles learning. Working on a real dataset and continuous heart monitoring system is beneficial for better treatments of patients. Paganelli, A.I et al.[10] provide systematic review and highlighting the application of SVM, Logistic Regression, KNN, and Random Forest in health monitoring. The authors discuss real-time classification of heart data and underline the significance of preprocessing .heart rate monitoring system is build by Mr. Ved Prakasha, Mr. Manoj Kumar Pandeyb[11] to monitor heart rate continuously via heart rate sensor. Author Rezazadeh, J.[12] integrates Random Forest, KNN, and SVM classifiers in an IoT-based system for detecting arrhythmias , emphasizes real-time data processing and energy efficiency in continuous heart rate monitoring. Fujiwara, K.[13] presents an IoT-driven atrial fibrillation screening system using HRV features derived from wearable sensors. Machine learning models, Random Forests and SVM used to classify arrhythmias effectively based on R-R interval variations. Priyanka Kakria [14] built an IoT-based health monitoring system for arrhythmia classification bradycardia tachycardia and normal heart rhythm. Author Allen, J., & Kyriacou, P.A.[15] build a model using wearable PPG sensor technology for HRV-based monitoring & machine learning algorithms are fitted to the data by using extracted HRV features to classify arrhythmic patterns effectively.

METHODS

1. Hardware System Design:

In this paper proposed a heart rate monitoring module designed using a heart rate sensor, microcontroller unit and communication components. The key hardware elements used in this system are:

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A.NodeMCU ESP8266 Wi-Fi Module:

This module works as the microcontroller unit (MCU), mainly used for data collection, processing, and wireless transmission. wi-fi module used due to its built-in Wi-Fi capabilities, easy programming, and cost-effectiveness.

B.Optical Heart Rate Sensor:.

A finger-based photoplethysmography (PPG) sensor is used to measure the pulse rate. It Identifies changes in blood volume by measuring light absorption levels, converting these fluctuations into analog voltage signals that correspond to each heartbeat. All hardware components are assembled on a printed circuit board to ensure proper connectivity and functionality. A regulated DC power supply is used to deliver a consistent voltage to both the NodeMCU microcontroller and the connected sensors.

2. PROPOSED SYSTEM

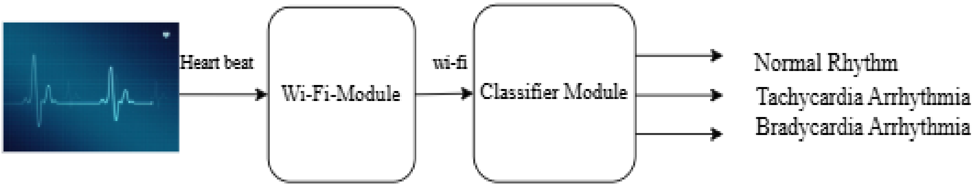

Figure1: Proposed System

A Figure1 shows the system architecture. The heart rate sensor is positioned on the user's fingertip, where it senses variations in blood volume by examining light absorption levels and generates an analog voltage signal corresponding to each heartbeat. This analog signal is then captured by the NodeMCU microcontroller through its ADC pin. To ensure the accuracy of the signal, preprocessing methods like noise reduction and averaging are applied, effectively minimizing motion-induced artifacts. Additionally, a digital band-pass filter is utilized to suppress unwanted disturbances, such as high-frequency noise from surrounding light and low-frequency baseline shifts, thereby isolating the specific frequency band linked to human heartbeats. The processed data is used to compute the heart rate in beats per minute (BPM).

Once the BPM values are collected, they are transmitted wirelessly using the ESP8266's built-in Wi-Fi module for further analysis. The time-series heart rate data is then classified into different categories—normal rhythm, bradycardia, tachycardia, or arrhythmia—using machine learning algorithms. This approach supports real-time heart rate monitoring and enables remote observation by healthcare providers. The classification process involves the implementation of Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), and Logistic Regression (LR), each of which analyzes the features extracted from the dataset recorded through the wearable sensor system. Table 1 summarized the characteristics of each classifier for arrhythmia classification.

Classifier	Characteristics	Arrhythmia Classification
Support Vector Machine (SVM)	Uses hyper plane separation; RBF kernel handles non-linear data	Bradycardia, Tachycardia, Normal rhythm
K-Nearest Neighbors (KNN)	Classifies based on nearest neighbors BPM values	Bradycardia, Tachycardia, Normal rhythm
Random Forest (RF)	Ensemble of decision trees; handles feature interactions	Bradycardia, Tachycardia, Normal rhythm
Logistic Regression (LR)	Linear model; computes probability scores	Bradycardia, Tachycardia, Normal rhythm

Table 1: Summary Table of Classifiers

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3. CLASSIFICATION TECHNIQUES

In this proposed model SVM(support vectormodel),KNN(K-nearest neighbor),Random forest and logistic regression classifier are build on accuracy factor of arrhythmia detection in to the 3 classes of arrhythmia ,normal rhythm,bradycardia,tachycardia.

A. SVM:

Supervised learning model SVM identifies the optimal hyperplane separating different classes based on input features. For arrhythmia classification, BPM data is used as the input feature set. The non-linearity of physiological signals is addressed using kernel functions like the Radial Basis Function (RBF), which enhances the model's ability to classify complex patterns [16]. SVM is designed to identify the most suitable hyper plane that distinctly divides data points into their respective classes. For a binary classification problem.

$$Minimize \;= \frac{1}{2}\left|\left|W\right|\right|^2 \tag{1}$$

Subject to:

$$y_{i=(w.x_i+b)\geq 1} \quad i=1,2,3,\ldots,n \tag{2}$$

Where: w = weight vector b = bias term y_i = class label (±1) x_i = feature vector (BPM values)

For non-linear cases, the Radial Basis Function (RBF) kernel is used:

$$K(x_i, x_j) = \; exp\left(-\gamma \times \left|\left|x_i - x_j\right|\right|^2\right) \tag{3}$$

B. KNN

KNN is a simple, non-parametric classification method that assigns the class label based on the majority vote of the 'k' closest neighbors in the feature space. For heart rate classification, each BPM reading is compared toneighboring instances, making KNN suitable for datasets with clear clustering tendencies [17]. KNN classifies a data point based on the majority label of its k nearest neighbor.

Euclidean Distance formula:

$$\mathrm{d}(\mathrm{x}, \mathrm{x_i}) \;=\; \sqrt{(\sum \text{ from } \mathrm{j} = 1 \text{ to } \mathrm{n}\; (\mathrm{x_j} \;-\; \mathrm{x_{ij}})^2)} \tag{4}$$

Where:
x = input data point (BPM) x_i = neighbor point n = number of features.

C. Random forest

Random Forest is known as ensemble learning technique composed of several decision trees. Each tree is trained on random subsets of the dataset, and the final prediction is determined through majority voting. RF's capability to handle high-dimensional and noisy data makes it particularly suitable for arrhythmia classification based on BPM and other derived heart rate variability features [18]. Random Forest builds multiple decision trees.Each tree outputs a prediction, and the final class is determined by majority voting.

Decision Tree Split Criterion (Gini Impurity):

$$Gini \;=\; 1 \;-\; \textstyle\sum_i^c pi`2 \tag{5}$$

Where: p_i = probability of class i at the node C = total number of classes

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Final Prediction:

$$\hat{y}=\mathrm{mode}\{T1(x),T2(x),\ldots,TN(x)\} \quad (6)$$

Where: T_i = individual decision trees N = total number of trees ŷ = final predicted class.

D. Logistic regression

Logistic Regression serves a baseline classifier, structuring the relationship between input features and class labels using a logistic function. In the context of arrhythmia detection, it estimates the probability of each heart rate reading belonging to a specific class[19].For multi-class classification (tachycardia, bradycardia,normal), SoftMax Regression is used:

$$P(y = j \mid x) = \exp(w_j^T x) / \Sigma_{k=1}^{K} \exp(w_k^T x) \quad (7)$$

Where: x = feature vector (BPM) w_j = weight vector for class j K = total number of classes.In The proposed system classification module threshold value used as per the report of American Heart Association(AHA) [20] and European Society of Hypertension [21] mentioned in table 2. The application is built in python programming language for classification module.

Rhythm type	**Heart rate threshold value**
Normal	60< = HR < = 100(BPM)
Bradycardia	HR < = 60(BPM)
Tachycardia	HR > = 100(BPM)

Table 2: Heart rate threshold value

RESULTS

The proposed system of heart rate monitoring and arrhythmia classification evaluated by using different four machine learning classifiers: (SVM) Support Vector Machine, (LR) Logistic Regression, Random Forest, and K-Nearest Neighbors (KNN). The system aimed to classify heart rate (BPM) data into three categories: tachycardia, bradycardia, and normalrhythm. The classification accuracy evaluated by model is described in table 3.

classifier	**Accuracy (%)**
Logistic Regression	99
Support Vector Machine	98.28
Random forest	99.2
K-nearest neighbor	97.76

Table 3: Accuracy Table of classifier

The results evaluated by Logistic Regression and Random Forest classifiers 99.00%, 99.20%, indicating their strong capability in correctly classifying heart rate patterns. The SVM classifier also exhibited high accuracy

(98.28%), effectively handling non linear reparability in the BPM dataset. The KNN classifier recorded an accuracy of 97.76%, slightly lower than the others, likely due to its sensitivity to the value of k and the distribution of neighboring data points.

Figure2 shows the classification accuracy comparison for machine learning models. The bar graph compares the performance of Logistic Regression, Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbor (KNN) classifiers on arrhythmia classification task.

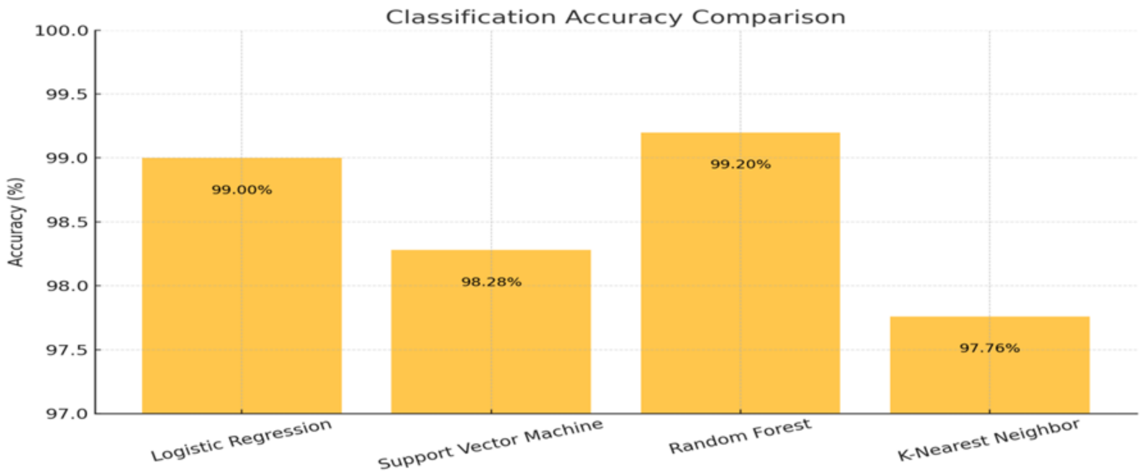

Figure2: Bar graph visualizing the classification accuracy of models

CONCLUSION

The proposed model effectively establishes a real-time monitoring of heart rate and arrhythmia classification framework by leveraging wearable sensors embedded with advanced algorithms of machine learning. Among the classifiers applied, and (LR) Logistic Regression models demonstrated superior performance, achieving an impressivetheRandomForestaccuracy of 99.20% in classifying arrhythmia conditions such as tachycardia, bradycardia, and normal heart rhythms. Thisstudy underscores the potential of integrating wearable sensor data and machine learning methodologies to facilitate accurate and continuous cardiac monitoring. Furthermore, the results affirm the viability of the developed system for deployment in remote healthcare settings, supporting early detection and timely medical intervention for cardiac patients.

FUTURE SCOPE

In future work, the system can be extended to incorporate additional physiological parameters, such as electrocardiogram (ECG) signals, peripheral oxygen saturation (SpO2), and respiratory rate, alongside BPM readings, to develop a more comprehensive and reliable arrhythmia detection framework. Furthermore, integrating cloud-based data storage and analytics would enable real-time monitoring capabilities and remote access for healthcare professionals, thereby enhancing the scalability accessibility, and overall efficiency of the system.

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