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AI Based Heart Rate Monitoring System for Sport Persons

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Abstract—Heart rate is a key physiological indicator for assess ing cardiovascular load, training intensity, and recovery status in sportspersons. Conventional monitoring techniques such as manual pulse checks or basic fitness bands are inadequate during high-intensity sports because they lack continuous, accurate, and intelligent analysis capabilities. This report presents the design and implementation of an AI based heart rate monitoring system for sports training that combines wearable sensors, an ESP32 based embedded platform, and machine learning algorithms to analyse cardiac activity in real time. The system acquires physiological signals from ECG and PPG based heart rate sensors, together with auxiliary parameters such as temperature. The raw data is pre-processed using filtering, normalization, and segmentation before extracting time-domain, frequency-domain, and nonlinear features. Multiple supervised learning models—Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, Na¨ıve Bayes, K-Nearest Neighbour (KNN), and Weighted KNN—are trained to classify heart rhythm patterns and risk levels. Experimental evaluation shows that Decision Tree and Weighted KNN achieve an accuracy of approximately 97.78%, while SVM reaches about 96.67%, demonstrating the suitability of AI for arrhythmia detection in sports scenarios. The proposed system categorizes heart rate into training zones, detects abnormal conditions such as tachycardia or bradycardia, and generates alerts when values deviate from safe thresholds. The overall solution is portable, low power, and scalable for multi sport applications, providing coaches and athletes with actionable insights for safe and optimized training sessions. Index Terms—Heart rate monitoring, ECG, PPG, Sports training, ESP32, Machine learning, Arrhythmia detection, IoT.

Key Points: AI, Heart Rate Monitoring, Wearable Sensors, Machine Learning, Sports Analytics, Athlete Safety

I. INTRODUCTION

HEART rate is one of the most informative and accessible indicators of cardiovascular status for athletes. During training and competitive events, sportspersons subject their bodies to rapid and sometimes extreme physical loads. Under such conditions, heart rhythm may change abruptly, and unde tected abnormalities such as tachycardia, bradycardia, arrhyth mias, or conduction blocks can lead to decreased performance, fatigue, dizziness, or even sudden cardiac complications. Traditional heart rate monitoring approaches—manual pal pation, basic wrist bands, or intermittent ECG checks—are unable to provide continuous, reliable, and context-aware information during high-intensity exercise. Clinical ECG sys tems, while accurate, are unsuitable for field use due to their bulk, wired connections, and dependence on clinical infrastructure. Consumer-grade fitness devices, on the other hand, typically provide approximate heart rate readings but do not perform deeper analysis such as arrhythmia detection, heart rate variability (HRV) analysis, or predictive risk assessment. Recent developments in wearable sensors, embedded sys tems, and artificial intelligence (AI) have enabled the design of real-time monitoring solutions that can analyse complex biosignals outside the hospital environment. Microcontrollers such as the ESP32 offer integrated wireless communication and sufficient processing capability to handle data acquisition and preliminary signal conditioning. Machine learning models can then be used to extract patterns from ECG and PPG signals and classify normal and abnormal cardiac activity. The project titled “AI Based Heart Rate Monitoring System for Sport Persons” addresses this gap by developing an AI driven monitoring platform specifically tailored for sports training. The system focuses on:

- Continuous monitoring of heart rate and related physio logical parameters during exercise.
- Real-time AI-based classification of cardiac patterns and risk levels.
- Instant alerts when heart rate exceeds safe physiological limits.
- Storage and visualization of historical data for perfor mance analysis. The rest of this report follows the typical structure: Section II describes the materials and methods, including hardware, software, and machine learning pipeline. Section III presents key results, while Section IV discusses the outcomes, limitations, and potential improvements. Appendices contain supporting information such as additional calculations, screen shots, and extended data.

II. MATERIALS AND METHODS

This section summarizes the components, system architec ture, and algorithmic methodology used to realize the AI based heart rate monitoring system for sports training.

A. System Overview

The system is designed as a wearable and cloud-connectable solution consisting of sensing, processing, communication, and visualization layers. The high-level architecture is illustrated in Fig. 1. Physiological signals are captured using ECG elec trodes and a heart-rate sensor module, interfaced to an ESP32 microcontroller. The ESP32 performs local pre-processing and transmits relevant information to a backend for

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advanced AI based classification and storage. A web or mobile interface allows athletes and coaches to monitor heart rate trends and risk predictions in real time.

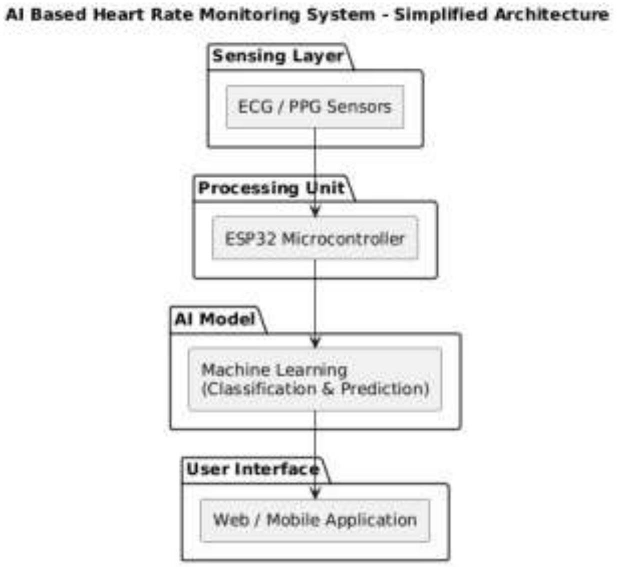


Fig.1. System architecture showing sensing layer, ESP32-based processing, AI model, and user interface.

B. Hardware Components

The main hardware components used are:

• ESP32 Microcontroller: Used as the central process ing unit due to its dual-core capability, integrated Wi Fi/Bluetooth, low power consumption, and built-in ADC channels suitable for sensor interfacing.

• ECG Sensor (AD8232): Captures biopotential signals produced by cardiac electrical activity. It provides ampli f ication and hardware filtering to improve signal-to-noise ratio.

• Heart Beat / PPG Sensor: An optical heart-beat sensor measures blood volume changes using photoplethysmog raphy. It provides a digital pulse output that can be directly read by the microcontroller.

• Temperature Sensor (DS18B20): Measures body or skin temperature, supplying context that can correlate stress or environmental influences with heart rate.

• ECG Electrodes: Ag/AgCl electrodes are placed on the subject's body to acquire reliable ECG signals with minimal motion artifacts.

• Power Supply: A regulated DC power source or battery pack provides stable operating voltage for the ESP32 and sensors.

C. Software Components and Tools

On the software side, the following tools and libraries are used:

• Embedded Firmware: Developed in C/C++ using the Arduino IDE for ESP32, responsible for sensor interfac ing, data acquisition, basic filtering, and wireless trans mission.

• Data Analysis Environment: Python with NumPy, Pan das, Matplotlib, and Seaborn is used for offline analysis, visualization, and model development.

• Machine Learning Framework: Scikit-learn is em ployed for implementing various classification algorithms such as SVM, Decision Tree, Random Forest, Logistic Regression, Na¨ ıve Bayes, and KNN.

• Database / Storage: SQLite or MySQL is used for storing historical records of heart rate, ECG features, and prediction outcomes.

• Frontend Interface: HTML, CSS, and JavaScript are used to implement a simple user interface showing login, parameter entry, and prediction pages.

D. Data Flow and System Operation

The logical movement of data through the system is illus trated using a Data Flow Diagram (DFD) in Fig. 2. Raw ECG and heart-rate signals are acquired by the sensors and delivered to the ESP32, which performs first-level filtering and feature extraction. Selected attributes are then forwarded to the AI model, which outputs a predicted risk level and associated heart rate zone. The results are presented to the user and stored for later review.

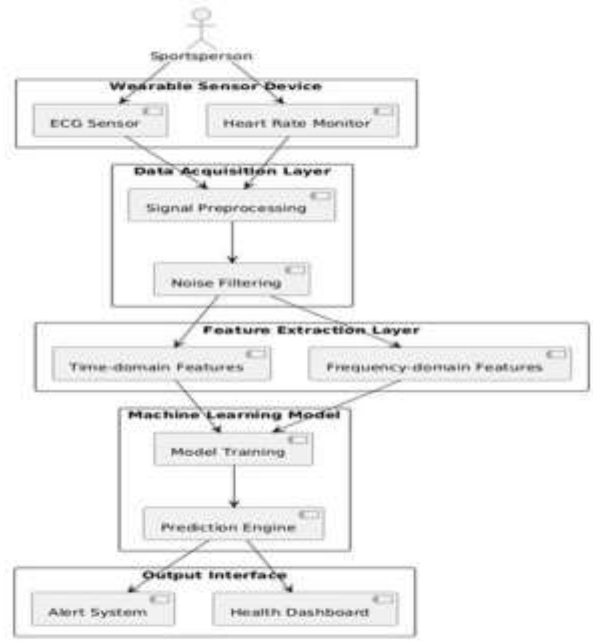


Fig.2:Data flow diagram

At the software interaction level, a sequence diagram (Fig. 3) describes how the user, interface, server, and AI model interact. The user logs in, enters or streams real-time parameters, and receives predictions and alerts. The backend maintains records for long-term performance tracking and analytics.

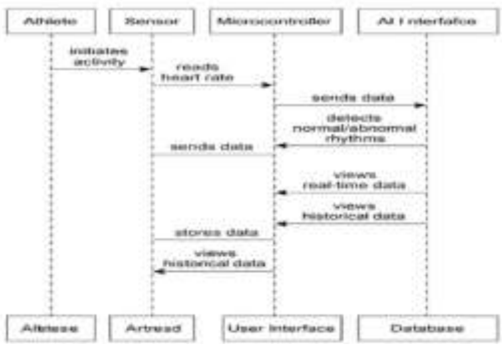


Fig. 3. Sequence diagram

E. Signal Pre-Processing

Signal pre-processing is essential to remove noise and artifacts before feeding data to the machine learning models. The steps include:

• Noise Filtering: High-pass filters remove baseline wan der; low-pass filters attenuate high-frequency noise from muscle activity and electromagnetic interference.
• Segmentation: ECG signals are segmented around R peaks into windows suitable for feature extraction.
• Missing Data Handling: Any missing values are treated using forward or backward filling, or replaced by mean values computed over valid segments.
• Normalization: Features such as amplitude and interval durations are normalized to a common scale to avoid dominance by large-magnitude attributes.

F. Feature Extraction

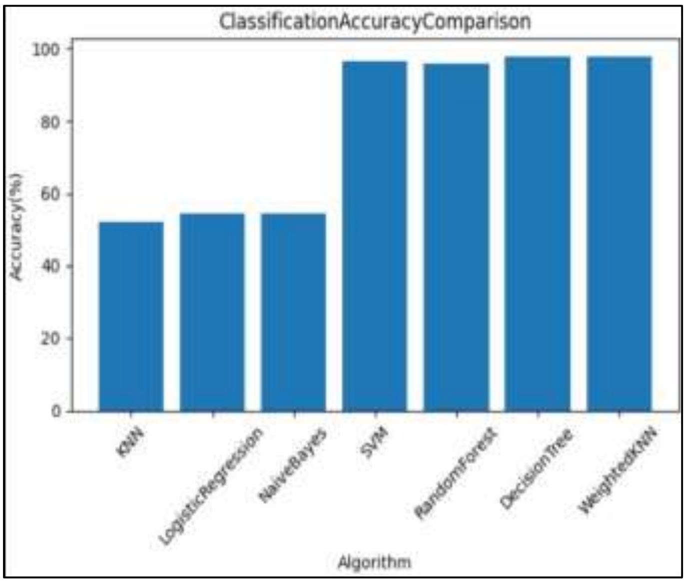
Features are extracted from the cleaned ECG and heart rate signals in the following domains:
• Time Domain: RR intervals, heart rate (beats per minute), QRS complex duration, PR interval, and tem poral variability.
• Frequency Domain: Power spectral density measures and low-frequency/high-frequency (LF/HF) ratios for HRV analysis.
• Nonlinear Features: Entropy-based measures and Poincar´ eplot indices to capture complex variations in heart rhythm.
Feature selection methods such as Principal Component Anal ysis (PCA) and Random Forest feature importance are applied to reduce dimensionality and highlight the most discriminative attributes. Several supervised learning classifiers are evaluated:
• K-Nearest Neighbour (KNN) and Weighted KNN: Distance-based classifiers that assign class labels based on the nearest neighbours in feature space; the weighted variant emphasizes closer neighbours.
• Support Vector Machine (SVM): Constructs optimal separating hyperplanes in a transformed feature space, suitable for complex decision boundaries.
• Decision Tree and Random Forest: Tree-based methods that handle non-linear relationships and feature interac tions effectively.
• Logistic Regression: A linear classifier used as a baseline for comparison.
• Naive Bayes: A probabilistic model assuming conditional independence among features. The dataset is split into training and testing subsets, and model performance is evaluated using accuracy and confusion matrices. Cross-validation is used where appropriate to ensure robustness of results.

III. RESULTS

This section presents key experimental results obtained from training and evaluating the machine learning models, and from functional testing of the end-to-end system.

A. Classification Performance

The performance of each classification algorithm is sum marized in Table I. Accuracy values are reported for the test dataset after hyperparameter tuning.



The results indicate that simple linear models and un weighted KNN perform moderately, while SVM, Decision Tree, and Weighted KNN achieve high accuracy. This demon strates that heart rate and ECG-derived features form complex, non-linear decision boundaries that are better captured by tree based and kernel-based models.

B. Functional and System Testing

System testing includes:
• Functional Testing: Verifying correct data acquisition from sensors, proper communication between ESP32 and backend, and accurate execution of the prediction pipeline.
• Performance Testing: Measuring response time for pre diction and ensuring that alerts are generated with mini mal latency, suitable for real-time training scenarios.
•Usability Testing: Evaluating the user interface for clarity of health parameter entry, prediction display, and interpretation of risk levels. Sample test cases include different users with varying age, gender, ECG readings, heart rate, and temperature, leading to different predicted risk levels (e.g., low risk, high risk, or no risk). These tests validate that the AI model responds appropriately to realistic physiological variations.

C. User Interface and Experience

The implemented interface provides:
• A home page with project overview.
• A login page for authenticated access.
• A health parameter entry page for entering ECG values, heart rate, and temperature.
• A prediction page that displays the risk level, deviation percentage, and textual interpretation.
This simple but functional flow ensures that both technical and non-technical users, such as coaches and athletes, can easily use the system.

IV. DISCUSSION AND SUMMARY

The experimental results clearly show that AI-based clas sification of heart rate and ECG-derived features is effective for sports-oriented monitoring. High accuracy values for SVM, Decision Tree, and Weighted KNN confirm that machine learn ing techniques can successfully model the complex patterns present in physiological signals collected during exercise. The proposed system addresses several limitations of exist ing heart rate monitoring solutions:

- It offers real-time analysis instead of periodic or offline evaluation.
- It goes beyond simple heart rate display by performing intelligent classification and risk assessment.
- It is portable and suitable for use in typical sports environments.

However, some limitations remain:

- Motion artifacts and electrode displacement during in tense activity can still degrade signal quality.
- The performance of the models depends on the quality and diversity of the training data.
- Integration with medical workflows and validation in clinical settings would be required before deployment in high-risk applications.

Future improvements may include the integration of deep learning models for automatic feature extraction directly from raw ECG signals, enhanced sensor fusion (combining ac celerometer, SpO2, and respiratory data), and cloud-based analytics for longitudinal monitoring.

Conclusion

The AI-Based Heart Rate Monitoring System for Sports Persons aims to deliver an intelligent, accurate, and real-time assessment of an athlete's cardiovascular condition. This project successfully demonstrates how artificial intelligence and machine learning can be integrated with physiological input parameters to predict the user's heart condition. By collecting data such as ECG values, heart rate, body temperature, age, height, weight, and medical history, the system analyzes and classifies the user's cardiac status into normal or abnormal categories. The developed system offers a reliable method for monitoring heart health, especially for sports professionals who undergo high-intensity physical activities. Athletes are often at risk of unnoticed cardiac abnormalities, which can escalate if not detected early. The implemented model provides an early warning mechanism that helps in preventing severe health issues during training sessions. With its simple user interface, the system ensures smooth operation and encourages frequent usage. The integration of AI algorithms enhances the accuracy of predictions, making it a useful tool for proactive health management.

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