The Design and Implementation of Smart ECG Machine using Machine Learning

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Abstract

This research paper develops a portable, AI-based system for real-time heart disease monitoring and prediction, less expensive, heavy diagnostic tool by integrating ECG analysis with vital signs like SpO2 and pulse rate. The system consists of an Arduino UNO R4 WiFi microcontroller interfaced with MAX30102 pulse oximeter and AD8232 ECG module to collect data, which is transmitted to MATLAB for signal processing, feature extraction (e.g., R-peaks, RR intervals), and machine learning classification of arrhythmias such as bradycardia, tachycardia, and ventricular tachycardia. To further assess the model's effectiveness, we performed confusion matrix and receiver operating characteristic (ROC) analysis. Predictions and vital readings are displayed as a result on an OLED screen, enabling accessible, non-invasive early detection with high accuracy.

Keywords: ECG (electrocardiogram), Machine Learning, Confusion Matrix, MATLAB, Cardiovascular Diseases

Introduction

Heart diseases have a significant negative impact on the quality of life of patients, increasing their vulnerability to sudden unexplained death, especially in cases of sudden cardiac arrest.[5]Cardiovascular diseases, particularly arrhythmias like bradycardia, tachycardia, and ventricular tachycardia, pose vital global health risks due to their potential for unexpected complications such as heart attacks or strokes, yet traditional diagnostic tools remain bulky, expensive , and vulnerable on clinical settings. In the coronary heart disease (CHD) monitoring algorithm, the Pan-Tompkins algorithm is used to identify the R-peak of denoised ECG.[3] The ECG signal waveform is related to an individual's heart structure and characteristics of the body, every individual ECG signal is different and not easy to be imitated and hacked. In addition, the collection of ECG signals is convenient and related hardware costs are not prohibitive.[2] This research paper interposes portable, AI-driven monitoring system that assimilated real-time ECG waveform capture with vital signs including SpO2 and pulse rate, leveraging modest hardware for accessible home- based screening. Electrocardiogram (ECG) demonstrates the electrical activity of the human heart and the ECG signal morphologies provide information about various types of arrhythmias based on different cardiac conditions.

Fast and accurate identification of arrhythmia from the ECG wave graph can potentially save many lives and much in terms of health care costs worldwide.[9]

By employing the Arduino UNO R4 WiFi microcontroller alongside MAX30102 pulse oximeter and AD8232 ECG sensors, the system transmits data to MATLAB for enhanced signal processing, feature extraction, and machine learning classification, carry instant predictions on an OLED display to enable early intervention and improved patient outcomes. In contrast, non- invasive fetal electrocardiograph (fECG) monitoring that only uses electrodes attached to the abdomen of a mother may not only locate the fetal R wave and compute the fetal RR (fRR) interval, but may also describe the whole process of fetal-heart activity in every fECG cycle using the ECG morphology.[1]

The primary goal focuses on overcoming limitations of manual ECG analysis and commercial monitors through non-invasive, continuous assessment in resource-limited environments Newer approaches using artificial intelligence (AI) and continuous wearable monitoring show promise in improving early detection.[5] Therefore, a promising future direction is the development of an adaptive- window POAFD technique that selectively denoises only the contaminated segments, thereby enhancing both efficiency and signal fidelity.[3]Moreover, because of the smaller fQRS amplitude, it is easily concealed in the other mixed signals.[1]Secondary aims contain achieving high prediction accuracy via AI models trained on R- peaks, RR intervals, and user parameters like age and gender. Early detection via this embedded solution supports pre-emptive healthcare, decrease hospital dependency and increase accessibility for outer users.

Problem Statement

The early detection and continuous observing of heart diseases, such as arrhythmias, are essential to decrease mortality and improve patient outcomes, yet present diagnostic systems are much expensive, bulky, and inaccessible, especially in outer or resource-constrained environments. Existing solutions typically require hospital infrastructure and well-trained persons, making them unsuitable for wide-scale, at-home screening. Manual ECG interpretation is time- intensive and sensitive to human error, while commercial monitors lack intelligent prediction capabilities and integration with crucial parameters like SpO_2 and pulse rate. There is an urgent need for a portable, real-time device that not only collects high-quality ECG and important sign data but also analyse and predicts cardiovascular risks using modest machine learning approaches. The accuracy of the present approach depends on the quality and diversity of ECG databases, and expanding to larger, multi- centre datasets could enhance generalizability. [5] cardiovascular disease is the wide term for problems with the heart and blood vessels. These problems are much often due to atherosclerosis. This condition happens when fat and cholesterol build up in blood vessel (artery) walls. This buildup is called plaque. Over time, plaque can narrow blood vessels and cause problems throughout the whole body mostly heart. If an artery becomes blocked, it can create to heart attack or stroke and Arrhythmias. The progress of ECG monitoring systems has also spurred the development of predictive systems for specific health conditions.[4]

Arrhythmias are abnormalities in the heartbeat distinguish by irregular, too fast, or too slow heart rhythms. Given the comprehensive nature of the derived features and the limited participant pool, feature selection was necessary to ensure model efficiency and accuracy [6] Abnormal electrical impulses cause irregular heartbeats called cardiac arrhythmias. There are mainly two classes of arrhythmia. The first class is bradyarrhythmia, accompanied by low heart rates (less than 60 beats/minute). The second class is tachyarrhythmias with a heart rate greater than 100 beats/minute.[9] They occur when the electrical signals that handles the heart's beating sequence do not work properly, responsible for heart to beat in an irregular pattern, too quickly (tachycardia), too slowly (bradycardia), or with irregular timing. Arrhythmias can be harmless or serious health risks, sometimes leading to symptoms such as dizziness, high chest pain, or fatigue, and in severe cases, complications like stroke or heart failure. Ventricular Tachycardia and Tachycardia are types of fast heart rate arrhythmias, whereas Bradycardia is a type of slow heart rate arrhythmia. All belong to the broader category of cardiac arrhythmias affecting heart rhythm regulation and function.

Ventricular Tachycardia (VT)

VT is a rapid, abnormal heart rhythm originating from the heart's lower chambers (ventricles), typically defined as a heart rate greater than 100 beats per minute (bpm) due to unusual electrical signals.

Symptoms: May include high chest pain, dizziness, palpitations, difficulty in breathing, fainting, and, in severe cases, cardiac arrest or instant death.

Risks: VT can decrease the heart's efficiency, leading to low blood pressure and poor blood and oxygen delivered to the whole body.

Causes: Most commonly linked to coronary artery disease, heart failure, heart attack, electrolyte abnormalities, and certain drugs

Tachycardia

Tachycardia is a usually term for a high heart rate (over 100 bpm in adults) regardless of where the rhythm originates in the heart.

Symptoms: Palpitations, dizziness, irregular breathing, chest pain, and, occasionally, fainting. Risks: Severe forms can cause to inefficient blood pumping and serious complications.

Bradycardia

Bradycardia is an irregular slow heart rate, typically below 60 bpm in adults.

Symptoms: Fatigue, dizziness, fainting, and weakness in body, especially if heart rate is too low to maintain adequate blood flow.

Risks: Extreme bradycardia may cause to low blood pressure, less oxygen delivery, and fainting. Causes: May be due to aging, heart conduction system disease, medications, or metabolic issues.

Methodology

This research paper offers a systematic solution to the challenges of heart disease monitoring by developing a portable, AI-enabled system that integrates ECG waveform analysis with essential parameters such as SpO_2 and pulse rate. Utilizing the Arduino UNO R4

WIFI as the central controller, the system continuously collects sensor data through the MAX30102 pulse oximeter and AD8232 ECG module for real-time health monitoring. The collected data is transferred to MATLAB, where advanced signal processing and a machine learning-based classification model error free predict arrhythmia types with a high accuracy. we hypothesize that physiological data collected via wearable technology, combined with feature engineering and traditional machine learning techniques, can effectively classify individuals into high- and low-risk.[6] The prediction, along with important readings, is displayed on an OLED screen, providing instant and user-friendly output. This solution decrease dependency on bulky, expensive hospital equipment by enabling accessible, continuous cardiac health assessment in any environment.

About ECG

An ECG, or electrocardiogram, is a medical test that collect the electrical activity of the heart over a period of time. It works by placing small electrodes leads on the body, commonly on the chest, arms, and legs, which detect the tiny electrical signals generated each time the heart beats. The heart contracts in a rhythmical manner with regular excitement of myocardium, pumping blood throughout the body. In the process myocardium contraction, slight current is generated by heart and conducted to body surface, causing potential changes in each part of the body.[7]. Signals are then graphed as waveforms, allowing doctors to assess the heart's rhythm, rate, and overall function. ECGs are widely used to diagnose a variety of heart conditions, such as arrhythmias, heart attacks, and other cardiac abnormalities. The test is fast, harmless, and non- invasive, making it a standard tool in both emergency and routine cardiac care. Depending on the need, ECGs can be performed while the patient is at rest.

Fig 1. ECG Waveform

The P, QRS, and T waves on an electrocardiogram (ECG) represent specific electrical signal occurring in the heart during each heartbeat:

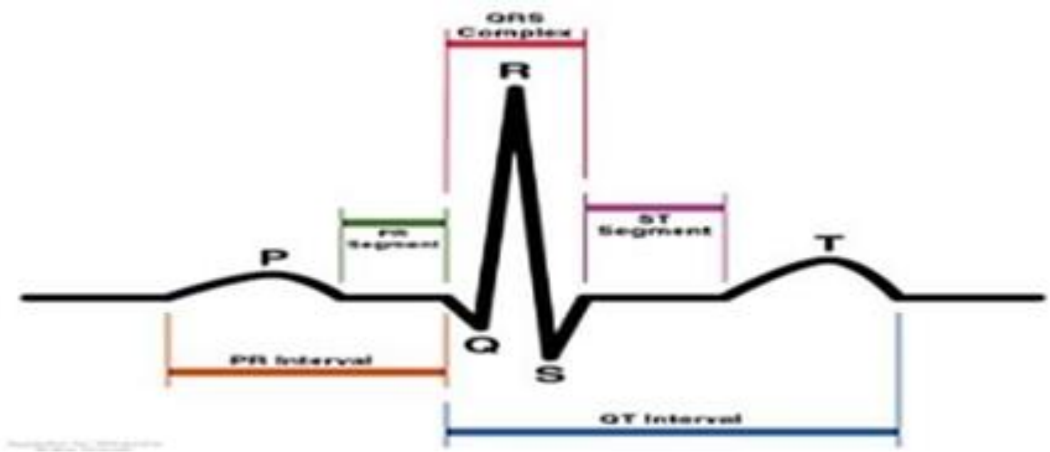

Fig 2. Components of a normal ECG waveform

P Wave

Represents: Atrial depolarization (activation of the atria)

Details: Initiates the contraction of the atria, allow blood to flow from the ventricles.

QRS Complex

Represents: Ventricular depolarization (activation of the ventricles)

Details: Corresponds to the electrical signal that trigger ventricular contraction, which pumps blood to the lungs and the rest of the whole body. It is also the most remarkable wave on the ECG.

T Wave

Represents: Ventricular repolarization (recovery of the ventricles)

Details: show the process of ventricles returning to their resting electrical state after contraction. It commonly follows the QRS complex and is slightly asymmetric.

These waves collectively reflect the heart's electrical activity during a heartbeat and are important for diagnosing various heart conditions. The normal value of heart beat lies in the range of 60 to 100 beats/minute. A slower rate than this is called bradycardia (Slow heart) and a higher rate is called tachycardia (Fast heart). If the cycles are not evenly spaced, an arrhythmia may be indicated.[11]

ECG Data Collection

These initial expresses raw electrocardiogram (ECG) waveforms in real-time from the heart's electrical signal via the AD8232 ECG module, which uses three electrodes leads placed on the chest and abdomen to detect signals like P, QRS, and T waves. The QRS complex is a key element of the ECG waveform and enhancing it allows for precise identification of R peaks.[8] The module converts these bioelectric potentials into analog voltage levels readable by Arduino's analog pins, ensuring continuous monitoring without invasive procedures, though open to noise from motion or poor electrode contact. Its measurement of heart activity is done where annotations for various arrhythmias are included. This dataset has widely been used for developing classification algorithms for the detection of various heartbeat types and heart rate variability.[10]

Vital Parameters

Parallel to ECG, in this measures blood oxygen saturation (SpO2) and pulse rate using the MAX30102 optical sensor wear on the wrist, which employs red and infrared LEDs to catch light absorption ratios through process of photoplethysmography (PPG). Arduino processes these through I2C communication, processing SpO2 from AC/DC ratios and pulse from peak detection in PPG waveforms, providing context sensitive vital signs that enhance arrhythmia prediction accuracy.

Signal Processing

Raw ECG data transfer serially from Arduino enters MATLAB here for preprocessing, applying high-pass Butterworth filter and smoothing to remove baseline wander, noise (50/60 Hz), and muscle artifacts. This process and clean the signal for reliable analysis, transforming noise contain inputs into filtered waveforms suitable for automated feature detection. The amplitude, temporal, statistical, and frequency-based feature of ECG is extracted for analysis of the signal. R- peaks and their corresponding T-peaks, amplitude, QRS duration, and overall signal statistic.[10]

Feature Extraction

Post-filtering, MATLAB identifies key ECG features like R-peak locations (using Pan-Tompkin's algorithm or thresholding), RR intervals (time between peaks), R-wave amplitude, and slope, merged with important parameters and user data (age, gender). Data is denoised and padded or cut to make them into signal segments of the same length in the preprocessing stage. The feature extraction phase is the main part for ECG signal classification.[7] These quantitative descriptors form a feature vector that captures rhythm irregularities indicative of bradycardia (<60 bpm), tachycardia (>100 bpm), or ventricular tachycardia.

Trained Model

A pre-trained machine learning classifier (e.g., Random Forest, SVM, or neural network) receives the feature vector to categorize cardiac states as Normal, Bradycardia, Tachycardia, or Ventricular Tachycardia, leveraging patterns learned from labelled datasets. The user can select an interval, e.g., the P-R, and to obtain information about its contents. Abnormal cardiac rhythms in P-R interval can be detected using these developed algorithms, as the expansion of the atria.[11] The model integrates ECG-derived metrics with SpO2/pulse for integrated predictions, achieving high accuracy by weighting arrhythmia-specific thresholds.

Confusion matrix

A 4×4 confusion matrix is a multi-class classification performance for four classes, with rows as actual labels and columns as predictions; diagonals show correct predictions (true positives per class), while off-diagonals discover errors like false positives and negatives. Per-class precision (column-normalized diagonal) and recall (row- normalized) derive from it, alongside overall accuracy as total diagonals over samples.

Experimental Setup

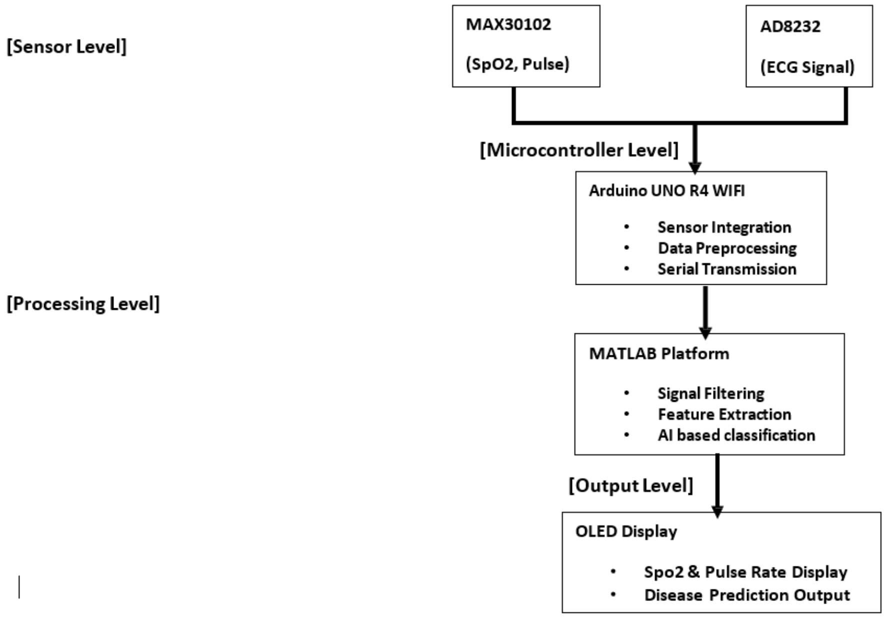

Fig 3. System flow diagram for smart ECG machine

Sensor Level Details

This fundamental level employs the MAX30102 pulse oximeter module, which uses red and infrared LEDs to compute SpO2 through photoplethysmography (PPG)—light absorption differences yield oxygen levels and pulse rate— alongside an integrated temperature sensor for calibration. The AD8232 ECG sensor catch biopotential signals with built-in amplification, high-pass filtering (to remove motion artifacts), and low-pass filtering for noise cancellation, enabling heart rhythm analysis from electrodes. Raw analog/digital signals from these sensors flow upward.

Microcontroller Level Processing

Run by Arduino UNO R4 WIFI, this level control initial sensor interfacing through I2C/SPI (common for MAX30102) and analog pins for AD8232. Key tasks include data preprocessing (e.g., peak detection for preliminary pulse rate, noise filtering), serial transmission over Universal Asynchronous Receiver/Transmitter (UART) to forward buffered data, and optional WiFi for remote logging/telemetry. Arduino libraries like MAX3010x simplify PPG signal acquisition and basic computations.

Processing Layer Analysis

MATLAB serves as the core computational engine, receiving serial data from Arduino for sophisticated offline processing: signal filtering (e.g., bandpass for 0.5-5 Hz pulse/ECG), feature extraction (e.g., peak amplitudes, RR-intervals via Pan-Tompkins for ECG or waveform analysis for SpO2), and AI-based classification—likely ML models like SVM or neural networks trained on PPG/ECG datasets to enhance accuracy amid motion artifacts or poor circulation. This step determined the refined SpO2 (via ratio-of-ratios algorithm) and pulse rate (BPM from peaks).

Output Layer

Executed output feed to an OLED display showing real-time SpO2 percentage, pulse rate (BPM), and possibly ECG waveform or health advisory, providing user-friendly response for clinical or personal monitoring. The vertical flow ensures low-latency from sensors to display.

Results & Discussion

Final outcome contains disease predictions, alerts (e.g., warning icons for abnormalities), and crucial displayed on the OLED screen via Arduino serial feedback, enabling immediate user output for early intervention. The block signifies the system's endpoint, promoting portable, non- clinical monitoring.

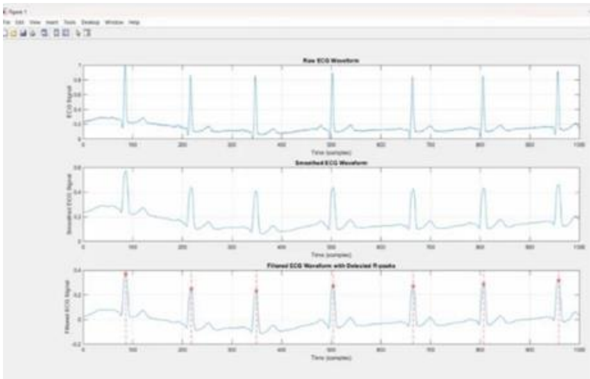

Fig 4. Original, smoothed, and filtered ECG signals with detected R-peaks

The above wave form is show by MATLAB are first plot displays the original ECG waveform with noise and baseline wander artifacts and second plot displays the smoothened ECG signal which reduces the noise and artifacts and third plot displays the filtered ECG signal with the detected R peaks marked by red asterisks and vertical dashed lines. R peak is identified by locating the highest points in each heartbeat cycle.

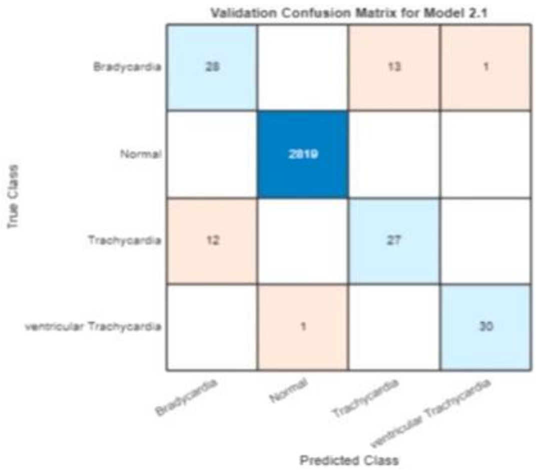

Fig 5. 4-Class Cardiac Rhythm Validation Confusion Matrix (Model 2.1): Emphasizes multi-class nature and domain

This confusion matrix shows the validation outcome for model in predicting classes like Bradycardia, Normal, Tachycardia and Ventricular Tachycardia. Rows show actual classes, columns predicted classes.

Future scope

Integration with IoT and Cloud Platforms for remote patient monitoring and real-time telemedicine consultations.

Expansion to Detect More Cardiac Conditions including myocardial infarction, atrial fibrillation, and heart failure beyond arrhythmias.

Development of Mobile Applications enabling users to visualize historical health data, receive alerts, and share reports with healthcare providers.

Improved Wearable Form Factor focusing on enhanced comfort, battery life, and waterproof designs for continuous long-term use.

Incorporation of Advanced AI Techniques, such as deep learning and ensemble models, for improved prediction accuracy and early anomaly detection.

Multi-Sensor Integration combining ECG and SpO_2 with additional bio signals like blood pressure and respiratory rate for comprehensive cardiovascular profiling.

Personalized Health

Recommendations generated using AI to guide lifestyle changes and medication adherence based on individual patient data.

Large-Scale Clinical Trials and Validation to adapt AI models for diverse populations and improve generalizability and reliability.

Real-Time Automated Alerts integrated with emergency response systems for timely intervention during critical cardiac events.

These future efforts will position the project at the forefront of emerging trends in AI-driven cardiovascular healthcare, enhancing accessibility, accuracy, and patient outcomes.

Conclusion

This research paper successfully demonstrates a portable, inexpensive AI-driven cardiovascular monitoring system that integrates real-time ECG analysis with important signs monitoring to enable early detection of arrhythmias like bradycardia, tachycardia, and ventricular tachycardia in non-clinical settings. It also addresses security and privacy concerns and looks into ECG authentication systems, including their preprocessing techniques, acquisition methodologies, and machine learning algorithms. By merging affordable hardware Arduino UNO R4 WiFi, AX30102, AD8232, and OLED with MATLAB-based signal processing and machine learning classification, the system overcomes limitations of traditional bulky diagnostics, delivering high-accuracy predictions through user-friendly display outputs.

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