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ECG Monitoring System for Real-Time Arrhythmia Detection

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Abstract: Many cardiac rhythm abnormalities develop gradually and may not produce immediate symptoms, making continuous monitoring essential for early identification. This work describes the implementation of a real-time cardiac monitoring system that integrates sensor-based data acquisition, wireless communication, and automated signal analysis. An AD8232 ECG sensor is used to capture cardiac electrical activity, which is processed by an ESP32 controller and transmitted to a cloud platform for storage and visualization. To support ECG analysis, additional parameters such as pulse rate and body temperature are also recorded. A web application developed using the Flask framework retrieves the stored data and applies machine learning models to identify irregular cardiac patterns. Experimental evaluation confirms stable signal acquisition, reliable heart rate computation, and accurate differentiation between normal and abnormal rhythms. The developed system offers a compact, low-cost, and scalable solution suitable for continuous cardiac monitoring in home and remote healthcare environments.

Keywords: ECG analysis, Arrhythmia detection, IoT healthcare, ESP32, AD8232, Cloud-based monitoring, Machine learning.

I. INTRODUCTION

Disturbances in the electrical conduction of the heart can lead to irregular heartbeat patterns, commonly referred to as arrhythmias. In many cases, these conditions remain unnoticed until they progress to a severe stage, increasing the risk of medical emergencies. Continuous observation of cardiac activity is therefore essential for timely diagnosis and preventive care. Conventional ECG systems used in hospitals provide accurate recordings but are limited to short-duration monitoring under clinical supervision. Wearable recorders such as Holter devices extend monitoring time; however, the collected data is generally reviewed after recording, which delays detection of critical events. As a result, temporary or infrequent rhythm abnormalities may go undetected. The integration of embedded systems with network connectivity has enabled healthcare monitoring beyond traditional clinical environments. At the same time, machine learning approaches have proven effective in analysing biomedical signals by identifying hidden patterns that are difficult to recognize through manual inspection. This work aims to develop a real-time ECG monitoring system by combining IoT-based data transmission with machine learning-driven analysis. ECG signals are continuously acquired using an AD8232 sensor, processed through an ESP32 microcontroller, and transmitted to a cloud platform. A web-based interface analyzes the incoming data and classifies cardiac activity as normal or abnormal. The system is designed to be affordable, portable, and suitable for long-term monitoring, particularly in homecare and rural healthcare scenarios.

II. SYSTEM DESIGN

The overall system is organized into four functional modules:

A. Physiological signal acquisition
B. Data processing and wireless communication
C. Cloud-based storage and visualization
D. Web-based analysis and classification

A. Physiological Signal Acquisition

The AD8232 ECG module is used to acquire cardiac electrical signals through surface electrodes placed on the chest. The module performs initial signal conditioning, including amplification and filtering, to reduce noise and baseline variations. The resulting waveform contains essential ECG components required for rhythm evaluation. Along with ECG acquisition, a photoplethysmography-based pulse sensor measures heart rate, while a temperature sensor monitors body temperature. Collecting multiple physiological parameters enhances the reliability of the monitoring system.

B. Data Processing and Communication
The ESP32 microcontroller functions as the main processing unit of the system. It converts analog ECG signals into digital form, detects characteristic peaks, and calculates heart rate values. Sensor readings are processed in real time and can be displayed locally for immediate reference.
Using its built-in Wi-Fi capability, the ESP32 transmits processed data to the cloud platform. Its efficient processing architecture supports continuous operation, making it suitable for long-duration health monitoring applications.

C. Cloud-Based Storage and Visualization
Sensor data is uploaded to the Thing Speak cloud platform, where it is stored with time stamps. The platform provides graphical visualization of ECG signals, heart rate, and temperature values, allowing users to observe both real-time behaviour and historical trends.

D. Web-Based Analysis and Classification
A web application developed using the Flask framework retrieves sensor data from the cloud through API calls. The application displays real-time plots and integrates a machine learning model to automatically identify abnormal cardiac patterns. Detected anomalies are highlighted on the dashboard to enable quick response.

III. METHODOLOGY

A. Signal Acquisition and Preprocessing
ECG signals are sampled at a frequency sufficient to preserve waveform details. Preprocessing steps include noise suppression, baseline correction, and peak detection. Heart rate is computed using intervals between successive R-peaks. All sensor data is synchronized prior to cloud transmission.

B. Machine Learning Model Development
Public ECG datasets are used for training and evaluating machine learning models. Feature extraction is performed to obtain parameters such as RR intervals, heart rate variability, and waveform morphology. The dataset is normalized and divided into training and testing sets. Several supervised learning algorithms, including K-Nearest Neighbours, Logistic Regression, Naïve Bayes, and Support Vector Machines, are evaluated. Feature reduction techniques are applied to improve computational efficiency. Weighted KNN and SVM models demonstrate superior classification performance and are selected for deployment.

C. Integration with Web Application
The trained classifier is integrated into the Flask application. Incoming ECG data is analyzed in real time, and classification results are displayed as normal or abnormal. All outputs are logged for further evaluation.

Results and Discussion
The developed prototype successfully captured ECG signals with clearly identifiable waveform components. Heart rate values obtained from ECG and pulse sensors showed close agreement, confirming measurement reliability. Stable cloud connectivity was maintained during extended monitoring periods.

The integrated machine learning model accurately differentiated between normal and irregular rhythms. The system reduces reliance on manual ECG interpretation and supports continuous remote monitoring.

IV. CONCLUSION

A real-time ECG monitoring system integrating IoT infrastructure and machine learning techniques has been presented. The combination of low-cost sensors, cloud-based storage, and automated analysis enables continuous and reliable cardiac monitoring. Experimental results confirm effective signal acquisition and accurate rhythm classification. Future work will focus on multi-lead ECG integration, mobile alert mechanisms, wearable power optimization, and large-scale clinical validation.

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