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IoT and ML based ECG Monitoring and Early Prediction System

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ABSTRACT

This project develops an end-to-end processing pipeline for detecting cardiac abnormalities through ECG signal processing enabled by IoT and ML technologies. The system incorporates an Arduino Uno, Protocentral ECG Module (ADS1292R), and electrodes (RL, LA, RA) to capture ECG signals. The ECG text files are transformed into CSV format and preprocessed through Butterworth bandpass filtering (0.5 Hz - 40 Hz), normalization, segmentation into fixed-length windows, and classification into normal, WPW syndrome, Long QT syndrome, and Brugada syndrome using dense neural networks and 1D CNNs. Models and visualization tools are validated and aided through synthetic ECG data generation. All data processing is performed on the Arduino Uno, preserving data privacy and minimizing costs. During the development and testing phases, PuTTY is utilized for monitoring serial communication of the ECG data. Cardiovascular diseases (CVDs) stand as one of the top killers globally, emphasizing the need for innovative solutions for continuous cardiac abnormalities monitoring to alleviate risks such as sudden cardiac death (SCD). This project creates an IoT and ML powered ECG monitoring and predictive system aimed at these challenges through low-cost, portable devices.

Keywords —*Electrocardiogram Monitoring, Internet of Things, Deep Learning, One Dimensional Convolutional Neural Networks, Arduino Microcontroller, Protocentral ECG Development Board, ECG leads, On-site Data Processing, Heart Disorder Identification, Preliminary Diagnosis*

INTRODUCTION

According to the World Health Organization (WHO), cardiovascular disease (CVD) is a considerable threat to global health, causing 17.9 million deaths each year. Conditions such as Long QT Syndrome (LQTS), Brugada Syndrome (BrS), myocardial infarctions (MIs), and numerous arrhythmias are known to have high mortality rates due to their potential of causing sudden cardiac death (SCD) if not appropriately diagnosed and treated in a timely manner. LQTS increases the likelihood of torasde de pointes and ventricular fibrillation due to high risks associated with prolonged QT intervals, while BrS is linked with ventricular arrhythmias, SCD, and marked by ST elevation in leads V1-V3. Within the category of emergencies, myocardial infarction is common and occurs due to blocked coronary arteries which damages the heart muscle, and subsequently, untreated arrhythmias can lead to syncope or cardiac arrest. While timely intervention with these conditions is essential, most traditional ECG monitoring systems are stationary, reliant on the supervision of a professional, and therefore, do not allow for constant surveillance, especially in remote or poorly equipped regions.

The rise of the Internet of Things (IoT) as well as Machine Learning (ML) technologies provide an innovative way to address these issues. IoT technology makes it possible to create small and inexpensive devices that can collect data in real time. This, in turn, enables automated analysis of intricate ECG patterns through ML, enhancing accuracy and efficiency in diagnosing heart diseases. Recent research has drawn attention to the potential of detecting high-risk conditions through ECG monitoring, highlighting the lack of clinical-grade solutions that aren't confined to clinical settings.

With this project, I intend to design an ECG monitoring system with early prediction capabilities using IoT and ML, tailored to leverage low-cost hardware and sophisticated ML algorithms for identifying cardiac disorders. The acquired ECG signals, are captured using an Arduino Uno micro- controller, Protocentral ECG Module (ADS1292R), and three electrodes arranged in lead I configuration (RL, LA, RA). Data with more advanced machine learning models is trained on Google Colab to classify ECG signals into normal, WPW syndrome, LQTS, BrS, MI, and arrhythmic conditions is done post-privacy preserving local pre-processing.

1. Literature Survey

In order to mitigate the global problem of CVDs (cardiovascular disease), there have been a number of research studies that attempted to detect heart problems using the ECG signal with clinical and electrophysiological aspects in mind. In [1] performed a detailed review of ion channel genetic disorders associated with sudden cardiac death (SCD) which included LQTS, BrS, Short QT syndrome, catecholaminergic polymorphic ventricular tachycardia (CPVT) and idiopathic ventricular fibrillation (IVF). This research merged clinical data, genetic data, and ECG results to analyze the electrophysiological mechanisms of these conditions to capture certain ECG features, for instance, QT intervals in LQTS and coved type ST elevation in leads V1-V3 for BrS and [2] analyzed ECG indicators of life-threatening arrhythmias as a common symptom within cardiac patients. The study evaluated clinical ECG records of patients with a complaint of syncope and captured Prolonged QT interval in LQTS, ST elevation in BrS, and polymorphic VT, which are recognized as highly dangerous arrhythmias constituting the diagnosis. The approach was based on retrospective study of ECG recordings, case studies, and consultation with specialists to set the boundaries for the diagnosis. The results underlined the importance of these ECG parameters in clinical decision-making.

The results further documented BrS deeper as the project understanding this condition worked on its precise detection, BrS being one of them. The study has no automated detection features and does not address portable devices detection, which the project attempts through local processing on Arduino Uno. In [4], analyzed a wide range of ECG syndromes like LQTS, BrS, MI, and clinical BrS ECG data to look for defining features of higher QT periods, ST acceptance, and Q-wave abnormalities. This exposed the case study gaps where literature review and synthesis are done to answer "how exploratory" with the self-described clinical relevance "focusing on diagnosing multi-condition detection." The extensive coverage adds justification to the clinical reasoning of the project's aim of detection of several conditions at once, but the study did not approach the interdisciplinary and automated approach of ML for less manual work, so this is the gap that this project fills via 1D CNN. In [5], studied ECG markers of SCD such as left ventricular hypertrophy (LVH) arrhythmias and ST elevation of QRS changes along-with higher QT periods and ST elevation were noted as high-risk indicators. The study's methodology consists of clinical ECG data analysis and pattern correlation with SCD consequences needing early diagnosis.

2. Methodology

The complete procedure of acquisition, preprocessing and classification for ECG signal is performed systematically in The IoT and ML Based ECG Monitoring and Early Prediction System, along with the integrated early prediction of cardiac abnormalities, normal conditions, Wolff-Parkinson-White (WPW) syndrome, Long QT syndrome (LQTS), Brugada syndrome (BrS), myocardial infarction (MI), and arrhythmia. With regards to the objectives of the system, its hardware features include Arduino Uno, Protocentral ECG Module (ADS1292R), and three electrodes, while its software features include Google Colab, Python with its libraries, Arduino IDE, and PuTTY. The proposed methodology aims to maintain privacy by local data processing while advanced machine learning (ML) models are trained in the cloud. Key stages in the pipeline include all system design components, data acquisition, preprocessing, segmentation, synthetic data generation, ML model development and evaluation, and iterative model refinement and extensive model testing.

3. Components

3.1 Arduino Uno:

The Arduino Uno is a popular microcontroller board for automation and embedded systems that is based on the ATmega328P. By taking in data from sensors, processing it, and managing output devices, it acts as the central processing unit. The Arduino Uno is the primary microcontroller due to its cost-efficiency and ease of use, and community sup- port. It has an ATmega328P processor, 14 digital input- output pins and 6 analog inputs, a 16 MHz ceramic resonator, and USB port for powering and communicating. The Uno variant offers sufficient processing power for initial data harvesting and preprocessing, making it favor- able for embedded systems characterized by portability and low-power consumption.

Fig 3.1: Arduino Uno

3.2 Protocentral ECG Module:

The choice of Protocentral ECG Module (ADS1292R) was made based on its competitive price, alongside its high-resolution ECG signal acquisition capabilities, directly aligning with the project’s need for cost-effectiveness. The module is equipped with 24-bit delta- sigma Analog to Digital Converter, enabling precise and noise- free signal capture. It has two differential input channels, thus making it applicable for lead I ECG configuration. In addition, it has a right leg drive (RLD) circuit for reducing common mode noise such as 50/60Hz power line interference. Stored energy on ADS1292R operating at 3.3V and idle current of 335µA illustrates the project’s aim on power efficiency. Communication with Arduino Uno is per- formed via Serial Peripheral Interface (SPI) which guarantees quick and dependable data transmission using modules.

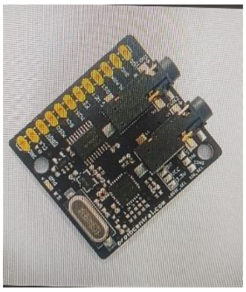

Fig 3.2: Protocentral ECG sensor

3.3 Three Electrodes:

The electrical activity of the heart is captured by means of three disposable ECG electrodes - RL (Right Leg), LA (Left Arm), RA (Right Arm). Each of these electrodes is an adhesive patch having a conductive gel which makes it adhere well to the skin, therefore ensuring that a good signal can be obtained from it. The electrodes are positioned in a lead I configuration – RA is placed on the right clavicle, LA on the left clavicle, and RL is placed on lower right abdomen as reference electrode. When this configuration is used, the potential difference of LA and RA is measured and RL acts as crude noise canceller via RLD circuit. Because of their low cost and wide availability, these electrodes prove useful within the scope of project budget limitations.

Fig 3.3: Three Electrodes

4. ACCOMPLISHMENT

4.1 Block Diagram

The system starts with a **patient** whose ECG signals are picked up using **electrodes**. These electrodes are placed on specific positions on the body to detect electrical impulses generated by the heart. The raw analog ECG signals from the electrodes are then fed into the **ADS1292R ECG module**, a low-power, high-resolution analog front end designed specifically for biopotential measurements. This module amplifies and converts the analog signals into digital form, ensuring that high-quality ECG data is available for further processing.

The **Arduino UNO** microcontroller receives the digitized ECG data from the ADS1292R module. Acting as an interface, the Arduino reads the incoming data and transmits it to the computer or cloud through a serial communication channel. It plays a crucial role in organizing and forwarding real-time ECG data efficiently to the next stage.

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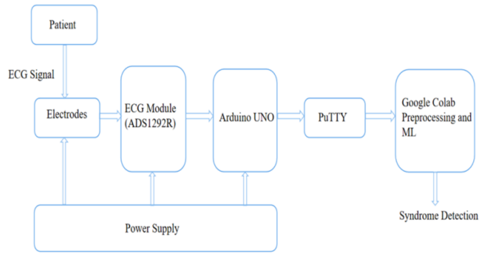


Fig 3.3: Block Diagram of ECG Monitioring System

Fig 4.1: Block Diagram of the Project

4.2 Software:

Arduino IDE: For programming the Arduino Uno micro- controller, the Arduino IDE version 2.0.0 was selected. It has a simple GUI for writing C/C++ programs and uploading firmware which includes SPI communication and serial data, interfaces required for communication with Protocentral ECG Module (ADS1292R) ECG Module.

PuTTY: For terminal emulation of serial communication with Arduino Uno, PuTTY was selected. It enables monitoring of ECG data in real time and logging into a text file which Unix like operating systems can easily manipulate. Python with Libraries: Version 3.11 of Python was used for preprocessing the data, generation of synthetic data, development of ML models along with other libraries like NumPy for mathematics, Pandas for data working, SciPy for signal work, TensorFlow for training the ML models, and Matplotlib for plots. Because of the large number of libraries available to Python, it becomes easy to accomplish many tasks which is why it was used extensively in this project.

Google Colab: Google Colab is a cloud where advanced synthetic data generation and ML model training can be done, providing GPUs for free. They make it possible to train the 1D CNN model efficiently. It can also be used collaboratively through its Jupyter notebook interface.

5. Final Results

The proposed pipeline works to preprocess, segment, and classify ECG data expectantly to detect the cardiac abnormalities, with the use of IoT and ML technology. Ultimately, the classification of waveform segments validated the technique's capacity to discern normal and abnormal ECG patterns.

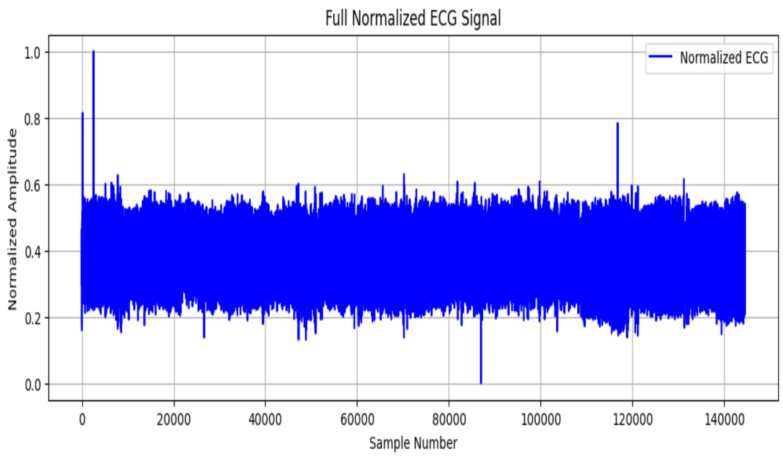
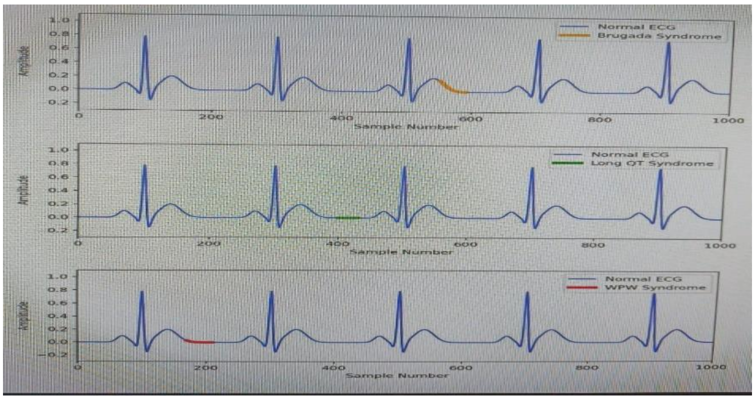


Fig 5.1: Full Normalized ECG Signal

It shows the entire normalized ECG signal, spanning 150,000 samples. The signal, plotted in blue, exhibits the characteristic P, QRS, and T waves of a normal ECG, with normalized amplitude ranging from 0 to 1. The normalization ensures compatibility with the ML models, and the consistent waveform pattern indicates stable data acquisition. The full ECG signal demonstrates the system's ability to capture a continuous, high-quality ECG over an extended period, with minimal noise due to the right-leg drive (RLD) circuit in the ADS1292R module.



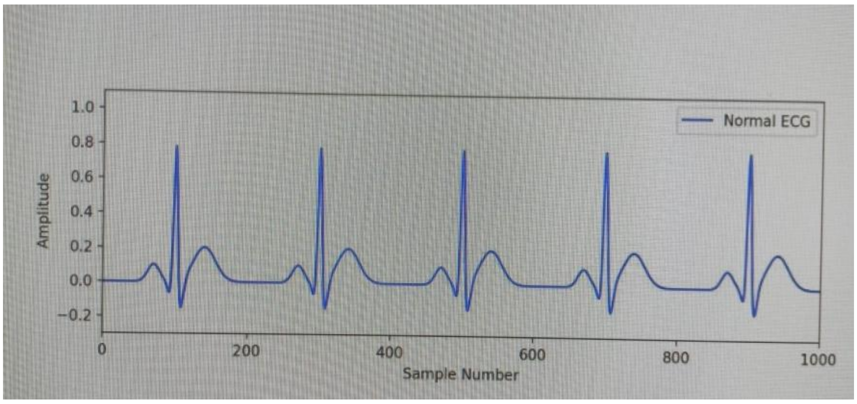


Fig 5.2: Waveforms

CONCLUSION

The hybrid approach of the suggested system incorporates IoT and ML to improve ECG monitoring. ECG classification through the use of ML increases the capability to find irregularities. This is an improvement in the care of the heart as well as attempts to reduce avoidable mortality. It's a revolution in future social health care requirements. The adaptability and precision of these advanced models can greatly increase their usefulness in the future. Preceding signal steps are very important in enhancing the model's accuracy. In the field of time series data, deep learning models (CNNs) outcompete the traditional approaches. The last update aimed: Better results can be attained training with more datasets.

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