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IoT-Assisted Electrocardiogram (ECG) Monitoring System for Health-Care Application

Journal of Electrical Systems

Abstract: The scope of care and health services that can be provided to patients at home is expanding because of sophisticated advancements in currently accessible information technologies. This paper proposes a MATLAB GUI developed for users to analyze the recorded ECG signal. The program intends to improve cardiovascular disease (CVD) patients' access to medical care by facilitating better patient monitoring and prompt intervention. This implementation uses a patient path estimator, patient table, and alert management schemes within the hospital to facilitate localization and timely intervention for the treatment of CVD patients, since real-time monitoring of patients from different locations remains a critical challenge for IoT-based healthcare systems.

Keywords: MATLAB GUI, ECG Signal, Cardio Vascular Diseases.

1. INTRODUCTION

Heart problems are the primary reason for unexpected death and produce a significant mortality rate worldwide each year. Surprisingly, heart disease sufferers are determined to remain at home without putting any strain on their hearts. Nonetheless, a large proportion of patients fail horribly before receiving treatment because they do not feel disabled until the disease has progressed to a critical level. Because bodily tissues and fluids conduct electricity, electrical activity in the heart can be recorded on the skin using electrodes placed on the limbs or chest. Willem Einthoven is regarded as the father of ECG. Electrocardiography is a technique for studying the electrical activities of the heart. Electrocardiography is the recording or graphical representation of the electrical activity of the heart. It depicts the distribution of electrical signals generated by the SA node as they travel through the atria, followed by the AV node, bundle of his, Purkinje fibers, and ventricles contracting. IoT-based solutions are having a significant impact in today's healthcare business as well as tomorrow's emerging IoT-based healthcare monitoring systems. The Internet of Things has the potential to save 50,000 lives each year by preventing unnecessary deaths caused by healthcare errors. By coordinating important patient information and synchronizing relevant resources, it promises patient well-being and safety. Patients place a premium on safe and high-quality healthcare services. As a result, healthcare data security and patient privacy are critical challenges that will have a significant impact on Health-IoT's future success. Privacy protection is a critical issue in the IoT-based healthcare system.

The main noninvasive method for diagnosing cardiovascular disorders is the electrocardiogram (ECG). The required information regarding the electrophysiology of cardiac disorders and potential ischemia changes is provided by a cleaned ECG signal. It offers important details regarding the operation of the heart and circulatory system. The thesis aims to identify cardiac arrhythmias in ECG signals automatically. This thesis employs a recently discovered digital signal processing and pattern reformation technique to detect heart arrhythmias. The process of identifying cardiac arrhythmias in an ECG signal involves three steps: first, identifying the QRS complex in the signal; second, extracting features from the complexes; and third, classifying beats using the feature set that was recovered from the QRS complex.

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The automatic identification of cardiac arrhythmias in the ECG signal is reflected in the automatic classification of heartbeats. Therefore, in order to identify cardiac arrhythmias in the ECG data, we created automatic methods for heartbeat classification in this paper.

The initial stage in automatically identifying cardiac arrhythmias in an ECG signal is the recognition of the QRS complex. A novel algorithm for accurate detection of QRS complex in ECG signal peak classification approach is used in ECG signal for determining various diseases. As knowing the amplitudes and duration values of P-Q-R-S-T peaks determine the operation of heart of human. Therefore, duration and amplitude of all peaks are found. R-R and P-R intervals are calculated. Finally, we have gathered the required information for disease detection. For detection of cardiac arrhythmias, the extracted features in the ECG signal will be fed to the classifier. The retrieved characteristics contain morphological features of each cardiac rhythm in the ECG reading. MATLAB software is utilized in the implementation of this project. For selecting and processing the signal in a simpler way, an interface is developed. The format for ECG signal data is ".mat". We have discovered bradycardia and tachycardia. The arrhythmias database from Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) [1] has been utilized for performance analysis.

4. LITERATURESURVEY

The various elements of our suggested eHealth system are examined in the literature somewhat separately. References [4]–[6] concentrated on employing IoT to monitor ECG signals in real time, whereas the to identify CVD, writers in [3], [7], and [8] used an intelligent telecardiology system that used wireless ECG signals. The issues with real-time ECG data collection, transmission, and visualization over the Internet are covered in [4]–[5]. ECG signals are sent in real time via the Internet from a patient in an IoT environment — which may or may not be clinical — to a particular hospital or clinic. Before being used, the obtained data were processed to correctly depict the characteristics of the ECG signal and extract certain necessary features (such as wavelet coefficients). However, the patient's location was difficult to determine because of the persistence of signal acquisition. Dr. Sudhir G. et al. [9] used "Feature Extraction of EEG Signals using Wavelet and Principal Component analysis". The wavelet transforms method and principal component analysis, the two best techniques for feature extraction, are used in this study to provide a comparative analysis and outcomes of feature extraction of various types of EEG data. An electroencephalogram is a recording of brain electrical activity. And we must extract the traits in order to categorize these illnesses. Thus, this study provides successive wavelet and PCA results for the EEG data associated with seizures, slow wave activity, brain tumors, and epileptic seizures. A method based on the Dyadic wavelet transform approach was suggested by Ruchita Gautam and Anil Kumar Sharma [10]. This method is used to determine the QRS complex. This method calculated the heartbeat by focusing on the interval between two successive R waves. This method uses the ECG waveforms to separate the wave P R & T, which is related to the properties of the ECG waveforms, and to detect theses Ventricular Late Potentials. The primary goal of this approach is to identify the R waves, and the threshold is set at 75% of the greatest peak.

5. METHODOLOGY

Based on the proposed algorithm, an ECG diagnosis device is available for 24-hour continuous monitoring of the patient. Different implementations of the technique on the Arduino Uno board show that the computational cost is low enough that the ECG analysis and classification may be conducted in real-time. In such a design, the ECG signal is detected by worn sensors, transmitted via short-range communication (e.g., Bluetooth) to the wearable device for processing and analysis, and lastly transmitted by wide-area communication (e.g., Wi-Fi) to a remote device for further analysis and storage. The MIT-BIH Arrhythmia database is used for study of ECG signals which is available online through PhysioNet, is the outcome of a collaboration between Beth Israel Deaconess Medical Centre and MIT, and it is one of the most widely used databases for research. The collection contains 48 half-hour snippets of two-channel (two leads) ambulatory ECG recordings from 47 people. The real time recorded data of a patient can be interpreted with the help of the proposed MATLAB GUI. With the use of this GUI, task of reading the ECG graph manually is eliminated. A typical ECG analysis's proposed structure is classified as follows:

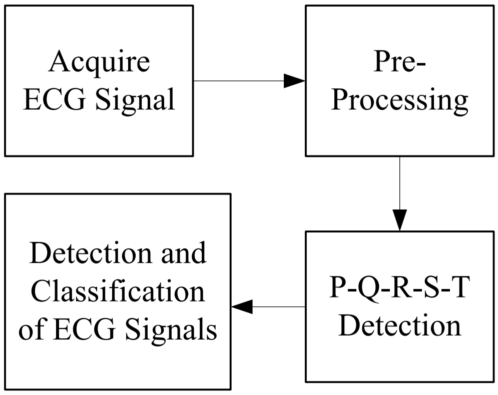


Fig.1: Flow Diagram

3.1. Acquiring ECG Signal

Using external electrodes, the ECG captures the electrical conduction signals of the heart as characteristic lines. The ECG's deviations from baseline are represented by the letters P, Q, R, S, and T. The P wave is reflective of a trial depolarization. The impulse, which originates from the pacemaker cells of the SA node or sinoatrial node, is often directly coupled to the left and right atria. An individual in good health does not exhibit atrial repolarization on the ECG waveform. The QRS complex is led by the P wave. The two ventricles' depolarization is correlated with the QRS complex. The depolarization wave from the inner layer of the myocardium distributes to the outer layer. The ventricular septum's depolarization is reflected in the general Q wave. The R wave then appears and moves in an upward direction. A downward deflection is indicated by the S wave, which comes after the R wave. The T wave indicates that the ventricles have repolarized. The absolute refractory period is the length of time that separates the beginning of the QRS complex from the T wave's maximum peak. The remaining part of the T wave is referred to as the relative refractory period. The time frame known as the refractive period is when cardiomyocytes do not react to triggers. Cardiomyocytes are completely insensitive to stimuli during the absolute refractory period, but in certain situations, a new action potential may be evoked during the relative refractory phase. Here, the patient's electrical cardiac activity is measured over a predetermined amount of time using the Ad8232 single lead heart rate sensor, which also functions as an ECG sensor. The electrical activity within the heart data can be transferred to a cloud server for monitoring, or it can be observed via a serial monitor. The three electrodes on the single lead heart rate sensor have cable colors varying. Red, Yellow, and Green are these. The sensor pads are attached to the electrodes. The sensor pads' proximity to the heart serves as validation of the improved measurement. The colors of the associated sensor pads and their locations on the body are displayed in Table 1.

TABLE. 1: Table containing sensor pad colors and their placement

Sensor Pad Colors	**Placement**
Red	Right Arm (RA)
Yellow	Left Arm (LA)
Green	Right Leg (RL)

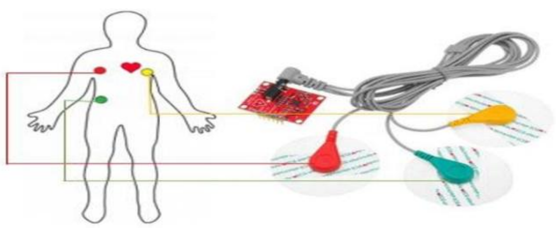


Fig.2: Electrodes

The extraction of an ECG signal from a patient's body is depicted in Fig. 2. The nine connecting pins on the Ad8232 single-lead heart rate sensor include three electrodes or sensor pads that are attached to the body. The AD8232 ECG sensor diagram is displayed in Figure 3. To extract the signal and display it on a serial monitor or cloud server, the remaining five of the six pins are connected to the microcontroller [17]. The Arduino Mega 2560 is a microcontroller board based on the ATmega2560. It has 54 digital input/output pins (of which 15 can be used as PWM outputs), 16 analog inputs, 4 UARTs (hardware serial ports), a 16 MHz crystal oscillator, a USB connection, a power jack, an ICSP header, and a reset button. Fig. 5 displays an image of the suggested system's hardware implementation.

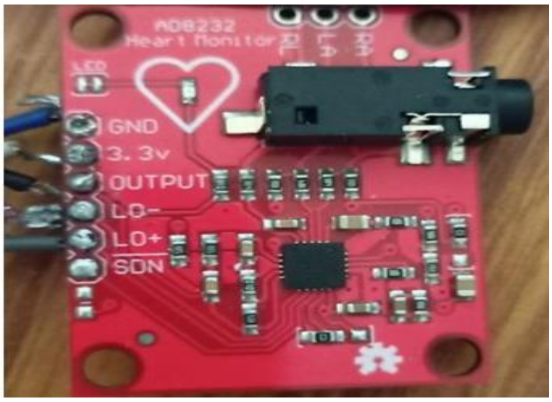


Fig. 3: Pin diagram of AD8232 Single lead heart rate sensor

Fig. 4: Pin diagram of Arduino MEGA-2560

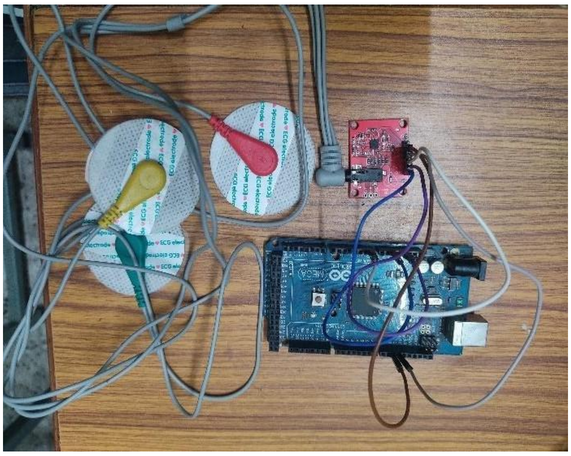


Fig.5: shows how the sensor AD8232 is implemented hardware-wise using ESP32 to retrieve ECG data

Figure 5 shows the Ad8232 single lead heartbeat sensor, which extracts the electrical cardiac signal from three sensor pads. Here, the laptop or PC is linked to the Arduino MEGA2560 in order to supply it with electricity.

The necessary power for the AD8232 heartbeat sensor is provided via Esp32. When utilizing this sensor, it is strongly advised to turn off the laptop's power from the charger in order to reduce further noise. The electrical signal from the heart is captured by the three sensor pads. The captured data is then analyzed in MATLAB with the help of Arduino IDE.

a) Pre –Processing

Baseline drift, electrode contact noise, polarization noise, internal amplifier noise, noise from muscle activity, and motor artifacts are just a few of the undesired noise and artifact effects that are inherent in ECG signals. Artifacts and noise were caused by the motions of the electrodes. Thus, we need to remove above noise and baseline drift from the ECG signal before moving on to the feature extraction step. Since wavelet filtering may be used to calculate the R-peak locations without altering the original signal's shape or location, we suggest using it to filter the ECG data. Based on prior experimental findings, two factors need to be taken into account to maximize the signal filtering: the sampling frequency of the signal and the understanding that the majority of noise is present outside of the 1.5 Hz to 50 Hz frequency range. We employ a band pass filter for this purpose, which is made up of a 1.5 Hz cutoff high pass filter. Baseline variations are eliminated using this filter. This filter's output cascades into a low pass filter with a 50 Hz cutoff frequency. High frequency noise is eliminated by this filter. Each filter has its own unique mother function parameters, both in terms of scale and kind. Therefore, order 6 is equal to the automatic computation of the ideal scale for high pass filtering when the sampling frequency is 256. Order 2 is the ideal scaling order for the low pass filtering. The Figure displays the outcomes of the previous steps.

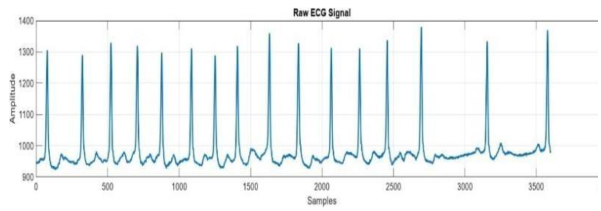


Fig..6: Raw ECG Signal

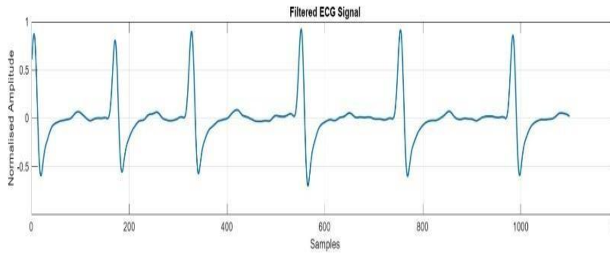


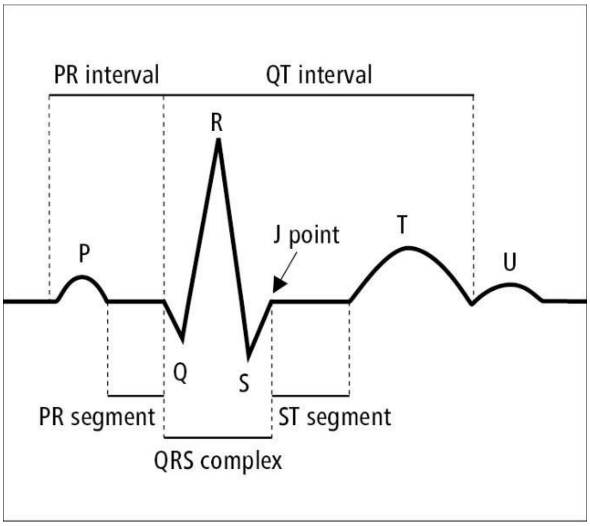
Fig..7: Filtered ECG Signal

b) PQRST Wave Detection

Every ECG cycle is comprised of three waves: the P-wave, which indicates atrial depolarization, the QRS complex, which indicates ventricular depolarization, and the T wave, which indicates the ventricles' rapid repolarization. A typical ECG signal is displayed along with its time intervals. The majority of clinical characteristics that are helpful in diagnosing the illness are located in the interval between the signal amplitude value and the ECG component parts. For instance, the Long Q-T Syndrome (LQTS), a deadly illness that claims thousands of lives annually, is recognized by the Q-T characteristic. Since inverted T waves can result from a dangerous condition called coronary ischemia, the shape of the T wave is a crucial component that must be accurately identified. Because the ECG signal exhibits time-variant behavior, developing an algorithm to automatically extract ECG features is extremely challenging. We are subject to various physiological limitations and noise due to these signal qualities.

Several techniques have been presented in recent years for the detection of certain traits. They presented a technique in which they extracted wavelet characteristics and classified data using SVM. We presented a technique in this paper for identifying the amplitude and time interval of the different ECG wave components. Our method correctly detects the R-peak in the first stage. To do this, we employed wavelet. Using a local search around the observed R-peak, the other ECG components are found in the second stage. Let's sum up this strategy: Wavelet transform has been used to determine the R-wave's location. The ECG signal's R-R intervals are divided into the following segments: Determine the wave's maximum and lowest within a certain interval, which correspond to the Q and S waves. We need to supply a deterministic point in order to locate P-wave and T-wave since they depend on other factors. These points include the beginning of the T-wave, the end of the S-wave, and the beginning of the Q-wave.

Fig..8:ECG Wave peaks and intervals



c) Detection and Classification of ECG Signals

PQRST Peaks and different intervals like R-R,P-R, S-T are analyzed deeply to build the algorithm for detecting and classifying the ECG Signals. Mean values have been considered while developing the algorithm. The 8 cases have been developed while studying the observed peaks and intervals. The cases are as –Normal Sinus rhythm, Borderline ECG, Minor abnormalities, some abnormalities (heart rate is not in range), Considerable abnormalities, Major abnormalities, Serious and Extreme abnormalities and Inconclusive ECG signal.

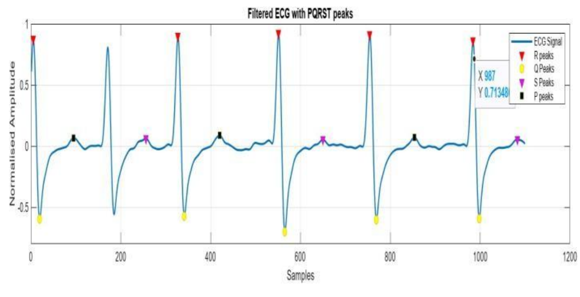


Fig..9: ECG Signal with PQRST peaks

6. CONCLUSION

The health monitoring system has become a significant concern in the current technological era. If the monitoring could be done remotely from any location, it would be a big plus of the globe. Because of its increased mobility and speedier response time, the need for remote health monitoring systems has increased. One of the most delicate and important organs in the human body is the heart. The sensor data in this system can identify a number of heart illnesses and disorders. Thanks to the internet, the data is viewable from any location in the globe. The most significant and practical heart indications are the ECG and BPM readings. These data can be used to identify cardiac abnormalities and normalcy. In this case, Doctors worldwide can watch this data, which are gathered by two distinct sensors and shared on the cloud server via an IoT device. Furthermore, a doctor can be alerted as soon as an aberrant state is discovered by the real-time inspection of the data. If a doctor notices something strange, they can act quickly to treat it. The entire system saves a lot of time, money, and effort. It can be manufactured in a non-commercial or commercial capacity. By utilizing this occurrence, maximum profit can be made at a very cheap cost.

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