A REAL TIME HEALTH MONITORING SYSTEM FOR IOT-ENABLED DEVICES USING WEARABLE SENSORS

K. Raja Kumari[1], DGanesh[2], J.Srinivas[3]

Department of Electronics & Communication Engineering

Usha Rama College Of Engineering &Technology, Andhra Pradesh. -521109

ABSTRACT:

The IOT-based Smart Health Monitoring and ECG Denoising System presents a comprehensive solution for real-time health monitoring and analysis. By leveraging Arduino Uno, ECG sensor, and MAX30102 sensor for measuring vital parameters such as heartbeat, SpO2, and body temperature, the system offers continuous monitoring of the user's health status. The collected data is transmitted to a mobile application via the Thing Speak IoT cloud platform, providing users with remote access to their health information and enabling healthcare professionals to monitor patients' conditions effectively. Additionally, the system incorporates LED indicator lights and a buzzer to remind users of medication intake at predefined intervals, enhancing medication adherence and overall health management. Furthermore, the system implements ECG denoising and analysis algorithms using Python code running on a laptop. This feature allows for the extraction of clean ECG signals from noise and the analysis of cardiac activity for detecting anomalies or irregularities. By processing the ECG data in realtime, healthcare providers can gain valuable insights into the user's cardiac health and promptly intervene in case of any abnormalities. Overall, the proposed system offers a user-friendly and efficient approach to health monitoring and management, leveraging IoT technology and data analysis techniques to improve healthcare outcomes and enhance user well-being.

Index terms: electrocardiogram (ECG), Internet of Things (IoT), noise localization, smartphone,wearable sensor(Temp,Sp02,Heartbeat).

I. INTRODUCTION

In recent years, the fusion of advanced sensor technologies, wearable devices, and machine learning has catalyzed transformative developments in the realm of healthcare. This project introduces an Health Monitoring System with Machine Learning Analysis a sophisticated healthcare solution designed to revolutionize patient care. Leveraging wearable ECG sensors, heartbeat sensors, pulse oximeters, Hear Beat and machine learning, the system enables continuous real-time monitoring of vital signs. The primary focus is on the analysis of electrocardiogram (ECG) data to predict health status and facilitate early interventions. Additionally, the system incorporates an Internet of Things (IoT) framework for seamless communication with healthcare providers and integrates a medication reminder system to enhance patient adherence to prescribed regimens. In an era where health monitoring and management are becoming increasingly important, the integration of Internet of Things (IoT) technology has revolutionized the way we approach healthcare. The IoT-based Smart Health Monitoring and ECG Denoising System presented here represents a significant advancement in this field, offering a comprehensive solution for real-time health monitoring and analysis. By combining state-of-the- art sensors, microcontrollers, and data analysis techniques, this system aims to empower individuals to take proactive control of their health and well- being. The prevalence of chronic health conditions and the need for continuous monitoring have underscored the importance of developing innovative healthcare solutions that are both accessible and effective. In response to this need, our system utilizes Arduino Uno, ECG sensors, MAX30102 sensors, and IoT connectivity to measure vital health parameters such as heartbeat, SpO2, and body temperature. These parameters are then transmitted to a mobile application through the Thing Speak IoT cloud platform, enabling users to monitor their health status remotely and facilitating healthcare professionals' ability to provide timely interventions. Additionally, the system incorporates features such as LED indicator lights and a buzzer to remind users of medication intake, enhancing medication adherence and overall health management. Through this introduction, we aim to provide an overview of the Smart Health Monitoring and ECG Denoising System, highlighting its potential to revolutionize healthcare delivery and improve patient outcome.

II. RELATED WORK:

The rise in popularity of IoT-driven ECG monitoring sensors is attributed to their compatibility Concurrently, these systems have been noted for their ability to reduce both time and cost compared to traditional ECG monitoring methods However, wearable ECG monitoring systems face significant challenges, primarily stemming from noise contamination due to body motion and poor electrode connections Recently introduced real-time algorithms for ECG noise detection at IoT-enabled sensors or gateway devices. However, these noise detectors function as binary switches, meaning they discard ECG segments if noise is detected, otherwise, they are used for subsequent decision-making processes. Additionally, these noise detectors lead to a decrease in data transmission which are crucial for continuous monitoring. For instance, if these noise detection systems are overly sensitive to noise, even a slight presence of noise in a segment may lead to discarding the entire ECG segment, reducing the efficiency of the clinical decision-making system. Therefore, these algorithms fail to consider application requirements in defining the sensitivity of the noise detection system. This is important because not all applications require the same level of clean ECG data for extracting clinical information. Hence, a tunable noise detection system, where the noise tolerance level can be adjusted based on the application requirement, For example, a clear presence of the QRS complex is sufficient for heart rate variability analysis and can be useful for many applications. The authors employed CEEMD methods to decompose ECG signals into various intrinsic mode functions. They then utilized predetermined threshold values for each decomposed level to identify noisy and noise- free ECG signals. The adoption of a fixed threshold constrains the method's ability to generalize effectively. Unlike previous works [12] and [14], which proposed a machine learning approach for noise detection, offering greater adaptability, this study demonstrated its system's performance across three diverse datasets. Nonetheless, akin to other research, it still employs a binary classification framework for noise detection, lacking flexibility to adjust to specific application requirements. Moreover, despite claiming real-time capability, the algorithm's reliance on cloud-based feature extraction indicates that it doesn't operate entirely on IoT-enabled edge devices. Consequently, this design choice inadvertently escalates transmission costs instead of reducing them through edge-based noise detection. In this study, we have developed a novel, configurable ECG- noise detection system designed for real-time ECG data collection. The system was deployed on a smartphone (acting as a mobile gateway device) and evaluated using real- time ECG data containing various artifacts, as depicted in Additionally, we assessed the performance of the offline version of our system using publicly available datasets to demonstrate its generalization capacity and reliability. We utilized and transmission cost metrics to highlight the significance of our proposed system compared to existing approaches. He key contributions of this article are outlined as follows:

1) Low-Computational and Configurable ECG Noise Detector: Real-time ECG noise detection requires low computational costs to minimize response delays in wearable devices. While threshold-based ECG detectors are commonly used to reduce computational burden, an adaptive threshold is necessary for effective noise detection across diverse datasets. Moreover, defining noisy ECG signals should be based on the requirements of specific clinical applications rather than simply identifying any noise presence. Our proposed system addresses these challenges by defining an adaptive threshold for partial ECG noise detection and evaluating its performance across various publicly available datasets. We also conducted low- computational testing by deploying our model on a smartphone, as shown in Fig. 3, and assessed its real-time performance.
2) Traditional signal quality assessment methods identify noise-free and noisy ECG segments, which are then removed before transmission to the server for clinical decision- making. However, existing models often fail to recover partial noise- free ECG segments, resulting in a high dropping rate. In our study, we employ a real-time ECG noise detector to localize noisy segments within ECG data. Consequently, instead of discarding entire ECG segments, our proposed system can recover partial noise free system The performance evaluation of the proposed system is conducted using two standard R-peak detection algorithms.

III.EXISTING SYSTEM:

The block diagrams of the Existing detection system First, we divide each ECG signal into a 10- s segment and pass it to the noise detection model. If an ECG segment is recognized as noise-free by the noise detection model, the segment is transmitted to the cloud node. On the other hand, in the case of a noisy segment, the model localizes (location in the segment and length) and measures noise level, the percentage of noise present in ECG segments. If the measured noise level in an ECG segment is below the selected noise tolerance level, determined by the application requirement, the ECG segment is transmitted to the cloud including noise location, which can be used to remove the noisy portion of the ECG segment before passing it to the clinical decision making system. It often incorporate a combination of signal processing techniques, machine learning algorithms, and adaptive filtering methods. These existing methods form the basis for the development of real- time tunable ECG noise-aware systems for IoT-enabled devices. By incorporating adaptability and tunability into the signal processing algorithms, these systems can effectively handle varying noise levels and environmental conditions, enabling accurate monitoring and diagnosis of cardiac conditions in remote health

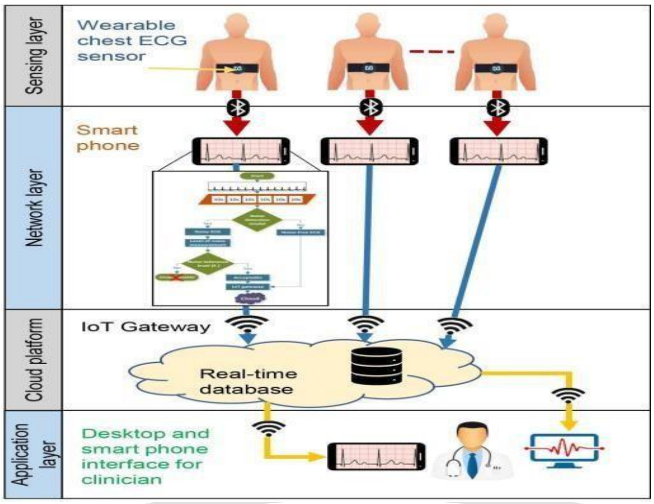

Fig 1: The IoT-driven telemetry ECG system framework, comprises several layers.

IV.PROPOSED SYSTEM:

The proposed Smart Health Monitoring and ECG Denoising System aims to address the limitations of existing methods by offering an integrated and comprehensive solution for health monitoring, analysis, and medication adherence support. The system consists of several key components and functionalities: Arduino Uno and MAX30102 Sensors: These components are used to measure vital parameters such as heartbeat, SpO2, and body temperature in real-time. The Arduino Uno acts as the central microcontroller, collecting data from the sensors and processing it for transmission. ECG Sensor and Code: The system incorporates an ECG sensor to capture electrocardiogram signals. These signals are transmitted to a laptop running Python code specifically designed for denoising and analyzing ECG data. The Python code applies signal processing techniques to extract clean ECG signals from noise and identify cardiac abnormalities. Thing Speak IoT Cloud Platform: Health data collected by the system, including vital parameters and denoised ECG signals, is transmitted to a mobile application through the Thing Speak IoT cloud platform. Thing Speak facilitates real-time data transmission, enabling remote monitoring and analysis by healthcare providers or caregivers.

LED Indicator Lights and Buzzer: The system includes LED indicator lights and a buzzer to provide timely reminders for medication intake at predefined intervals. This feature enhances medication adherence by alerting users to take their medication as prescribed. Mobile Application: The system is integrated with a mobile application that allows users to monitor their health status and receive medication reminders. The application displays real- time health data transmitted from the system and provides personalized insights and recommendations based on the user's health profile.

The proposed system offers a comprehensive approach to health monitoring and management, combining real-time data collection, advanced signal processing, remote monitoring capabilities, and personalized medication adherence support. By integrating multiple components and functionalities into a single platform, the system aims to empower individuals to take proactive control of their health and improve healthcare outcomes

1) Experiment Using the proposed Wearable Sensor Devices:
2) In this phase , our proposed algorithm was tested in real-time using wearable ECG, temperature, SpO2, and heart rate sensors. The algorithm, along with the existing model, was deployed on a smartphone by developing a Python code for execution in the

Android environment. Unlike the previous experiment where ECG data were sourced from existing datasets, here, the ECG signal was collected directly from the wearable ECG sensors. The same process was followed for collecting data from other wearable sensors in real-time. To assess the quality of transmitted packets, especially with higher noise tolerance levels, a different approach was adopted. Initially, peaks in the ECG signal collected using wearable devices were manually detected. Subsequently, the performance was evaluated in offline mode, comparing the detected peaks with the ground truth.

1) **Thing Speak IoT Cloud Platform:** Health data collected by the system, including vital parameters and denoised ECG signals, is transmitted to a mobile application through the Thing Speak IoT cloud platform. Thing Speak facilitates real-time data transmission, enabling remote monitoring and analysis by healthcare providers or caregivers.

2) **LED Indicator Lights and Buzzer:** The system includes LED indicator lights and a buzzer to provide timely reminders for medication intake at predefined intervals. This feature enhances medication adherence by alerting users to take their medication as prescribed.

3) **Mobile Application:** The system is integrated with a mobile application that allows users to monitor their health statusand receiv medication reminders.The application displays real- time health data transmitted from the system and provides personalized insights and recommendations based on the user's health profile Overall, the proposed system offers a comprehensive approach to health monitoring and management, combining real-time data collection, advanced signal processing, remote monitoring capabilities, and personalized medication adherence support..By integrating these hardware components and functionalities, the system enables comprehensive health monitoring, ECG analysis, medication adherence support, and remote data transmission for improved healthcare management and outcomes.

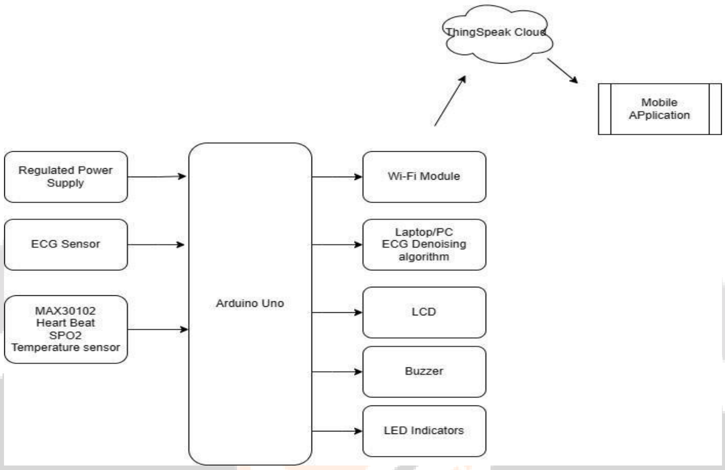

Fig 2: Block Diagram of proposed system

1.Algorithm:

This algorithm aims to detect noise in an electrocardiogram (ECG) signal and localize the noisy segments, ultimately providing a partially noise-free ECG signal.

Step 1: The algorithm calculates the first derivative of the1 min ECG segment (`X(n)`) to capture the rate of change of the signal over time. It computes the first derivative `β[k]` for each sample `k`.

Step 2: 1. The algorithm detects maximum peaks from the first derivative of the ECG signal (`β`) using a sliding window approach. 2. It defines a window size `ws` based on the ECG sampling frequency (`Fs`), which is half of the sampling frequency. 3. It initializes a counter `cnt` to count the highest peak from each window. 4. For each window `i`, it extracts the batch of samples within the window and identifies the index of the maximum value (`batchmax Index`). 5. An adaptive threshold `η` is set as half of the maximum value of the first derivative 6. It compares each maximum peak with the threshold. If a peak is greater than the threshold, it's considered significant, and it's stored.

Step 3: 1. The algorithm defines a binary channel `Gbin(n)` where 1 represents noise-free segments and 0 represents noisy segments. 2. For each peak detected in Step 2, it calculates the duration between consecutive peaks (`R − R[i]`) in milliseconds. 3. If the duration is within a certain range (between 300 and 2000 milliseconds), it marks the corresponding segment as noisy (setting `Gbin` to 1); otherwise, it marks it as noise-free (setting `Gbin` to 0).

Step 4: 1. The algorithm calculates the percentage of noise in the ECG signal by counting the number of segments marked as noisy (`sum(Gbin == 1)`) and dividing it by the total number of segments (`length(Gbin)`). 2. If the percentage of noise (`P`) is less than or equal to a predefined noise tolerance level (`λ`), the algorithm concludes that the ECG is noise-free (`D = 0`); otherwise, it categorizes it as noisy (`D = 1`). The output `D` indicates whether the input ECG segment is partially noise-free or not. This algorithm provides a method to detect and localize noise in an ECG signal, allowing for the transmission of a partially noise-free signal.

V.RESULTS AND ITS SIMULATION:

This Arduino sketch is designed to monitor various physiological parameters such as heart rate (HR), blood oxygen saturation (SpO2), temperature (in Fahrenheit), and electrocardiogram (ECG) signal. Fig 3 the graph represents a denoised signal with the following characteristics The denoised signal is plotted against time instances. The x-axis represents the time instances, while the y-axis represents the amplitude of the denoised signal. The RMSE value indicates the average deviation between the denoised signal and the original signal. A lower RMSE value indicates better accuracy of the denoised signal. The SNR value indicates the ratio of the signal power to the noise power. A higher SNR value indicates a stronger signal relative to the noise, implying better quality of the denoised signal. The window size and polynomial order are parameters used in the denoising algorithm (likely the Savitzky -Golay filter) to remove noise from the original signal. These parameters affect the smoothness and accuracy of the denoised signal. The graph visualizes the denoised signal with specific denoising parameters, providing insights into the effectiveness of the denoising process and the quality of the resulting signal

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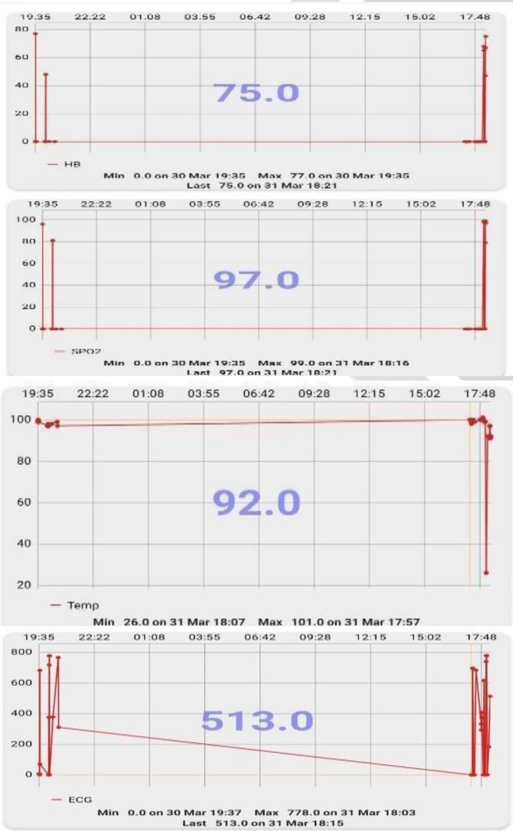
PARAMETERS	**REAL Time Data**	
	Min	Max
Body Temperature	0.0	92.0
ECG	0.0	513.0
Heart Rate	0.0	77.0
Pulse Oximeter(SP02)	0.0	97.0

Table 1: Four Experimental real time data from wearable sensors



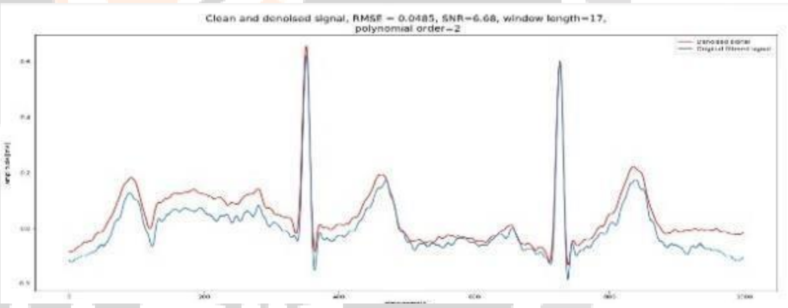


Fig 3: Time instances at which the denoised signal is Sampled vs amplitude values of the denoised signal

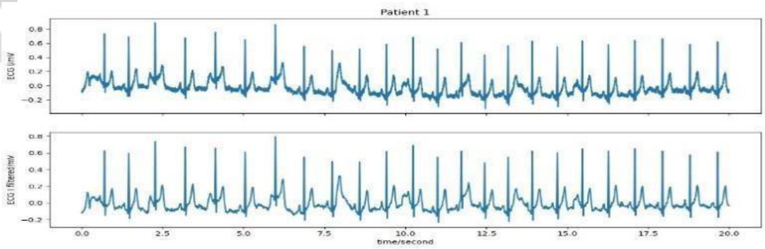


Fig 5 The ECG noise signal without filter

And with filter or noise free signal

Fig4:Monitoring various parameters

such as Body Tem ,ECG, heart rate,spo2

1. Reading MAX30102 Sensor: - IR value is read from the sensor. - If IR value falls below a certain threshold (indicating no finger on the sensor), it displays a message on the LCD and resets the heart rate to zero. 2.Heart Rate Calculation: - If a beat is detected using `checkForBeat` function, it calculates the beats per minute (BPM) and updates the heart rate variables. 3. Temperature and SpO2 Calculation: - Temperature in Fahrenheit is read from the sensor. - SpO2 is calculated based on the heart rate. Different mapping conditions are applied depending on the heart rate range.Monitoring various parameters such as Body Tem ,ECG 4. Display on LCD: - Heart rate, SpO2, and temperature are displayed on the LCD. 5. Electrocardiogram (ECG) Reading: - Analog signal from ECG sensor is read. 6. Abnormal Condition Check: - Abnormal condition is flagged if heart rate is greater than 90, or if SpO2 is between 60 and 80, or if temperature is greater than 100°F. 7. Buzzer Control: - If abnormal condition persists for 5 seconds, the buzzer is turned on. - After 6 seconds, the buzzer is turned off. 8. Data Transmission: - Data including heart rate, SpO2, temperature, and ECG are sent over serial communication every 30 seconds. - The sketch continuously monitors various physiological parameters and alerts in case of abnormal conditions. It displays the readings on an LCD and sends the data over serial communication for further processing or monitoring. Additionally, it provides visual indications through LEDs and audible alerts using a buzzer. If a beat is detected using Check for beat function, it calculates the beats per minute (BPM) and updates the heart rate variables.

VI.CONCLUSION:

Conclusion, the development of the Smart Health Monitoring using wearable sensors and denoising ECG Signal System represents a significant advancement in healthcare technology, offering a comprehensive solution for real-time health monitoring, analysis, and medication adherence support. By integrating advanced hardware components such as Arduino Uno, MAX30102 sensors, and ECG sensor with sophisticated software algorithms for ECG denoising and analysis, the system provides users with valuable insights into their health status and facilitates timely interventions when necessary. The implementation of LED indicator lights, a buzzer, and a mobile application interface further enhances the system's functionality by providing visual and audible medication reminders and enabling users to monitor their health data remotely. Additionally, the integration of the thing Speak IOT cloud platform enables seamless data transmission between the system and the mobile application, facilitating real-time monitoring and analysis by healthcare providers or caregivers. The Smart Health Monitoring using wearable sensors and Denoising ECG signal System offers a user-friendly and effective approach to healthcare management, empowering individuals to take proactive control of their health and well-being. Through continuous monitoring, analysis, and support, the system aims to improve healthcare outcomes, enhance medication adherence, and ultimately contribute to better quality of life for users managing chronic conditions or complex health issues. Continued advancements and refinements in the system's design and functionality hold the promise of further enhancing its capabilities and expanding its impact on healthcare delivery and patient care

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