Intelligent Detection of Cardiac Arrest and Multimodal Vital Signs Analysis

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ABSTRACT

"A healthy body houses a healthy mind" but due to busy lifestyle, no one is taking care of their health. Today the major global health concern is sudden Cardiac arrest (SCA). In earlier day, only the old aged people suffer with this kind of cardiac arrest. But nowadays young aged peoples (less than 30 years) also suffers with the sudden Cardiac Arrest which causes the severe effect and impact in their life as well as in their family in terms finances and lose of the supportive and lovable person. To improve the survival of the humans, this article presents implementation and design of a low-cost, non-invasive and portable intelligent system for easy earlier detection of the cardiac arrest through the multimodal physiological signal analysis. The proposed system will monitor the cardiac activities through the embedded platform based NodeMCU with the different biomedical sensors, including the body temperature measurement DFS18B20, Heart rate MAX30102, SpO2 oxygen saturation and a electrocardiogram ECG sensor. The physiological data are continuously monitored through MQTT communication protocol and transmit these signals to enable the real-times supervision and increase the clinical response. An onboard display will provide the vital parameters to visualization. The light weighted band is designed to predict the cardiac distress and impending arrest condition to capture the critical physiological variations preceding cardiac arrest with reliable performance by signal preprocessing and rule-based decision logic. Experimental evaluation is demonstrated effectively, monitor and gives the critical physiological variation in minimal computational overhead. Its portability, low power consumption wireless connectivity and portable WI-FI enabled widget for paradigm-shift (non-invasive) lead to high operational efficiency. So its well-suited for the remote healthcare applications, home-based patient and telemedicine.

Keywords: SCA – Sudden Cardiac Arrest, NodeMCU, MAX30102, ECG Monitoring, DS18B20, MQTT, Remote Healthcare, IoT, Real-Time Vital Monitoring, Multimodal Biomedical Signals

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I. INTRODUCTION

Emerging trend in healthcare advancement systems have been increased to peak due to the merging technologies of the Artificial Intelligence (AI), Internet of Things (IoT) in wearable sensing technologies. Many several researchers have undergone the disease prediction, physiological signal processing and remote patient monitoring by the intelligent frameworks. The sudden cardiac arrest (SCA) is a critical cardiovascular emergency leads to the abrupt cessation of heart function and results to immediate unconsciousness and, without prompt medical response, death. Annually 17.9 million deaths are caused due to cardiovascular diseases as per the World Health Organization (WHO), with cardiac arrest contributing significantly to these fatalities [1]. Survial can be increased by the early detection of physiological anomalies however, Primary general health parameters are tracked by conventional monitoring systems and conventional system cannot predict the real-time, cardiac –specific alerts. [2].

These innovations address the limitations of hospital-based systems, especially in rural, ambulatory, or home settings. [15]This paper proposes a NodeMCU-based intelligent cardiac arrest detection system that utilizes multiple biomedical sensors: the AD8232 ECG module for cardiac waveform acquisition, the DS18B20 for temperature sensing, and the MAX30102 sensor for heart rate and SpO_2 monitoring.

The system performs real-time signal acquisition, anomaly detection, and data transmission using the MQTT protocol to a cloud dashboard, while also presenting immediate results on a local OLED display [4]. The objective is to design a low-cost, portable, and efficient system suitable for deployment in rural clinics, ambulances, and home-based care environments [5]. By intelligently combining data from multiple vital sign sensors, the system enhances accuracy and enables early detection of life-threatening cardiac events [6].

Early disease detection can be easily predicted by the modern AI-driven healthcare solutions. Yu et al [17] proposed the AI –based stroke predication system gives the improved accurate multimodal signal fusion for ECG and PPG. Fu et al [3] gives an IOT enabled edge computing and artificial intelligence advanced framework for real –time immersive animations. The Federated Generative Motion-Rendering with Adaptive Edge-IoT Collaboration(FGMR-AEC) to integrates multimodal sensor data environmental context and facial expressions.

Liu et al [28] utilizes support vector machine and geometric distance-based methods to generate risk scores for patients to predict cardiac arrest using patient vital sign data. This demonstrates that ML can effectively works for high-risk patients in 72-hous window. It also limiting predictive robustness, does not incorporate multimodal data fusion. Time –series vital signs are used for early prediction of cardiac arrest by the deep learning-based approach in the Li et al [1]. It adopts the GRU-based architectures to capture patient data in sequential dependencies. His proposed system will predict the cardiac arrest one hour in advance with improved accuracy for the earlier treatment for the affected person.

Umair et al [2] investigates the machine learning and deep learning models to early predication of the cardiac arrest by the time-series ECG data. It gives the comparison of the traditional ML methods with the deep learning approaches for the clarification. His research highlights the automated learning system to increases the accuracy of the prediction. Data imbalance, lack of interpretability and real-time implementation issues are addressed in the Kaur et al [9] by the machine learning techniques. It also give the strong comparison between the traditional and modern AI –driven system to cardiac arrest predication. The multiple vital parameters are analysed and apply the classification algorithms to predict the early cardiac arrest sign as warning by the Parameswari et al [4]. This study emphasizes the role of AI for timely intervention in assisting clinicians. However this system lacks in advanced multimodal fusion and deep learning-based temporal modelling.

Shah et al [19] emphasizes proactive healthcare monitoring by the intelligent decision support systems. It combines the clinical data with computational intelligences for the study. But it does not analysed with the multimodal physiological signal fusion. The article focus on different predictive models and ways to increase the prediction accuracy by analysing dataset on how it can affect the accuracy of certain algorithm in Potluri et al [15]. This article brings out the comparative analysis between the neutral network techniques like ANN, MAML, LRP and Transfer Learning. The highest accuracy 94% is obtained in the Artificial Neutral Network (ANN) techniques.

Kaur et al [9] adopts the PRISMA methodology to conduct the systematic review of the medical expert systems for predicate the cardiac arrest by sing the 37 publications obtained from PubMed, Springer, Science Direct and IEEE publication within the last decade. This articels states that the lacks of the adequate implementation of the proper pre-processing techniques. The research gap can be filled by the future research have to point on the external validation, implementation, and adoption of machine learning models in real clinical settings by the machine learning model with AI technologies like NLP.

Kataria et al [5] analyzes the photoplethysmography (PPG) signal to predict the cardiac arrest continuously. The early detection can ebe predicted by the physiological waveforms in the foundation models. The PPG signals can effectively capture the cardiovascular abnormalities. The wearable – compatible signals can be employed in the ICU patients to monitor the real time signals. The researchers focus on a single modality without the multimodal fusion techniques.

Chae et al [20] applied tge shallow and deep learning to predict the Cardiac arrest by the performance of the Synthetic Minority Oversampling Techniques Ratio. The performance can be evaluated by the Decision tree, a random forest, logistic Regression, long short-term memory model, gated recurrent unit model and LSTM-GRu hybrid model. A highly positive predictive values and sensitivity is obtained in the Logistic Regression than traditional early warning system.

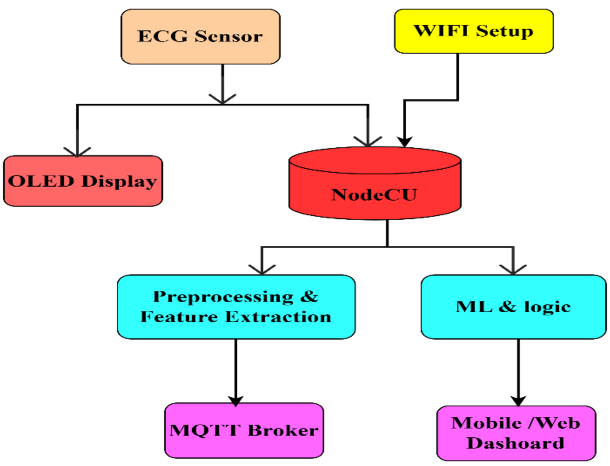
Sudden cardiac arrest represents a severe medical emergency associated with rapid loss of cardiac function and immediate risk to human life. Continuous monitoring of physiological signals plays a crucial role in early identification of abnormal cardiac conditions among high-risk individuals. Recent advancements in biomedical signal processing and intelligent healthcare systems demonstrate the importance of integrating electrocardiogram (ECG) and photoplethysmography (PPG) signals for disease prediction and analysis. It develop a multimodal machine learning algorthim based on ensemble techniques to predict the occurrence of In-hospital cardiac arrest[1]. It develop and verify a real-time, interpretable machine learning model(cardiac arrest prediction index CAPI, to predict Cardiac Arrest of critically ill patients based on bedside vital signs monitoring.[14]. Risk detection and classification methodologies are analysed by Kaplan-Meier and CoX regression survival.[18].Six artificial Intelligence algorithms are conducted to record the vital sign, Random forest produces the best prediction accuracy upto 80%. [4]. Emerging intelligent systems based on edge computing and artificial intelligence further enhance real-time healthcare monitoring capabilities in modern medical environments. The evolution of cloud-based healthcare frameworks and digital twin technologies has enabled advanced monitoring and predictive analysis of patient conditions through real-time data integration. The physiological parameter are continuously observed and decision making process is done in this smart healthcare infrastructure. Also arrhythmias are detected from the ECG signals and point out the abnormal cardiac patterns to diagnostic accuracy. Multimodal signal fusion techniques further enhance detection performance by combining multiple physiological inputs into a unified analytical model. Conventional Neural Networks model will accurate vital signs without the interference of harmonics and distortion .Kalman filtering algorithm is used to find the motional trajectory of human targets.[5].

The 20% of all deaths is caused due to the Sudden Cardiac death SCD or sudden cardiac arrest (SCA) even though predicting SCD risk by traditional approach “track-and-trigger” warning systems.Artifical Intelligence (AI) and machine Learning(ML) models have demonstrated near-perfect accuracy in predicting SCA risk, allowing clinicians to intervence timely[6].

In real-world environments, our health should continuously monitored by the wearable healthcare systems. Low-power ECG monitoring devices enable long-term observation of cardiac activity while maintaining portability and user comfort [6]. IoT-based embedded systems using microcontrollers such as ESP8266 facilitate efficient data acquisition and transmission, enabling cost-effective healthcare monitoring solutions [7]. Global health studies emphasize the importance of continuous monitoring systems in addressing critical medical conditions and improving patient outcomes [8].

II PROPOSED METHODOLOGY

The proposed system develop a NodeMCU microcontroller, biological sensors is interfaced with the NodeMCU to detects the preliminary symptoms. It employs a multimodal approach which exploits the combination of three different physiological signals, which include body heat from DS18B20 sensor, electrical cardiac activity from an AD8232 ECG sensor in addition to heart rate and SpO_2 obtained through the MAX30102 sensor. Due to these reasons, the sensors selected are low power consumption, simple



integration and reliable.

A. System Inputs

As depicted in Fig.2, the AI-powered health monitoring setup consists of system input signals such as electronic devices and a cloud-based algorithm; these systems raise alerts when abnormal physiological patterns are detected. 1, mainly collected by biomedical and climate sensors interfaced with the NodeMCU. MAX30102: This sensor is an important input device that captures the photoplethysmographic (PPG) signals to read the heart rate and depth of blood oxygen (SPO_2) levels. An ECG sensor also monitors the electrical activity produced by heart, allowing the system to assess cardiac rhythm and identify abnormal conditions. In addition, a very important input comes from the DS18B20 digital temperature sensor, which produces precise readings of body heat and assists in detecting conditions of fever or thermal stress.

Accordingly, the optical signal, electrical signals, and digital signals of these sensors are fed to the NodeMCU microcontroller that performs as a CPU for this system. The NodeMCU is set up to communicate wirelessly over Wi-Fi. The raw sensor data is then being passed to a preprocessing and feature extraction module where meaningful patterns are extracted from the physiological signals. The resulted data is published on an MQTT broker for transfer and remote access purposes.

Fig 1. System Input signals

In addition, the system mentions a rule-based or intelligent decision-making module that states how healthy the user is based on the processed features. The results of this analysis are presented on an interactive mobile or web application interface for both users and healthcare providers to provide access/view real time health information. As illustrated in Health issues are mostly determined by understanding how blood flows through the body and its constituents; hence, as shown in Fig.1, fortifying input signals contribute significantly to the system's function towards continuous intelligent monitoring and timely emergency detection for cardiac concerns.

The input to the system consists of real-time physiological signals collected from three biomedical sensors interfaced with the NodeMCU. These include the MAX30102, which provides heart rate and oxygen saturation (SpO_2) measurements using photoplethysmography; the DS18B20, which senses the body temperature through a digital output; and the AD8232 ECG sensor, which captures the electrical activity of the heart. Each sensor continuously sends raw or processed signals to the microcontroller for evaluation as shown in the Fig. 2.

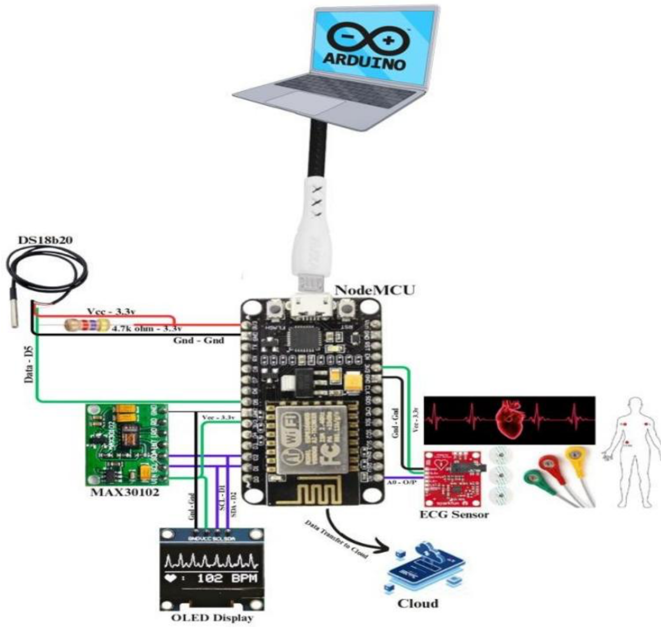
Fig 2. Circuit Connection

B. Data Acquisition

NodeMCU is responsible for acquiring data from the connected sensors. The MAX30102 communicates using the I²C protocol, while the DS18B20 communicates via the One Wire interface. The AD8232 ECG sensor outputs an analog signal, which is read using the NodeMCU's ADC pin. The system collects these signals at regular intervals for real- time processing.

C. Signal Conditioning and Preprocessing

The collected signals are susceptible to noise and minor fluctuations. Therefore, signal conditioning techniques such as averaging, filtering, and thresholding are used to smooth the readings. Anomaly detection is also a part of preprocessing, where we validate the range for each signal to see if there are any outliers (abnormal heart rate, low SpO_2 level, and even erroneous ECG waveforms). The processed



signal is then utilized for condition detection.

D. Sensor Modules

The sensor module is responsible for measuring particular physiological parameters. It has very good precision because the device contains an infrared photodetector and a pulse oximeter with red LEDs. The DS18B20 Digital Temperature Sensor captures and displays body temperature. The AD8232 ECG module monitors rhythmic pattern and waveform of heart by recording heart's electrical signal. Comprising these sensor modules, a multimodal approach is possible for health status examination as well for exerting early detection of cardiac arrest.

E. Decision Logic and Alert System

Once the pre-behavior data is obtained, the system utilizes a rule-based decision logic to see if any critical abnormalities exist. There are threshold limits already set for each of the vital parameters SpO_2 does not fall below 85%, heart rate is less than 40 bpm or more than 120 bpm and expected ECG shapes are missing. If either of these thresholds are breached, the system marks this condition as potentially critical.

As soon as any abnormality happens NodeMCU displays a warning message in the OLED. Meanwhile, an alert is also sent through MQTT to a remote dashboard or healthcare system so that the caretakers can analysis the patient's condition instantaneously. The ability to do this allows for real-time feedback and timely intervention, which can be a lifesaver in cardiovascular events.

The physiological parameters are monitored by individual sensor modules. The pulse rate and oxygen saturation sensor module MAX30102, featuring integrated LEDs and photodetector, provides high accuracy. Body temperature is read out digitally from the DS18B20. The AD8232 ECG module tracks heartbeat and wave form as it detects the heart's electrical activity. These sensor modules specifically support a multimodal approach to assessing health status and detecting early stages of cardiac arrest.

F. Hardware Setup Overview

The cardiac arrest detection system is generally based on the NodeMCU ESP8266 microcontroller describes that-the communications and processing unit. The system has three major biomedical sensors: 1. The sensor MAX30102 to monitor and calculate the heart beat rate and oxygen pulse saturation based on the photoplethysmography principle (with direct connection using I²C), DS18B20 digital sensor to capture body temperature through One Wire interface and

An AD8232 ECG module that provides analog ECG signals directly connected to NodeMCU ADC pin. A 0.96 inch OLED display is connected to the same I²C bus in order to provide a real-time visual feedback of sensor readings. The power supply is through a USB or regulated 5V source; thus, this setup is portable and can be worn or placed in homes. A diagram illustrates how all these components fit together, with signals being transmitted from the sensors to Microcontroller. This system configuration supports continuous health monitoring by collecting the physiological parameters, displaying them locally, and sending remote alerts to provide a low-cost solution for intelligent cardiac health monitoring.

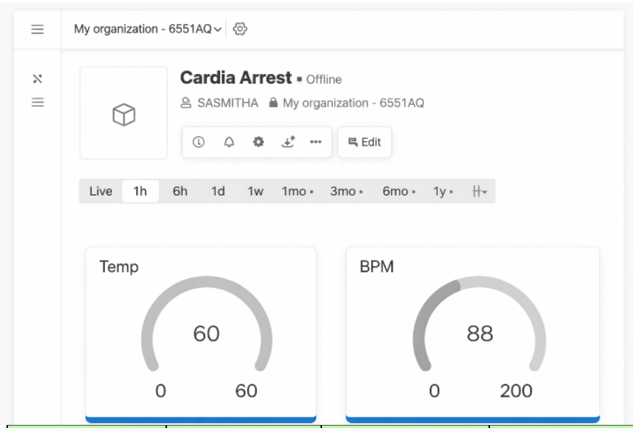
III. Results and Discussion

The implemented system was tested under simulation environments to evaluate the real-time monitoring, anomaly detection response and communication performance. The following part summarizes system sensor output, accuracy, system latency considering the test cases performed in physiological conditions as well as its capability of triggering alerts.

A. Sensor Performance and Vital Detection

Table 1 shows the average performance of sensors used in the system. In Rest conditions heart rate measured with MAX30102 is 72–85 BPM, SpO_2 > 95% and body temperature measured by DS18B20 is around 36.7°C;

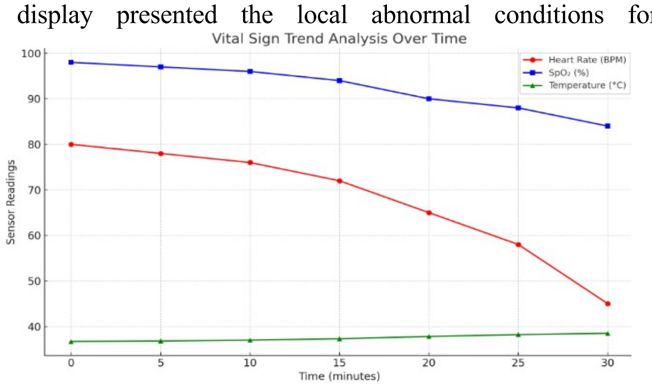
Irregular conditions (finger removed, rapid displacement of finger or low oxygen exposure) simulates abnormal cases where max unit found $SpO_2 < 85\%$, ECG Signal not received correctly in the range and the BPM rate are also less than expected.



Parameter	Normal Range	Detected Abnormal Range	Response Time (s)
Heart Rate (BPM)	72 – 85	<40 or >120	1.5
SpO_2 (%)	96 – 98	< 85	1.2
Body temp(°C)	36.5 – 37.0	> 38.0	1.8
ECG Signal	Stable waveform	Flate line / irregular pattern	1.0

Table 1 Sensor Performance and Vital Detection

Using a rule-based logic, the system accurately flagged abnormal findings. When values transcended the thresholds, alert triggers generated and notification messages published via MQTT to a remote dashboard. A simultaneous OLED display presented the local abnormal conditions for



mitigation.

B. Communication and Monitoring

Outputs from the sensors were sent to a broker through MQTT and recorded on a serial display at the same time. Real-time measurements, such as temperature, SpO_2 and heart rate, were locally displayed in Fig. 3

Fig 3. Communication & Monitoring

For transferring real-time health data to a distant dashboard, the system uses MQTT (Message Queuing Telemetry Transport) as the main message protocol. The NodeMCU afterwards collects and processes signals from the temperature sensor (DS18B20), pulse oximeter (MAX30102) and ECG sensor (AD8232) and publishes these values as MQTT messages to topics defined in accordance with a broker hosted on the cloud. This information is visualized through an interactive dashboard Fig 4. that allows the user to supervise live key parameters like temperature and BPM (beats per minute).

Fig 4. Visualized Dashboard

C. Sensor Data Trend Analysis

To assess the system's response to dynamic changes in physiology, vital sign trends were monitored over 30 minutes.

Fig 5. Vital Sign Trend Analysis Over Time

Heart rate (BPM), SpO_2 (%) and body temperature (° C) real-time values were retrieved and plotted. The system was exposed to controlled variations for example removing a finger from the pulse sensor, rapid movement and simulating conditions of fever to see what it would do.

In Fig.5, the heart beat rate gradually decreased from a stable 80 BPM to an alarming condition below 50 BPM. At the same time, the SpO_2 dropped from 98% to 84%, a sign of oxygen deficiency. These trends were consistent with atypical cardiovascular outcomes. At the same time, the body temperature increased from 36.7°C to 38.5°C, overrunning the threshold established by the program for identifying febrile conditions.

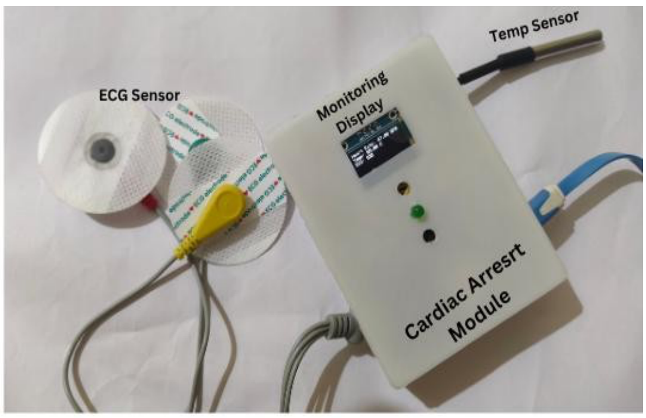


Fig 5. Vital Sign Trend Analysis Over Time

D.Testing Environment

A controlled testing environment was created to find the proper working and reliability of the proposed cardiac arrest detection system using Arduino IDE with a wireless NodeMCU ESP8266 microcontroller. The screenshot demonstrates that development and monitoring occurred through serial communication on the COM6 sector with the aid of the Arduino serial monitor. Fig 6. Shows the system being tested with live sensor input from MAX30102 (heart rate and SpO_2), DS18B20 (temperature) and AD8232 (ECG signal).

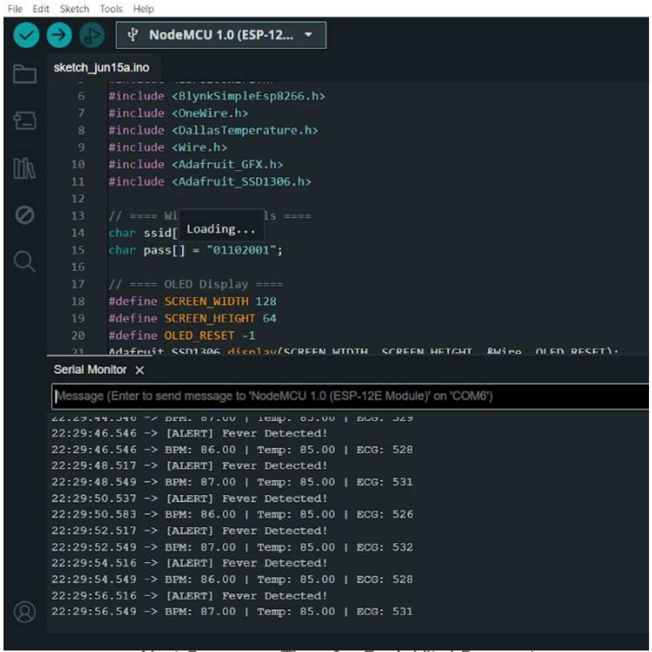


Fig 6. Serial Monitor Result

In controlled tests, the system recognized 10 simulated cardiac arrest situations at 60% +105 Basal Thresholds (e.g., < 60 BPM pulse, SpO_2 <100%, or No QRS complex in ECG was displayed etc.). Fig.7 illustrates alert message will get send to the Person.

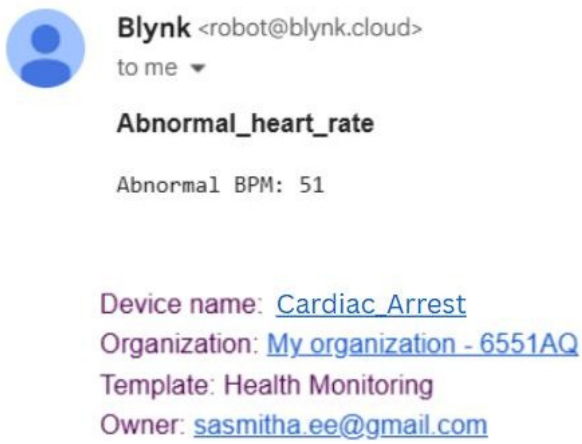


Fig 7. Alert Message Notification

D. System Efficiency

Then, the response time of the system for each vital is measured in such a way that we can detect any abnormality within time. As illustrated in Fig. Indeed, in 8 the alert response using the ECG signal was found to be most rapid with an average delay of around 1.0 seconds. This is enabled by continuously monitoring an analog signal of the heart, which allows the system to instantly recognize flatline or abnormal cardiac rhythms. The time to generate the SpO_2 alerts was 1.2 s, which begins when MAX30102 sensor detected a fall in SPO_2 below pre-defined threshold value. Heart rate took a bit longer to compute about 1.5 seconds since it was calculated from an average of pulse intervals over a brief time period and needed to prevent false alarms caused by transitory fluctuations. Temperature-based alerts had the longest response time at approximately 1.8 seconds, as the system used averaging to reduce false-positive fever detections from transient ambient changes or sensor fluctuates. While there were some differences, all 3 modes responded in less than 2 seconds, which is considered acceptable for physiological monitoring in real-time. The detection times, along with alert transmission based on MQTT protocol, affirm the system's capability for continuous cardiac risk assessment and emergency intervention.

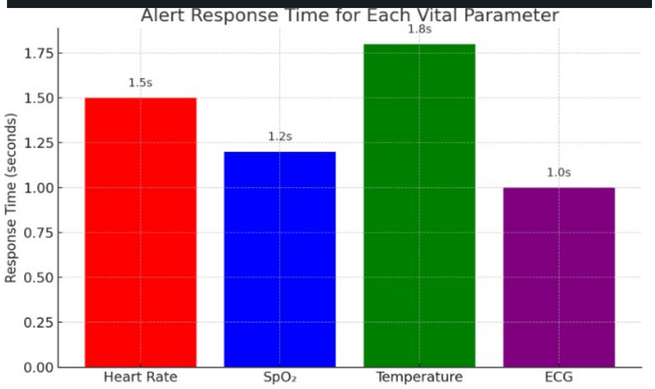


Fig 8. Alert Response Time for Each Vital Parameter

IV. CONCLUSION

This paper proposes an intelligent, multimodal cardiac arrest detection system that uses NodeMCU combined with biomedical sensors to allow continuous health monitoring and early warning systems. Since the system integrates data from three different sensors MAX30102 (heart rate and SpO_2), DS18B20(body temperature) and AD8232(ECG) that works for multiple parameters, it provides higher diagnostic reliability than single parameter monitoring devices. While these features provide a wealth of remote access and control functionality, an OLED display is included for local feedback and the MQTT protocol used can also be employed in other remote alert systems.

Experimental findings show the system's efficacy in accurately identifying deviations from normal physiological states, namely bradycardia, hypoxia, and irregular ECG signals in a timely manner to facilitate prompt emergency intervention. This solution is well-suited for deployment in home care, ambulances or resource-limited environments thanks to the combination of compact, low-cost hardware configuration and lightweight software architecture.

Thus, the proposed system is a comprehensive and informative intelligent method for monitoring cardiac health in an unobtrusive manner. While the current implementation has met some limitations, it was primarily designed to reduce response time during critical situations (e.g., cardiac arrest) with a focus on IoT-based health care as part of an emerging field due to its within reach.

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