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Smart Steering Wheel: Design of IoMT-Based Non-Invasive Driver Health Monitoring System to Enhance Road Safety

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ABSTRACT

The integration of Internet of Things (IoT) technology and medical devices in healthcare is termed the Internet of Medical Things (IoMT). This advancement holds promise for numerous applications aimed at mitigating the risk of loss of life through physiological signal monitoring. As the number of road accidents is rapidly increasing, a substantial number of car crashes occur due to medical conditions. Therefore, the need remains to develop an effective solution to enable the prevention of such accidents for enhanced road safety. Unlike existing approaches, this paper proposes a holistic IoMT-based non-invasive driver health monitoring system (DHMS) to monitor important vital signs for detecting abnormal health conditions. The proposed system consists of an embedded system, edge computing, cloud computing, and a mobile application with an alert system, to offer an end-to-end unified solution for driver physiological signal monitoring to detect abnormal health conditions that might lead to a road accident. The system is particularly suited to aid (elderly) people with medical conditions and can also be used for public transport to ensure passenger safety. A detailed experimental evaluation of the proposed system has been performed and its performance accuracy compared with standard medical devices, along with quality factors including usability, portability, and effective sensor placement.

1 | Introduction

In recent years, technologies related to health monitoring have significantly gained importance. The use of cutting-edge technologies such as the Internet of Things (IoT), edge computing, and cloud computing, has improved the accessibility of healthcare facilities [1]. IoT offers numerous opportunities as the world is getting increasingly connected. This transformation reduces human participation and improves efficiency, along with economic benefit and accessibility [2]. According to the World Health Organization (WHO), the incidence of heart disease worldwide is estimated to reach 23.3 million by the year 2030 [3]. An estimated 17.9 million people died from cardiovascular diseases (CVDs) in 2019. Out of these deaths, 85% were due to attacks and strokes [4]. People with cardiovascular disease need early detection and management using counselling, medicines, and lifestyle changes to overcome the potential risk [5]. As the number of vehicles has increased at a rapid rate around the world. The causes and severity of accidents depend on multiple factors related to humans, vehicles, and the environment, with the human factor causing more than 90% of bodily accidents [6]. Different approaches relying on facial expression analysis [7, 8], eye tracking [9], and health monitoring [10] have been proposed for improved traffic safety in recent years. Among them, health monitoring technology has become a prominent research area, which is based on the vital signs monitoring of a driver. In this context, vital signs such as electrocardiogram (ECG), heart rate, oxygen saturation, respiration rate, and body temperature are crucial factors for monitoring an individual's health status. According to a study performed by Harvard Health Watch, an average American spends 101 min per day driving [11]. Approximately 1.3% of car crashes are due to medical conditions per year [12]. Hence, there is an opportunity to prevent health-related accidents by monitoring the vital signs of drivers and issuing early warnings in the event of abnormal health conditions that could potentially lead to road accidents. Current health monitoring systems are primarily tailored for monitoring patients in home and hospital settings [13]. However, there is a clear need for an efficient and effective IoT-based health monitoring system to oversee driver health as a crucial road safety measure aimed at preventing road accidents.

IoT is the backbone of Industry 4.0 [14] and a rapidly evolving technology that has given rise to various applications in healthcare [15], where different terminologies are used, such as the Internet of Medical Things (IoMT) [16, 17], Healthcare Internet of Things (HIoT) [18, 19], Internet of Bodies (IoB) [20], etc. This evolution has created numerous opportunities for remote monitoring, and telemedicine, as well as for tracking sleep, monitoring stress and fatigue [21], and providing personalized healthcare [22, 23]. In [24] author identifies the role of IoMT applications in improving the healthcare system. Another study [25] introduced integrated safety by monitoring drivers, vehicles, roads, and other vehicles. However, an end-to-end solution for driver physiological signal monitoring is highly unavailable, which is highlighted in related works (see Section 2.5).

This paper proposes the design of an IoMT-based non-invasive driver health monitoring system (DHMS) that is aimed to minimize health-related accidents. Unlike the existing related approaches, the proposed framework presents a comprehensive end-to-end solution for driver physiological signal monitoring by considering the key vital signs such as ECG, oxygen saturation, heart rate, and body temperature, together to detect abnormal health conditions, with the integration of advanced communication technology, such as IoT, interactive user interface, and appropriate sensor placement on the steering wheel. The system is particularly well-suited for elderly individuals and those with medical conditions. Additionally, it can be employed in public transport to enhance passenger safety. The proposed system underwent extensive evaluation, comparing its performance accuracy with standard medical devices, yielding encouraging results. This system has the potential to enhance road safety and save lives by providing early alerts for abnormal health conditions.

This paper is organized as follows. Section 2 reviews related work categorized into on-board, global system for mobile communication (GSM)-based, Bluetooth-based, and IoT-based techniques for driver monitoring. Section 3 describes the proposed system design and implementation, which is followed by results and analysis in Section 4, and the conclusion in Section 5.

2 | Related Work

The literature review examined recent studies on driver monitoring, which can be classified into onboard vital sign-based monitoring methods, GSM-based monitoring methods, Bluetooth-based monitoring methods, and IoT-based monitoring methods. A summary of related work is provided in Table 1. Subsequently, we provide a detailed review of works related to each category as follows:

2.1 | Onboard Vital Sign-Based Monitoring Methods

In [26], the authors proposed a conductive fabric-based dry electrode utilizing an electroplating method. They employed a conductive fabric-shaping procedure to design a steering wheel cover to measure the ECG signals of a driver. Comparing the measured ECG signals of a driver in a normal condition to those in a drowsy condition and showed that the proposed ECG measuring system is useful for detecting drowsy drivers. Another study [27] used respiratory signal analysis for drowsiness detection. The respiratory signal, obtained using an inductive plethysmography belt, was processed in real-time to classify the driver's state of alertness as drowsy or awake. Their proposed algorithm was based on the analysis of the respiratory rate variability (RRV) to detect the fight against falling asleep. In [28], the authors proposed a systematic approach for the detection of atrial fibrillation (AF) rhythms in ECG hand-held devices. A set of 150 highest-ranked features is selected and fed into a random forest classifier to detect AF rhythms in addition to three other ECG rhythms/types for stress detection. In [29], a switchable phase-locked loop circuit-based architecture for continuous non-contact monitoring of driver health status was presented that used heart rate and breath rate detection simultaneously. Sensors could either be mounted on the steering wheel or attached to the seatbelt to detect vital signs. In [30], the author proposed driver vital signs monitoring, which includes heart rate, respiration rate, and heart rate variability using millimetre wave radio. The experimental results show a median error of 0.16 respiration per minute, 0.82 beat per minute (BPM), and 46 ms for heart rate (HR), and interbeat intervals (IBI) estimations corresponding to the relative accuracy of 99.17%, 98.94%, and 94.11%, respectively. Another study [31] used a single 60 GHz sensor for heartbeat interval and blood pressure using the correlation analysis and Bland–Altman plot.

2.2 | GSM-Based Monitoring Methods

In [32], an application based on alcohol detection, drowsiness detection, vital sign monitoring (ECG, and heart rate) along with the lane-based auto drive to avoid an accident with certain limitations that include lack of judgment of drowsiness/inattentiveness by eye aspect ratio (EAR) only, which can be improved drastically by the addition of EEG observations of the driver. The Raspberry Pi board is used along with GSM for

Paper	Communication Technology	Factors	Parameter/Vital signs	Test setting	Sensor Placement	Interface
[26]	On-board	Stress monitoring	ECG	Laboratory setting	Seat backrest	Laptop
[27]	On-board	Drowsiness	Respiratory signal	Simulator	Seat belt	Laptop
[28]	On-board	Heath	ECG	Laboratory setting	Steering wheel	Laptop
[29]	On-board	Health	Heartbeat Respiratory signal	Laboratory setting	Steering wheel Seat belt	Laptop
[30]	On-board	Health	Heart rate variability Respiratory signal	On-road driving	Windshield	Laptop
[31]	On-board	Health	Heart rate Blood pressure	Laboratory setting	Steering wheel	Laptop
[32]	GSM	Drowsiness Alcohol Health	ECG Heartbeat	Laboratory setting, On-road driving	Steering wheel	Laptop, Mobile
[33]	GSM	Health	ECG	Laboratory setting	Steering wheel	SMS
[34]	GSM	Health	Heartbeat Body temperature	Laboratory setting	Prototype	SMS
[35]	Bluetooth	Health Drowsiness	Electrocardiogram (ECG) Oxygen saturation (PPG)	On-road driving and static vehicle	Steering wheel	Laptop
[10]	Bluetooth	Health	ECG Oxygen saturation	Laboratory setting	Steering wheel Ear lobe	Mobile application
[36]	IoT Bluetooth	Health	Oxygen saturation Body temperature Heartbeat	Laboratory setting	Prototype	Database dashboard, On-board LCD
[37]	Bluetooth GSM	Drowsiness Fatigue	Electrocardiogram (ECG) Photoplethysmogram (PPG)	On-road driving Static vehicle	Steering wheel	Mobile application, Laptop
[38]	Bluetooth	Health	Heartbeat Temperature	Laboratory setting	Prototype	Laptop
[39]	IoT	Drowsiness Fatigue	Facial expression	Static vehicle	Dashboard	Mobile application
[40]	IoT	Health	Respiration Heartbeat	Laboratory setting	Steering wheel	Website
[41]	IoT	Health Drugs	Respiration Temperature Blood pressure Heartbeat	Laboratory setting	Steering wheel	Laptop
[42]	IoT GSM	Alcohol	Breath	Laboratory setting	Prototype	Mobile
[43]	IoT	Drowsiness	Eyes	Simulation	Dashboard	Laptop
[44]	IoT	Health	Heartbeat, eye blink	Laboratory setting	Steering wheel	Mobile application
Prop.	IoT GSM	Health	Electrocardiogram (ECG) Oxygen saturation Body temperature Heartbeat	Laboratory setting	Steering wheel	Mobile application, SMS

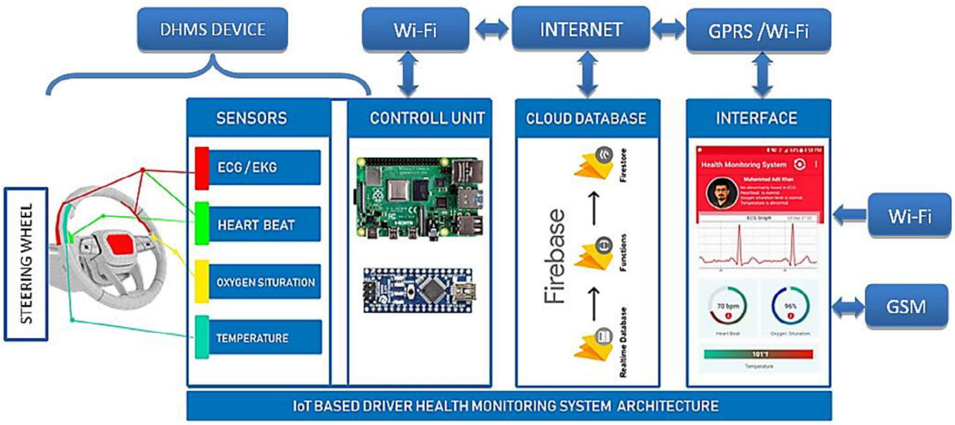


FIGURE 1 | Abstract view of the proposed system.

TABLE 2 | Layered architecture.

Blocks	Layers				Implementation
		Application layer			**Interface**
User interface	User authentication		Data visualization	Alert system	Android Smart Phone
		Storage layer			**Cloud database**
Cloud computing	Authentication		Real-time database	Firebase storage	Firebase
		Network layer			**IEEE standard**
		Wi-Fi			IEEE 802.11b
		Processing			**Model**
		Feature extraction ⇒ Analysis			Heartpy
		Pre-processing layer			**Libraries**
Edge computing	Data acquisition ⇒ Data sampling Normalization ⇒ Noise removal				Numpy Pandas Matplotlib Scipy Heartpy MAX30102
			Sensors layer		**Hardware**
	Serial sensor	i2c sensor	Analog sensor		Raspberry pi 4 Arduino Nano ADS1115
Embedded system	ECG (AD8232)	Oxygen saturation (MAX30102)	Heartbeat (Heart sensor)	Body temperature (LM35)	
	Arduino Nano		Analog to digital converter ADS1115 (i2c module)		
		Raspberry pi 4			

long-range communication and short message service (SMS) is triggered upon detection of any abnormality and the car shifted to auto-drive mode. The authors in [33] presented the design and development of a smart steering wheel for heart attack detection. The Arduino board is used for real-time monitoring along with the GSM module. On the abnormal heart rhythm of a driver, an emergency SMS along with the current location is sent automatically within 30 s. In addition, a warning alert is triggered when abnormal behaviour is detected to warn the driver to park on the shoulder of the road and take a vasodilation pill from a built-in compartment. Another study presented [34], a useful application for tracking and monitoring real-time health. Patients will be tracked, traced, monitored, and helped to take care of so that effective medical treatments may be given as

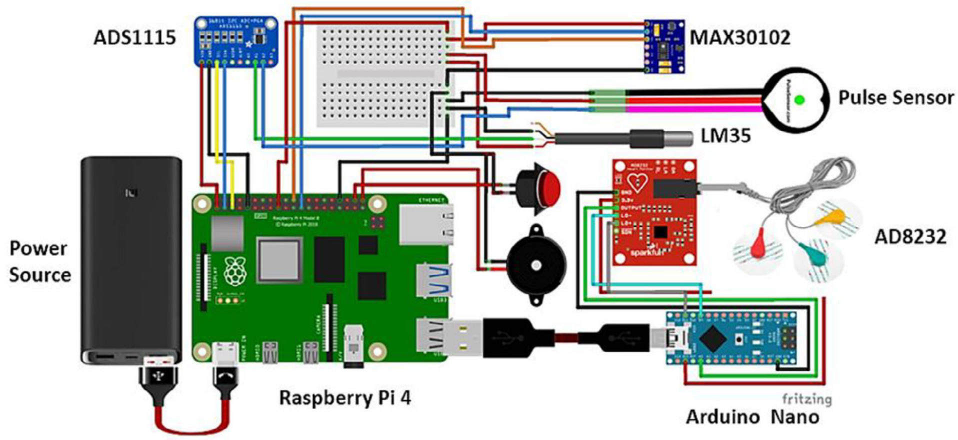


FIGURE 2 | Circuit diagram of the proposed system.

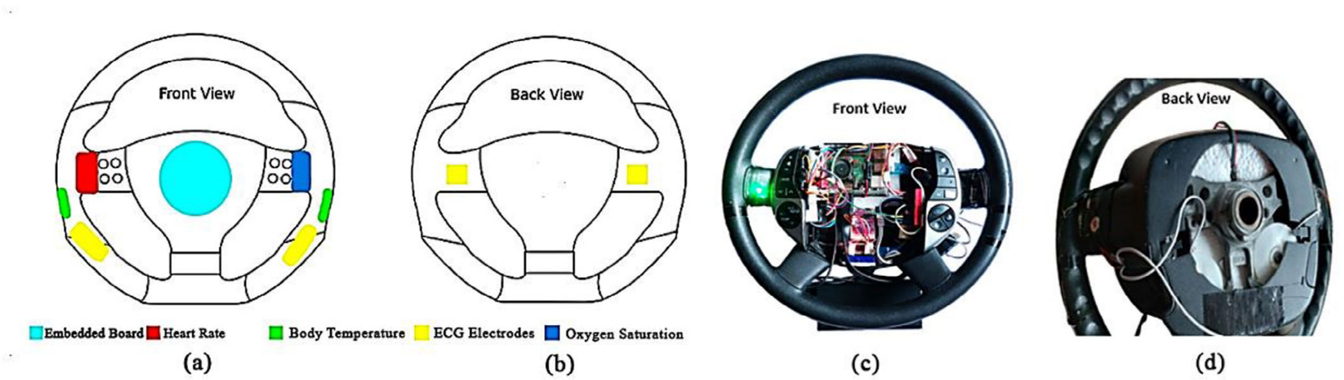


FIGURE 3 | Prototype placement of sensors and controller on the steering wheel: (a,c) show the front view of the steering wheel and (b,d) show the back view of the steering wheel.

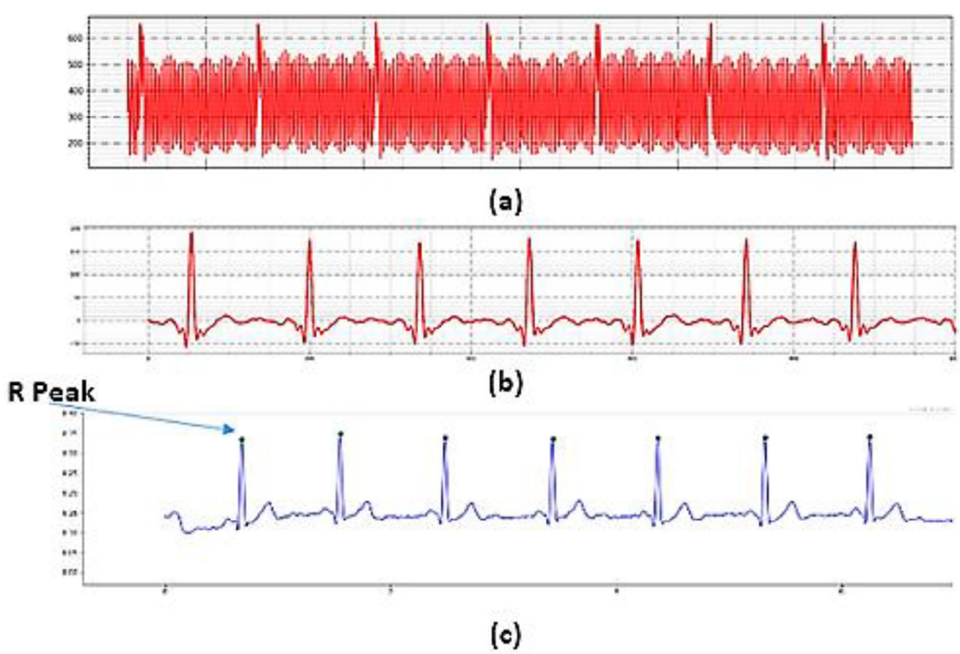


FIGURE 4 | ECG signal pre-processing. (a) Raw signal, (b) filtered signal, and (c) detected R peaks shown as dots.

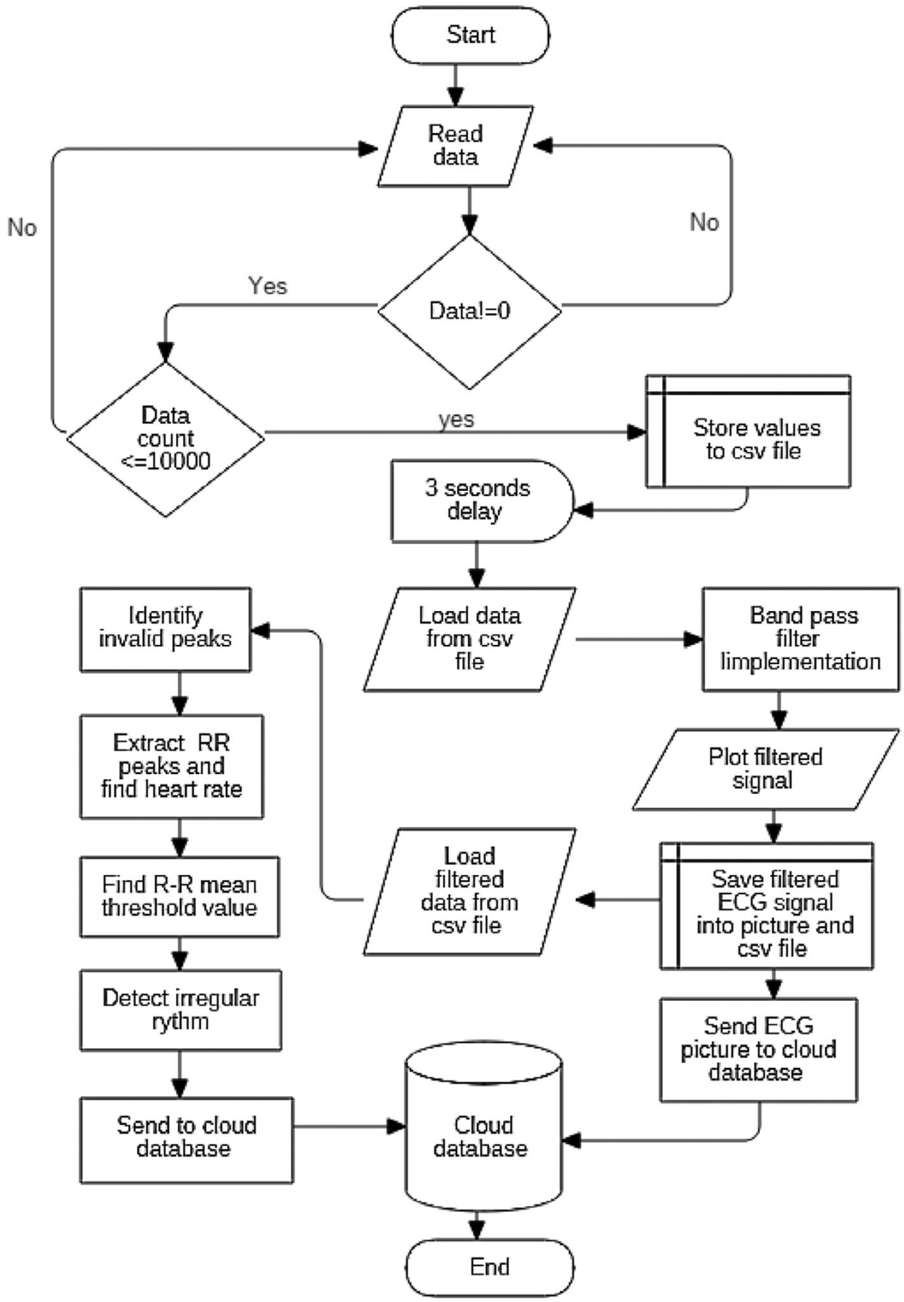


FIGURE 5 | Detailed flowchart of ECG signal processing.

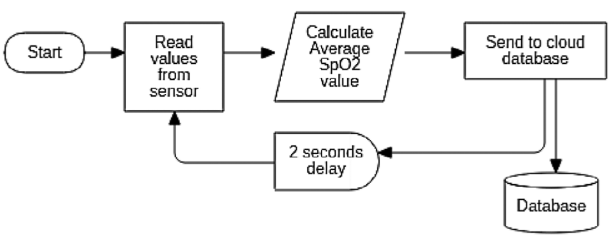


FIGURE 6 | Flow chart illustrating the oxygen saturation processing.

needed. A specialized doctor who monitors the patient will use specific sensors to collect data, which will then be compared with a configurable threshold via a microcontroller. In the event of an emergency, an alert SMS will be sent to the doctor's mobile number along with the measured values via the GSM module. Moreover, the GPS provides the location information of the monitored person who is under surveillance all the time.

2.3 | Bluetooth-Based Monitoring Methods

In [35], the design of a smart steering wheel was proposed for drowsiness and health monitoring. The important vital signs such as heart rate variability, heart rate, and oxygen saturation are measured using an ECG signal and pulse oximeter mounted on the steering wheel to record and analyse the data by Bluetooth communication with a laptop. In [10], the authors focused on designing a new practical system for monitoring two vital

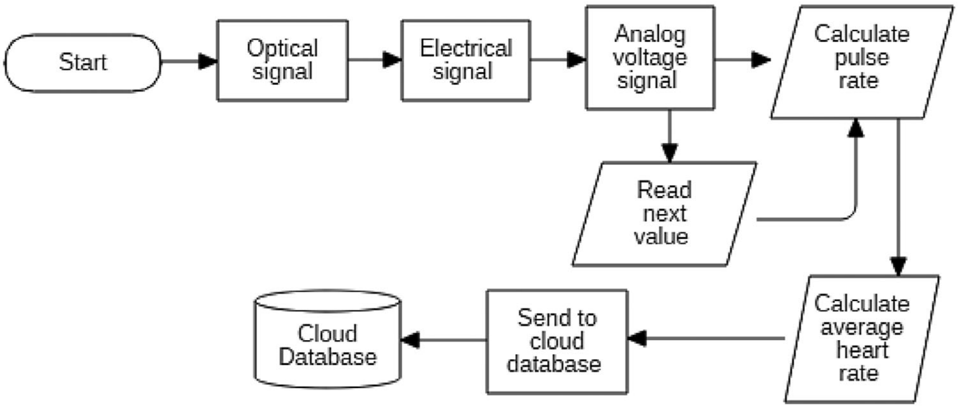


FIGURE 7 | Flow chart illustrating the heart rate sensor processing.

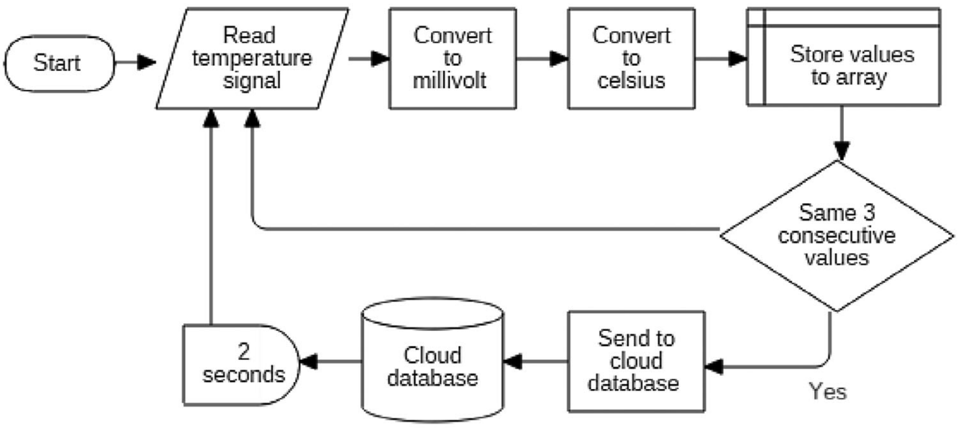


FIGURE 8 | Flow chart illustrating the body temperature processing.

physiological signals such as photoplethysmography (PPG) and electrocardiography (ECG) to detect a driver's abnormal health status during driving such as heart rate, oxygen saturation level, and certain respiratory and cardiac dysfunctions with an alert system to warned immediately to react and consult a doctor. The goal is to monitor the driver's health condition by using Bluetooth technology to visualize vital sign data on a mobile application. Another study [36] developed a non-invasive hybrid model for vital signs (oxygen saturation, heart rate, and body temperature) monitoring by using IoT and Bluetooth-based communication for vital sign data visualization on mobile applications and website portals, respectively. The interactive interface for mobile applications is achieved by using Bluetooth (HC-05) communication between biosensors and smartphones. In [37], the author presented a smart steering wheel that uses Bluetooth communication to visualize ECG and PPG data on a smart mobile with the emergency alert system by using GSM communication (SMS) for the driver's emergency using a smartphone and automatic emergency location alarm system based on Google map was also presented. In [38], a body sensor network (BSN) was used as a health monitoring system for monitoring driver health status periodically and information about abnormal behaviour was sent to both the transport office and healthcare provider. The proposed system monitors a driver's physiological parameters such as pulse rate, and body temperature, using sensors and is transferred to a smartphone using Bluetooth communication.

2.4 | IoT-Based Monitoring

In [39] a real-time drowsiness and fatigue detection system based on an image processing technique in which the camera was mounted on the dashboard, and it works on vehicle On-Board Diagnostic II details along with image processing data with sound alert. Raspberry Pi communicates with the Android App via message queuing telemetry transport protocol and triggers alerts when drowsiness or fatigue is detected. In [40], the authors used K-band non-invasive vital signs monitoring, and values of vital signs are stored on an open-source server using the internet for future correspondence. The proposed system was tested with five different subjects with the error of heart rate and respiratory rate at 8.6% and 2.3%, respectively. For automatic alerts, GSM and a buzzer were used for alert notification in case of abnormal heart rate and respiration rate. Another study [41] proposed an IoMT device to monitor blood alcohol concentration level and physiological data as the driver touches the steering wheel and data sent over the internet to be cross-checked with regular baseline information. If a driver is clear-headed, they are allowed to drive; otherwise, the vehicle engine gets automatically locked

FIGURE 9 | Firebase real-time database: Driver's database structure.

FIGURE 10 | Firebase real-time database: Doctor's database structure.

and the blood alcohol concentration data is displayed on the infotainment. The data is sent to an Internet of Things analytic tool which could be accessed by the user later. In [42], the author presented an IoT-based system that prevents drunk driving by sensing alcohol intoxication levels in a driver's breath. When the system detects an exceeding level of alcohol in the breath sample, the system will cut the electric supply which reduces risk. In [43], the author proposed IoT-based driver drowsiness detection based on eye tracking. Another study [44] proposed an IoT-based solution that tracks eyes to detect sleeping along with heartbeat detection.

2.5 | Discussion

As reviewed above in the literature, the onboard vital sign-based monitoring methods [26, 27] and Bluetooth-based monitoring methods [35, 10] generally do not offer an end-to-end solution that enables remote monitoring for the problem at hand. GSM-based monitoring methods attempted to address this shortcoming by enabling remote monitoring of drivers [32, 33], but have an inherent limitation of not supporting real-time streaming of data (from different sensing modalities), which is highly desirable for a thorough analysis remotely for quick emergency aid. IoT-based monitoring methods [39–41] overcame this problem by allowing effective real-time interactive remote monitoring based on employing different vital signs or visual cues. However, existing IoT-based methods used either facial features [39] to detect drowsiness by using a camera, alcohol detection, respiration rate, or heartbeat to monitor health conditions [40], or a combination of both vital signs and drugs [41, 42] without employing ECG information that is considered more informative from a medical viewpoint. Therefore, the need remains for a holistic end-to-end IoT-based real-time solution that also incorporates ECG into an interactive remote monitoring framework with an alert mechanism and edge computing that reduces the effects of throughput, latency, and packet loss issues is largely unavailable in the literature.

The proposed DHMS aims to address these limitations by offering a holistic end-to-end IoMT-based non-invasive driver monitoring system to minimize the occurrence of health-related accidents by considering the important vital signs such as ECG, oxygen saturation, heart rate, and body temperature, together to detect abnormal health conditions such as bradycardia, tachycardia, arrhythmia, hypoxia, and hyperthermia, with effective communication technology (such as IoT), interactive user interface, and appropriate sensor placement on the steering wheel. Unlike existing works, we performed edge computing utilizing a commercial off-the-shelf board (Raspberry Pi) to reduce the effects of throughput, latency, and packet loss issues. This is expected to contribute towards achieving enhanced road safety and allowing quick emergency response to avoid implications in medical emergency scenarios.

2.6 | Background

This section provides definitions for technical and medical terms used throughout the article as follows:

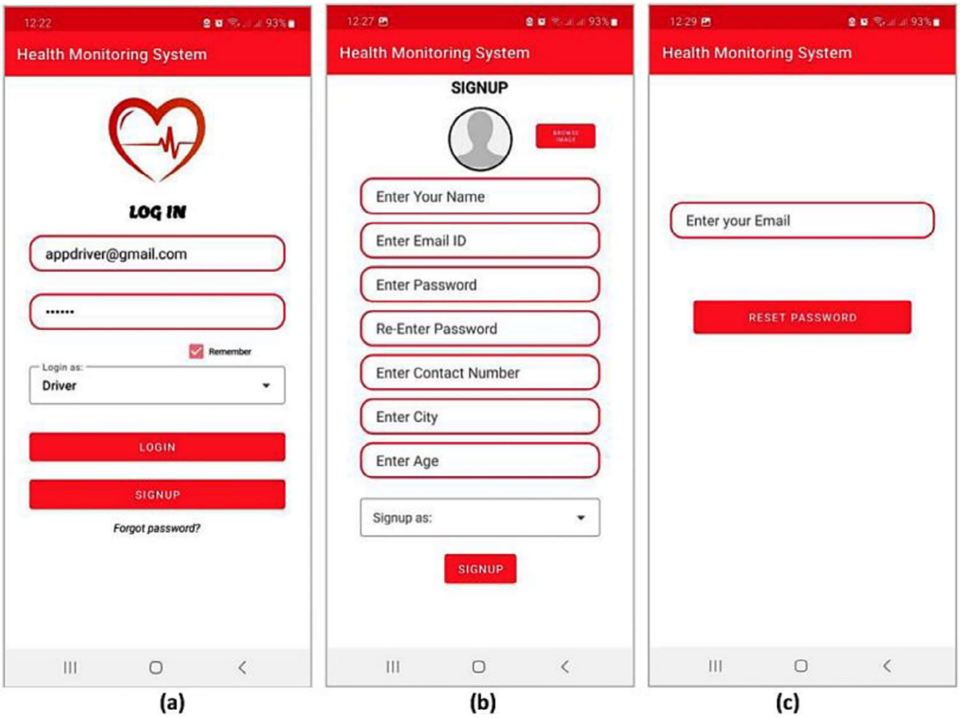


FIGURE 11 | User authentication: (a) User login, (b) signup, and (c) password recovery activities.

Tachycardia: Tachycardia is characterized by a rapid heartbeat, typically more than 100 BPM in adults. It can be caused by various factors, including stress, exercise, fever, and certain medical conditions.

Bradycardia: Bradycardia is characterized by a slower-than-normal heartbeat, typically less than 60 BPM in adults. It can be caused by issues with the heart's electrical system or other underlying health conditions.

Arrhythmia: Arrhythmia refers to an irregular heartbeat. It can manifest as a slow, fast, or erratic heartbeat and can be caused by various factors, including heart disease, electrolyte imbalances, and other medical conditions.

Hypothermia: Hypothermia occurs when the body loses heat faster than it can produce heat, resulting in a dangerously low body temperature. Symptoms include shivering, confusion, and loss of coordination.

Hyperpyrexia: Hyperpyrexia is a term used to describe an extremely high body temperature, typically above 41.5°C (106.7°F). It can be a sign of a severe underlying medical condition and requires immediate medical attention.

Cyanosis: Cyanosis is a bluish discolouration of the skin and mucous membranes caused by a lack of oxygen in the blood. It is often a sign of underlying health issues affecting the heart, lungs, or circulatory system.

Firebase authentication: It is a Google service for user authentication in apps. It provides backend services, for authentication using methods that include passwords, phone numbers, and federated providers like Google and Facebook.

JavaScript Object Notation (JSON): It is a lightweight data interchange format. It is easy for humans to read and write and easy for machines to parse and generate. JSON is language-independent and commonly used for transmitting data between a server and a web application.

3 | System Design and Implementation

This section presents the design and implementation of the proposed system based on the IoT framework (see Figure 1). Broadly, the system consists of four major blocks as follows: embedded system, edge computing, cloud computing, and a user interface. Every block contains layers stacked on one another, which are interconnected and perform a set of functionalities (see Table 2). In the embedded system block, there is a sensor layer in which biomedical sensors, multiplexer, and the controller are connected with the embedded board (such as Raspberry pi 4) to read raw data based on i2c, analogue, and serial communication. In the edge computing block, there is a preprocessing layer that processes raw data by using multiple algorithms, libraries, and filters and a processing layer for data analysis. In the cloud computing block, there is a network and storage layer that uses the internet to send data over the network to a cloud database that provides the facility to store and stream data in real-time. In the user interface block, there is an application layer that provides an interactive graphical user interface in a native Android mobile application for both the driver and doctor to visualize data with an alert/notification system. The integration of sensors can be accomplished by attaching sensors to the steering wheel cover, making it simple to install in any car. This framework is an independent deployment that is not dependent on the current boards in the vehicle; thus, it can potentially be integrated into any vehicle. The comprehensive details of each block are as follows:

3.1 | Embedded System

The embedded block contains a sensor layer that consists of four biomedical sensors to read the vital signs of the driver such as

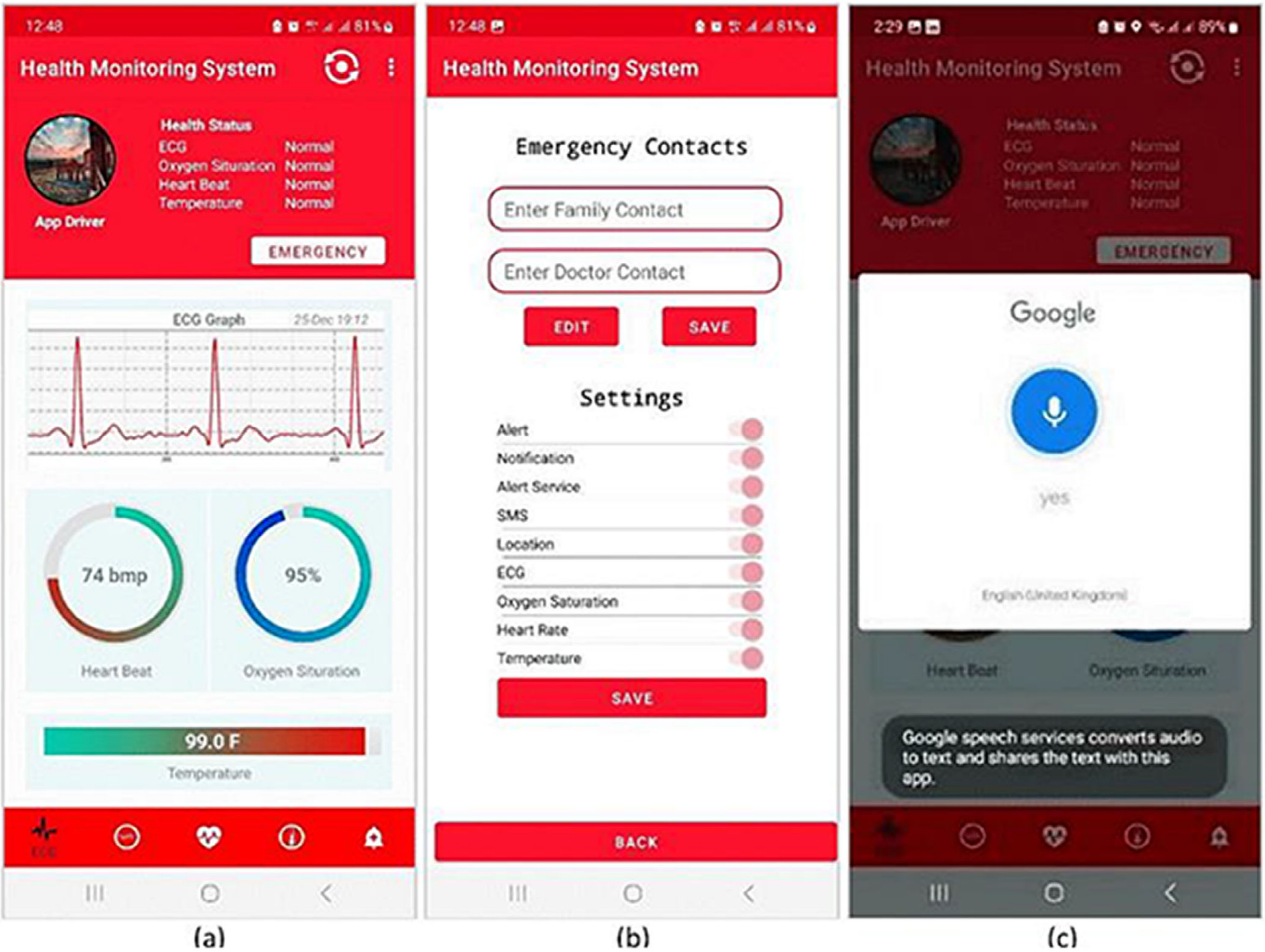
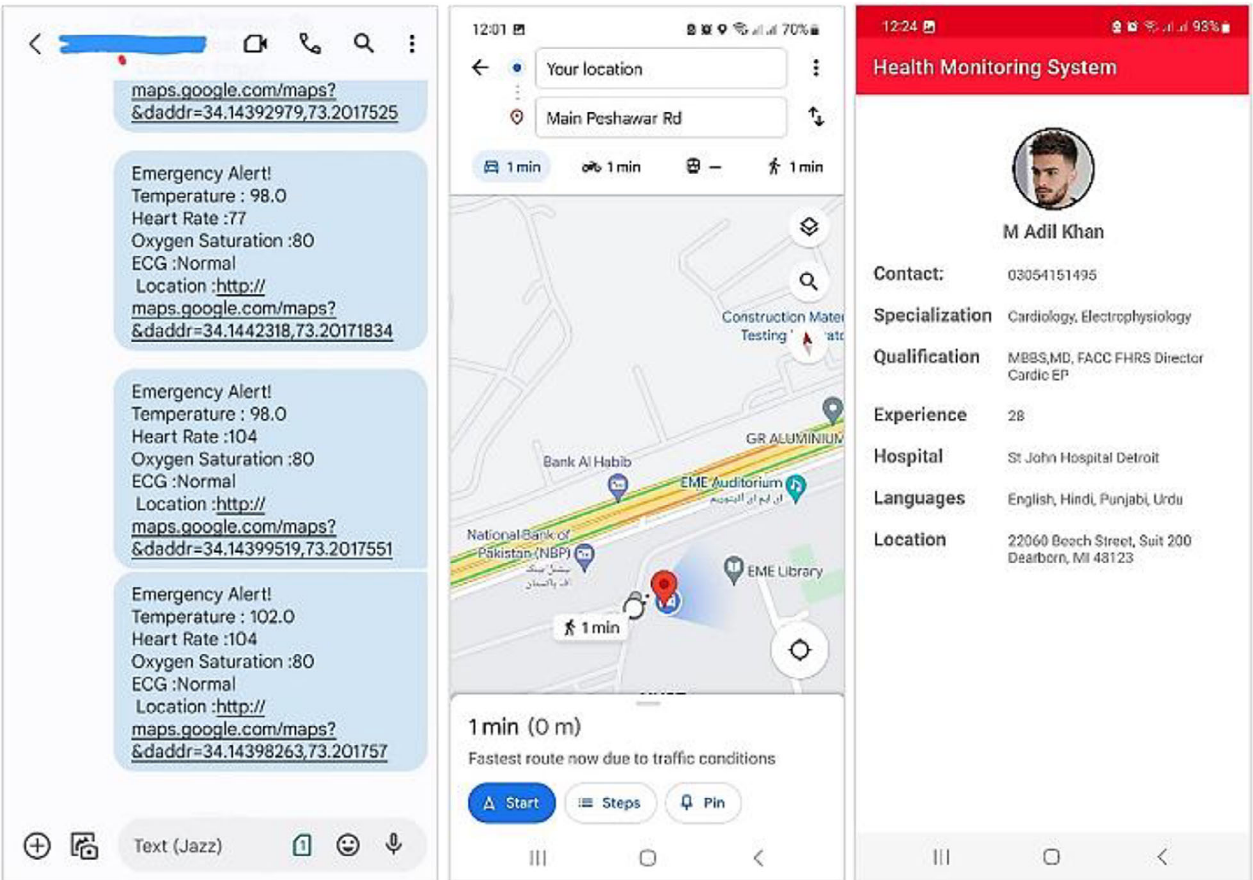


FIGURE 12 | Driver application user interface. (a) Driver main activity, (b) settings, and (c) emergency confirmation prompt.

ECG, oxygen saturation, heart rate, and body temperature, which are connected to Raspberry Pi 4. It is used for edge computing and acts as a getaway to provide internet connectivity for data streaming to cloud databases. This embedded board is based on Broadcom BCM2711, Quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5 GHz processer with 4GB RAM, standard 40 pin GPIO header, and built-in Wi-Fi, 2.4 GHz, and 5.0 GHz IEEE 802.11ac. 2.5A power supply can be used to power Raspberry Pi. There is a Micro SD card slot for loading the operating system and data storage [45]. We have proposed a generic framework in which other sensors and embedded boards can be used instead of the proposed sensors/ embedded boards. In the proposed configuration the ECG sensor (AD8232) is connected to Arduino Nano and further Arduino Nano is connected to Raspberry Pi through a USB serial port. The ECG signal is read by using Python script and data is stored in a .csv file for pre-processing in Raspberry Pi. The oxygen saturation sensor (MAX30102) is directly connected to Raspberry Pi by using the I2C protocol by using GPIO 23(SCL), and GPIO 22(SDA). Moreover, heartbeat and temperature (LM35) sensors are analogue-based sensors and there are no analogue input pins in Raspberry Pi. So, a 16-bit ADC multiplexer (ADS1115) is used between the sensors mentioned above and Raspberry Pi to read analogue values in Raspberry Pi. A power source (5 V, 2 A) is connected by using a USB to type C power cable. The push button and buzzer are attached to GPIO 20 and GPIO 21 pins, respectively as shown in Figure 2.

Biomedical sensors are mounted both on the top and bottom sides of the steering wheel, such as suitable positions are selected to read vital signs by considering comfort and the position where the driver holds the steering most of the time during driving. Figure 3a,b shows the front and back sides of the steering wheel sketch along with colour marking for placement of sensors and embedded board. In this sketch, Raspberry Pi is placed in the central portion represented by a light blue colour, whereas, the heart rate sensor is placed on the left side of the steering wheel which is represented by a red colour (left-hand thumb or index finger can be used), and the oxygen saturation sensor is placed on the right side from the centre and which is represented by a dark blue colour (right-hand thumb or index finger can be used). Moreover, two temperature sensors were placed on both the outer left and right sides of the steering wheel (palms of both hands will be intact), represented by green colour. ECG sensor electrodes are placed on the left and right sides of both the top and bottom of the steering wheel, represented by yellow colour. The driver can use either front or back side electrodes interchangeably for ECG recording depending on his comfort. On the other side, Figure 3c,d is the actual implementations with the configurations.



(a) (b) (c)

FIGURE 13 | Emergency user interface and doctor profile activities. (a) The emergency message, (b) the doctor profile, and (c) vital sign information.

3.2 | Edge Computing

Edge computing is followed by an embedded block that consists of pre-processing and processing layers. This block performs data acquisition, sampling, normalization, noise removal, feature extraction, and analysis of four different vital signs such as ECG, heart rate, oxygen saturation, and body temperature to determine the driver's health.

The subsequent mathematical model encapsulates the core components of our proposed system. The objective is to seamlessly integrate vital signs, to detect abnormal health conditions. In this model, each vital sign SpO2, Temp, HR, and ECG are independently processed in parallel. The health status for each vital sign is determined based on specific thresholds as in **1**.

$$\begin{cases} \textbf{Normal}, & \text{if Lower Threshold} \leq \text{Vital Sign}\,(t) \leq \text{Upper Threshold} \\ \textbf{Abnormal}, & \text{if Upper Threshold} < \text{Vital Sign}\,(t) \leq \text{Critical Threshold} \\ \textbf{Critical}, & \text{if Vital Sign}\,(t) < \text{Lower Threshold or Vital Sign}\,(t) \\ & > \text{Critical Threshold} \end{cases} \tag{1}$$

where vital sign, Vital Sign(t) represents the processed signal for the corresponding vital sign at time t. An overall health score, $S(t)$, is computed by summing the binary indicators of abnormality for each vital sign as in **2**.

$$S\,(t) = \sum_i \text{Abnormality}_i\,(t) \begin{cases} 1, \text{ if the } i\text{–th vital sign is abnormal} \\ 0, \text{ otherwise} \end{cases} \tag{2}$$

If the overall health score $S(t)$ surpasses a predefined threshold, an alert is triggered, indicating a potential health risk.

We have used parallel processing instead of sequential processing by using sub-processes. So that, the system is capable of reading data from all the sensors to process in real-time. The system has been designed in such a way that the vital sign data can be read only when the sensors are properly intact to the body. If the contact is loose or the fingers/hands are not properly positioned on the sensor, it ignores the garbage data values. Even during data acquisition from sensors, if a finger gets displaced from electrodes or other sensors, the software ignores values to not process, and it again starts reading data when fingers are properly intact with sensors. Details for every vital sign are as follows:

3.2.1 | ECG Signal Processing

Getting a smooth ECG is challenging because of noise interference. ECG signals are very fine and weak at the millivolt level [46]. So, it is important to remove noise to get a stable ECG

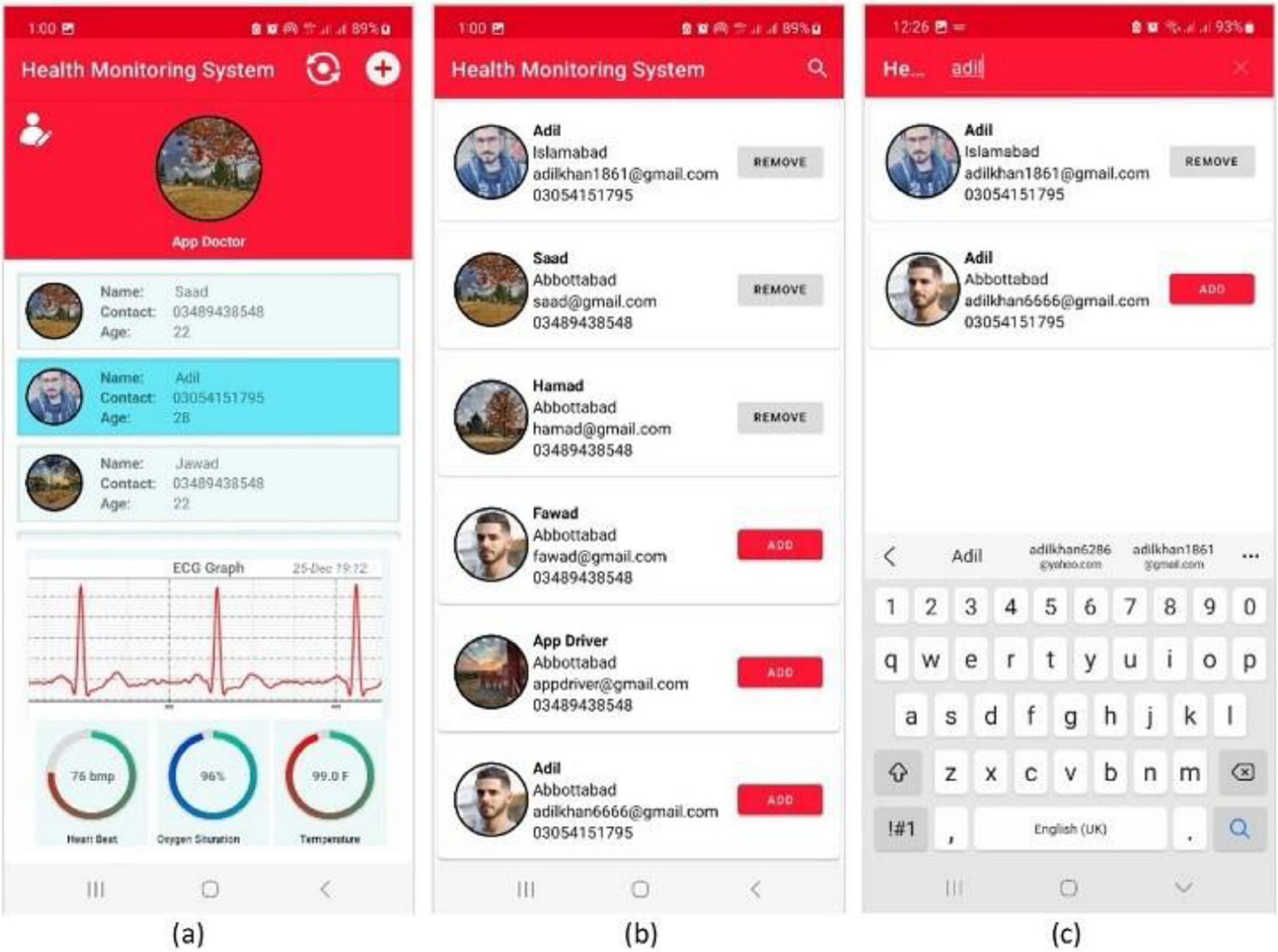


FIGURE 14 | Doctor application's user interface: (a) The main activity, (b) registered drivers list, and (c) search driver activity.

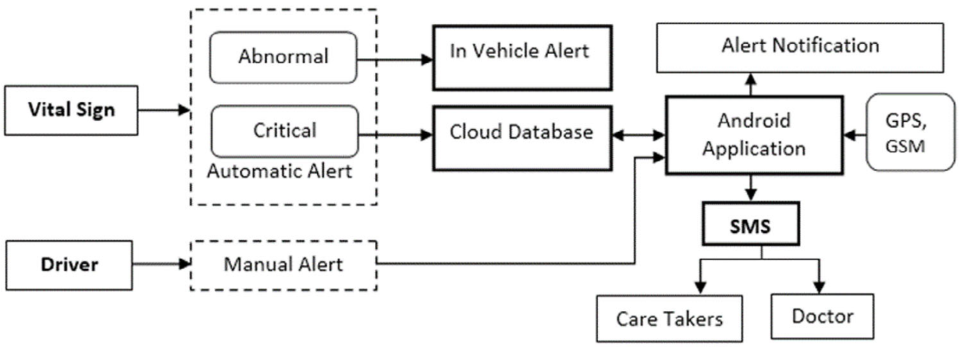


FIGURE 15 | Block diagram illustrating an automated alert system for abnormal and critical vital signs values, and a manual alert system for emergency scenarios.

for analysis. Various filters are available to remove noise from a signal such as low-pass filter, high-pass filter, band-pass filter, notch filter, Butterworth filter, Kalman filter, and so on. In this work, a band-pass filter is used that passes frequencies within a certain range and rejects frequencies outside that range. It could be either a digital or physical device filter that consists of combinations of resistors and capacitors. In this work, we used a Butterworth digital band-pass filter to eliminate 50 Hz/60 Hz noise. By using sampling frequency = 400 Hz, low-cut frequency = 1 Hz, high-cut frequency = 40 Hz, and order = 3. Figure 4a shows the noisy signal that is read by our device by implementing the aforementioned configuration of the Butterworth band-pass filter that gives a very smooth ECG signal (see Figure 4b). After removing noise from the raw ECG signal, to extract features for analysis, we used the Python Heart Rate Analysis toolkit (an open-source library [47],) to identify R peaks (see Figure 4c).

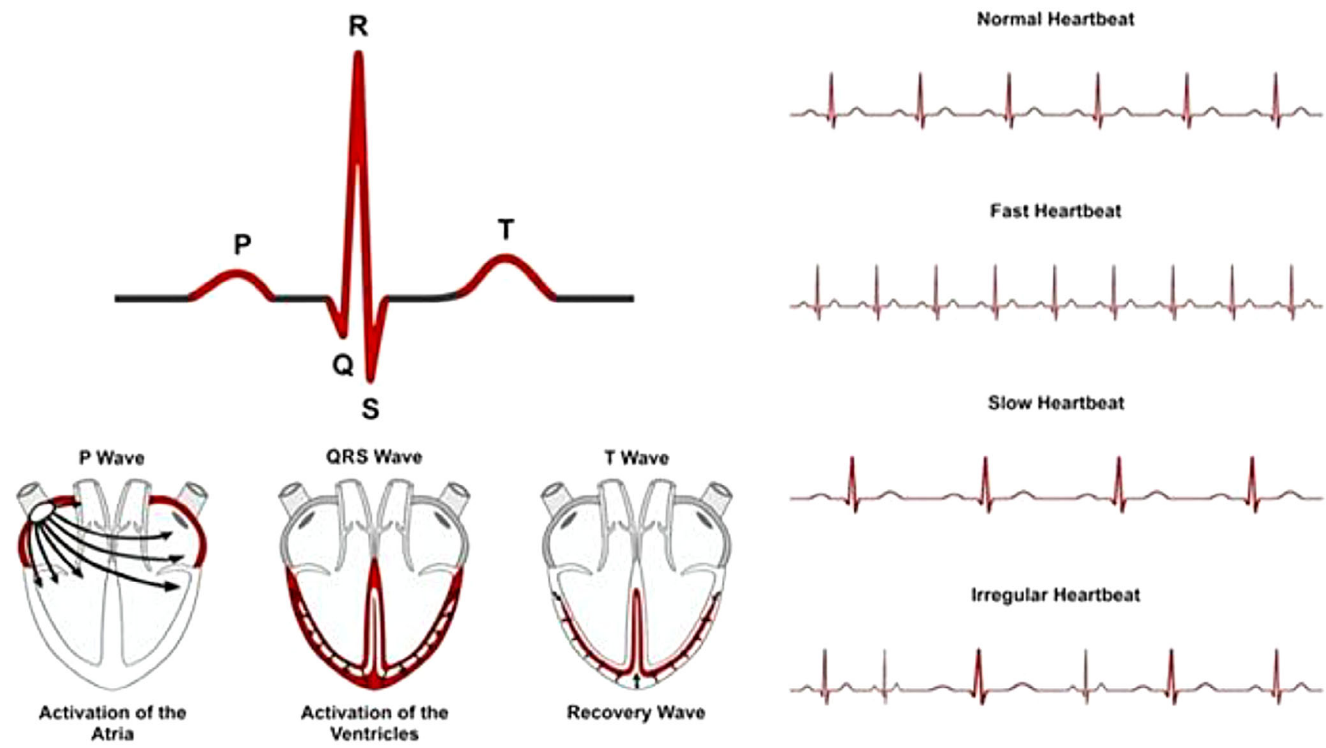


FIGURE 16 | Heartbeat with regular and irregular heart rhythms. Image taken from [57].

Moreover, invalid, and valid peaks are also identified. The toolkit is designed to handle noisy data but, in this case, we are providing pre-processed data to just find peak values through this toolkit. Furthermore, we used R-peaks to find the R–R interval difference to then measure the average R–R peaks difference to find out the threshold value that is used to identify the irregular rhythm of beats and their frequency of occurrence that can be used to identify irregular ECG rhythm [48] by using the following algorithm:

Step 1: Store all the retrieved valid peaks and store them in a linear array of peaks $[n]$.

$$peaks[n] = [a1,\ a2,\ a3,\ \dots\ an]$$

Step 2: Calculate the length of the peaks array.

$$len\_peaks = Len\,(peaks\,[n])$$

Step 3: Calculate the difference between adjacent peaks and store them in an array.

$$\text{peak\_difference}\,[j] = \text{peaks}\ \ [i+1]$$

$$-\text{peaks}\,[i]\ \ \text{for}\,i\,\text{inrange}\,(\text{len\_peaks} - 1)$$

Step 4: Find the mean of the peak differences and divide it by the total number of peaks.

$$\text{mean} = \sum_{\text{i}=1}^{n-1} \text{peak\_difference}\,[j] \div \text{len\_peaks for } j \text{ in range } (\text{len}\,(\text{peak\_difference}))$$

Step 5: Calculate the threshold value by dividing the mean value by 2.

$$\text{threshold} = \text{mean} \div 2$$

Step 6: Mark short and long R–R intervals using the threshold.
Step 7: Repeat Step 6 until all R–R mean values are compared with the threshold value ± upper and lower limits.
Step 8: Display the result.

For ECG signal acquisition and analysis, our script reads the raw ECG analogue signal. It reads ten thousand consecutive data points (ECG signal) and stores them in a .csv file if both ECG electrodes are intact with the body. If either of the electrodes is not properly attached to the body, the script assigns a value of '0' and does not write data points, clearing the array instead. After getting 10,000 data points (which is 667 samples per second), the infinite loop (for data acquisition) is terminated, and the control is passed to the signal filtering function. We specifically chose 10,000 data points as they yield approximately 15 to 20 heartbeats, providing sufficient data for ECG signal analysis based on empirical considerations. These signals can be obtained in 14 s when a driver is stable, and sensors are properly intact. Moreover, R peaks are identified to calculate the R–R interval which is used to calculate the mean threshold value to identify normal and abnormal ECG signals and, finally, the analysis is sent to the cloud database and fetched on a mobile application (see Figure 5).

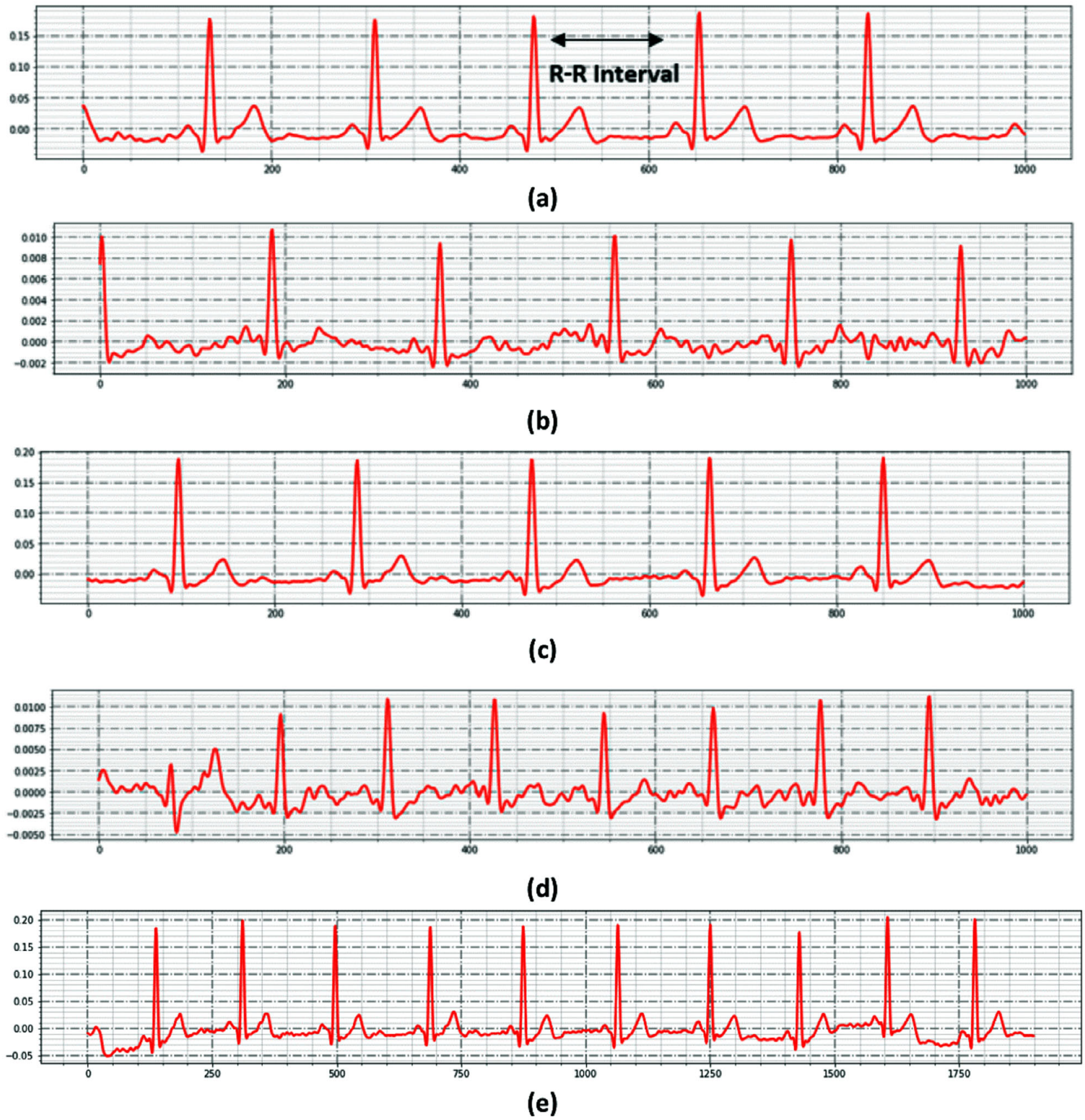


FIGURE 17 | ECG signal of five unique subjects (a–e) with no history of heart disease.

3.2.2 | Oxygen Saturation

This work used 'MAX30102,' an integrated pulse oximeter, and heart rate sensor that has two light emitting diodes (LEDs), a photodetector, a low-noise analogue signal processor, and optimized optics to detect pulse oximetry and heart-rate signals [49]. When the Python script is executed, the MAX30102 photodetector and LED light are turned on. Here the optical signal is converted into an electrical signal that generates analogue values to be stored in an array and processed by the MAX20102 library. We have used the default configuration of the MAX20102 library which includes a sampling rate of 400 and a sample average of 4. The script initializes the sensor to record raw values from an infrared and red LED which is processed to generate the average SpO2 level that is sent to the cloud database as shown in Figure 6 followed by a delay of 2 s this process goes on for continuous monitoring of oxygen saturation until the finger is placed on sensors. If a finger is removed from the sensor which is detected by the 'Interrupt (INT) pin,' the script will stop reading values until the finger is placed again on a sensor.

3.2.3 | Heart Rate

For heart rate measurement, a pulse sensor is used in the proposed system that can be attached to the ear lobe or fingertip. As there is no analogue GPIO pin in Raspberry Pi, an additional ADS1115 higher-precision analogue-to-digital (ADC) converter is

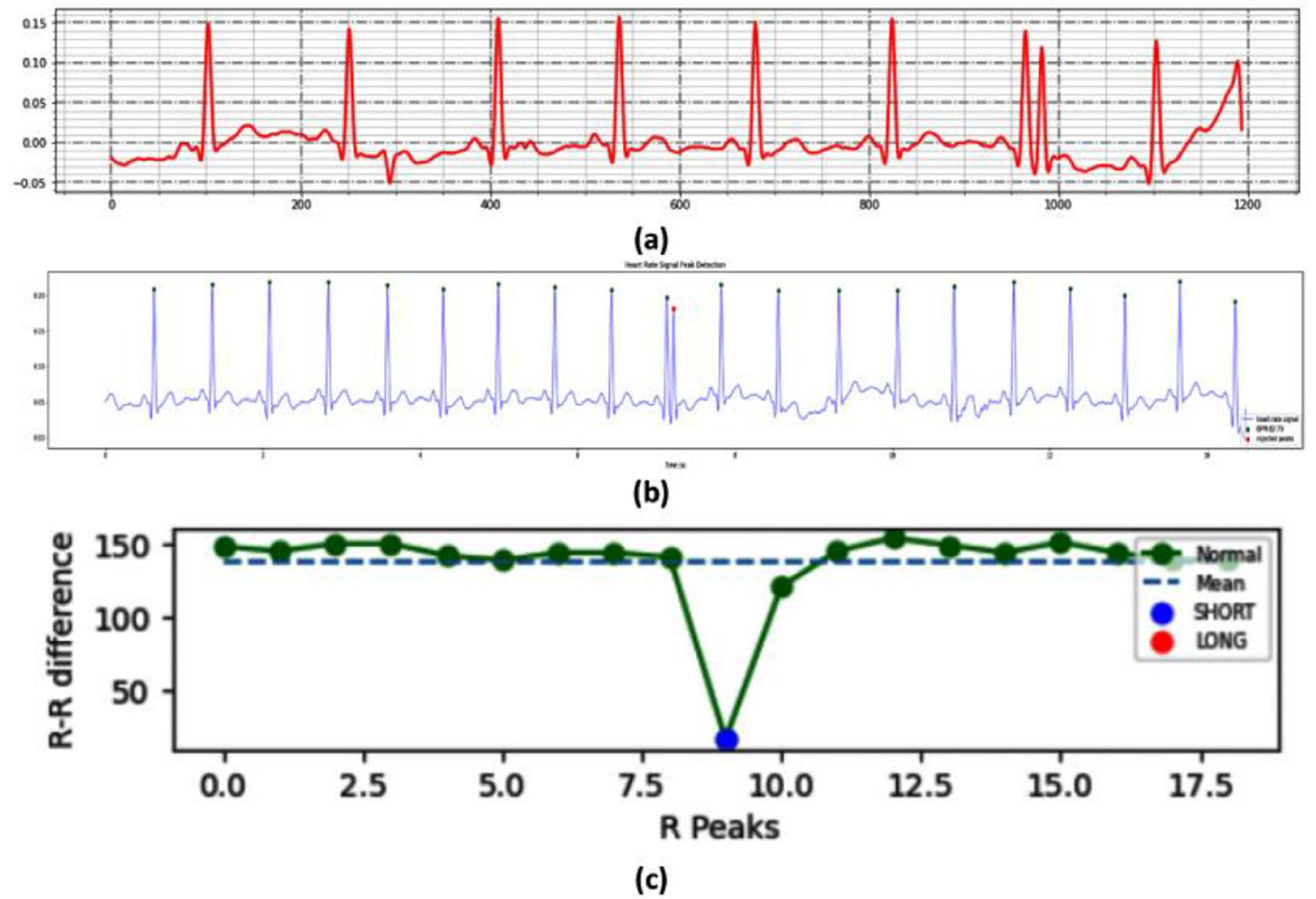


FIGURE 18 | Abnormal ECG with short R–R interval. (a) Filtered ECG signal by using Butterworth band-pass filter. (b) Detected R peaks. (c) Irregular R–R interval identification.

used between the heart rate sensor and Raspberry Pi. ADS1115 can be configured as four single-ended input channels with a programmable gain amplifier. Heart rate can be obtained from both the ECG sensor and pulse sensor. But the ECG sensor is not activated all the time and we want to measure heart rate continuously which is why we used a dedicated pulse sensor.

As the heart rate sensor is activated, the green light starts illuminating, thus indicating that the sensor is ready to read the heart rate to get accurate BPM data. It is important to have a fast and regular reading from the pulse sensor. By fast, we mean 500 Hz (1 sample every 2 ms) [50]. A dedicated sub-process is used for this purpose. We have used the Pulse Sensor playground library by Joel Murphy [51] which samples data at the rate of 250 samples per second by default. When a person places a finger on a sensor the optical signal is converted to an electrical signal, and we get an analogue value. Based on analogue value, the heartbeat is calculated by the aforementioned library and to get a stable heart rate our script stores heart rate value by checking three consecutive similar values that are to be sent to a cloud database which can be visualized on a mobile application (see Figure 7). Moreover, the sensor continuously reads analogue values to calculate heart rate and the process is continuous in a loop for real-time monitoring.

3.2.4 | Body Temperature

Body temperature is an indicator that shows the behaviour of the human body to respond to infection, inflammation, and trauma [52]. LM35 sensor is used for getting body temperature. LM35 series are precision integrated-circuit temperature devices with an output voltage linearly proportional to the Celsius temperature. The Python script reads voltage values from LM35 and directly converts them into Celsius linear scale factor, such that, if the temperature is 0°C, then the output voltage will also be 0 V. There will be a rise of 0.01 V (10 mV) for every degree Celsius rise in temperature. Our algorithm stores temperature (Celsius) values in a linear array continuously after every 1 s and checks if three consecutive values are the same, which ensures stable temperature to be taken and sent to the cloud database as depicted in Figure 8. This process goes on and the latest temperature value is updated on cloud database.

3.3 | Cloud Computing

The cloud computing module consists of a network and a storage layer that perform a set of operations. The network layer allows wireless connectivity by using the IEEE 802.11b standard. The

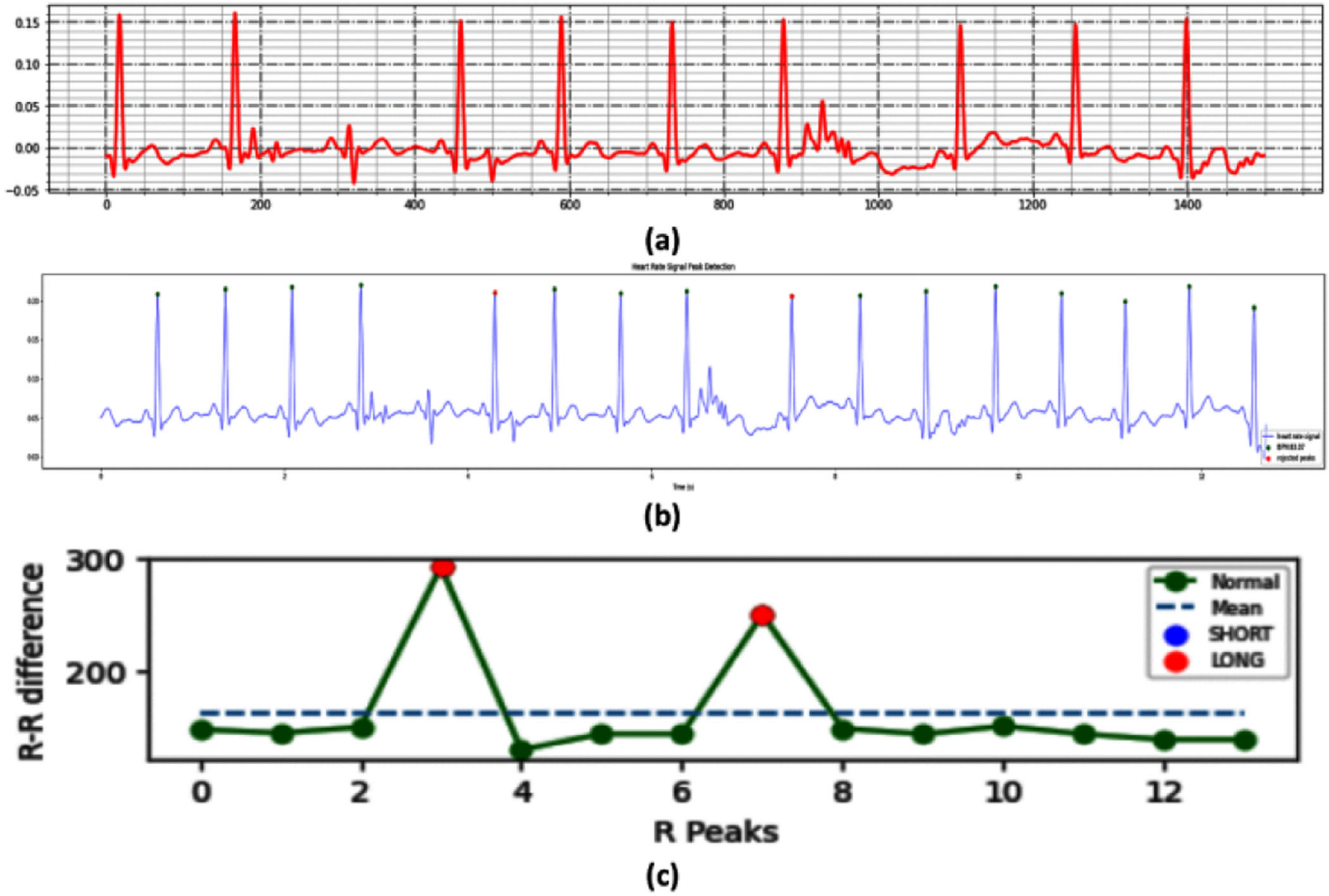


FIGURE 19 | Abnormal ECG with two long R–R intervals. (a) Filtered ECG signal. (b) Detected R peaks. (c) Irregular R–R interval identification.

storage layer is used to store and synchronize incoming data from both the DHMS device and mobile application. For this purpose, a cloud-hosted real-time database is used to store incoming data over the network in Jason format [53]. The data stored in JavaScript Object Notation (JSON) objects typically consists of key and value pairs, where the key serves as the unique identifier within the database, and the value contains the data being stored. Moreover, authentication, real-time database, and storage features of Firebase database are used for user authentication, vital sign real-time value storage/sync, and media storage respectively.

In this work, we created a database, named 'Driver Health Monitoring', and defined a data structure where our real-time database structure can be divided into two main nodes: driver and doctor, respectively. Driver node has a sub-node (JSON object) with the name of 'driver_registration' that generates a unique identity (ID) when the driver gets registered himself on the Android application and stores driver data in key/value along with vital signs node that creates key/value pairs for ECG state, oxygen saturation, heart rate, and temperature along with other information such as ECG time/date and image URL, as shown in Figure 9. The values keep updating in real-time as new data arrives and are synchronized with all the nodes (mobile applications). Any number of drivers can register on the Android application and the same JSON objects will be created for every driver.

For doctors, the same data structure is created, whereas, in the main node, there is a 'doctor_registration' sub-node that generates a unique ID for every doctor that registers himself on the Android application. Doctors can add drivers to visualize their vital signs. So, for this purpose, the 'assigned_drivers' node is created that stores general information about the driver. When a doctor adds a driver, the unique ID of the doctor is also stored in the driver's data. A doctor can add multiple drivers stored under the assigned driver's node as shown in Figure 10. In the Android application to add a driver, there is a button on the action bar. As the doctor presses that button, a new activity opens with a search bar, where the doctor needs to search for a driver using their email ID as a primary key. If the driver exists, it will show up with the add button. As the doctor clicks on the add button, they will be registered. And their real-time vital signs data will be visualized on the doctor's main screen. For login/sign-in, the Firebase authentication feature is used that authenticate the user based on email/password and user type (driver or doctor). The same database is configured and connected with the DHMS device that sends data to respective JASON objects.

3.4 | User Interface

The user interface is the block containing the application layer that provides an interactive interface where a user interacts to visualize vital signs with other functionalities. They can sign up,

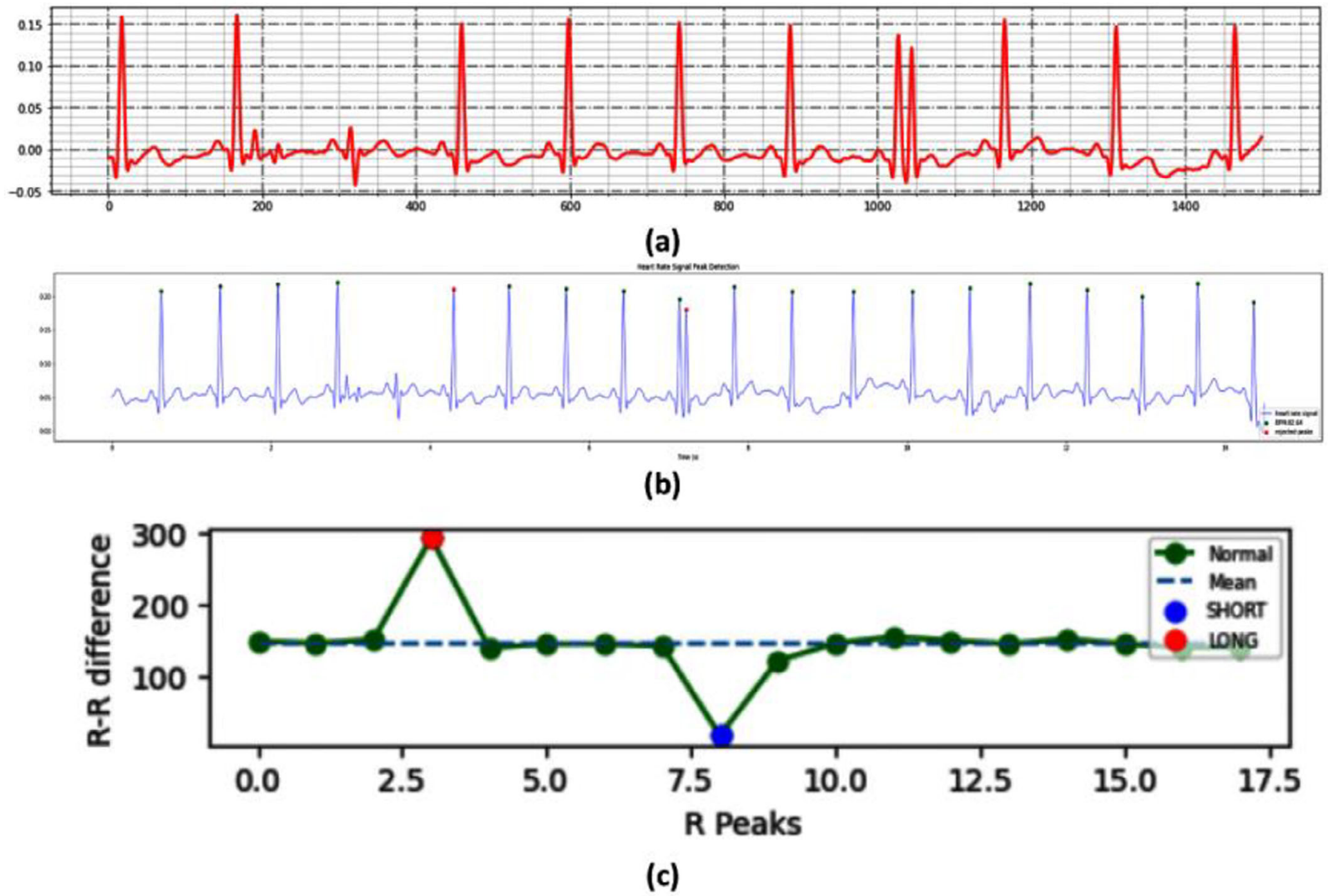


FIGURE 20 | Abnormal ECG with long and short R–R Intervals. (a) Filtered ECG signal. (b) Detected R peaks. (c) Irregular R–R interval identification.

sign in, and access the necessary functionalities, including real-time location, alert notification, alert status, and driver status, if applicable. All edge nodes that supply real-time data for numerous drivers are linked to and kept in sync with the Firebase real-time database.

With more than 2.5 billion active users across 190 countries, Android is the most widely used operating system in the world [54]. The Android application plays an important role in IoT-based driver monitoring systems.

3.4.1 | User Authentication

We developed a unified application both for the driver and the doctor (referred to as a user). When a user starts the application, the first screen of the application allows them to log in to the application or sign up as shown in Figure 11a,b. To sign up, when the user enters their information such as name, email ID, password, contact number, city, age, and profile image, and then presses the sign-up button, the information is stored in a cloud database, that is the Firebase, in this case. Afterwards, when the user uses the same credentials to log in (email ID and password), the information is authenticated through the cloud database using the Firebase authentication feature; if it is a valid user, the control goes to the main activity. The user can also click on the remember checkbox on the login screen to avoid retyping the email ID every time and if the user forgets the password, they can recover it by using the 'forget a password' feature as shown in Figure 11c. A new activity is opened, where the user needs to enter the same email ID as used at the time of creating an account and press submit. A recovery email is sent to their email box. When the user clicks on the link a new activity is opened and requests to reset the password.

The driver's main activity (home screen) provides necessary functionalities to the driver. The main activity screen can be divided into four sections as shown in Figure 12a, namely the action bar, information section, vital sign section, and bottom navigation bar. The action bar contains a sync and menu button, which fetches real-time data from the cloud database in case of an internet interruption. There is another tab in the menu that shows the registered doctor profile if any (see Figure 13c). The driver can also add a doctor so that the driver's vital signs can be monitored by a doctor remotely in case of a medical emergency and for quick assistance. Below the action bar, there is an information section that shows a user profile picture with their name and vital signs information fetched from the cloud database along with an emergency button for a manual alert. In this section, health status is marked based on vital signs readings as normal, abnormal, or critical, and compared with standard threshold values, which the user can check and take into

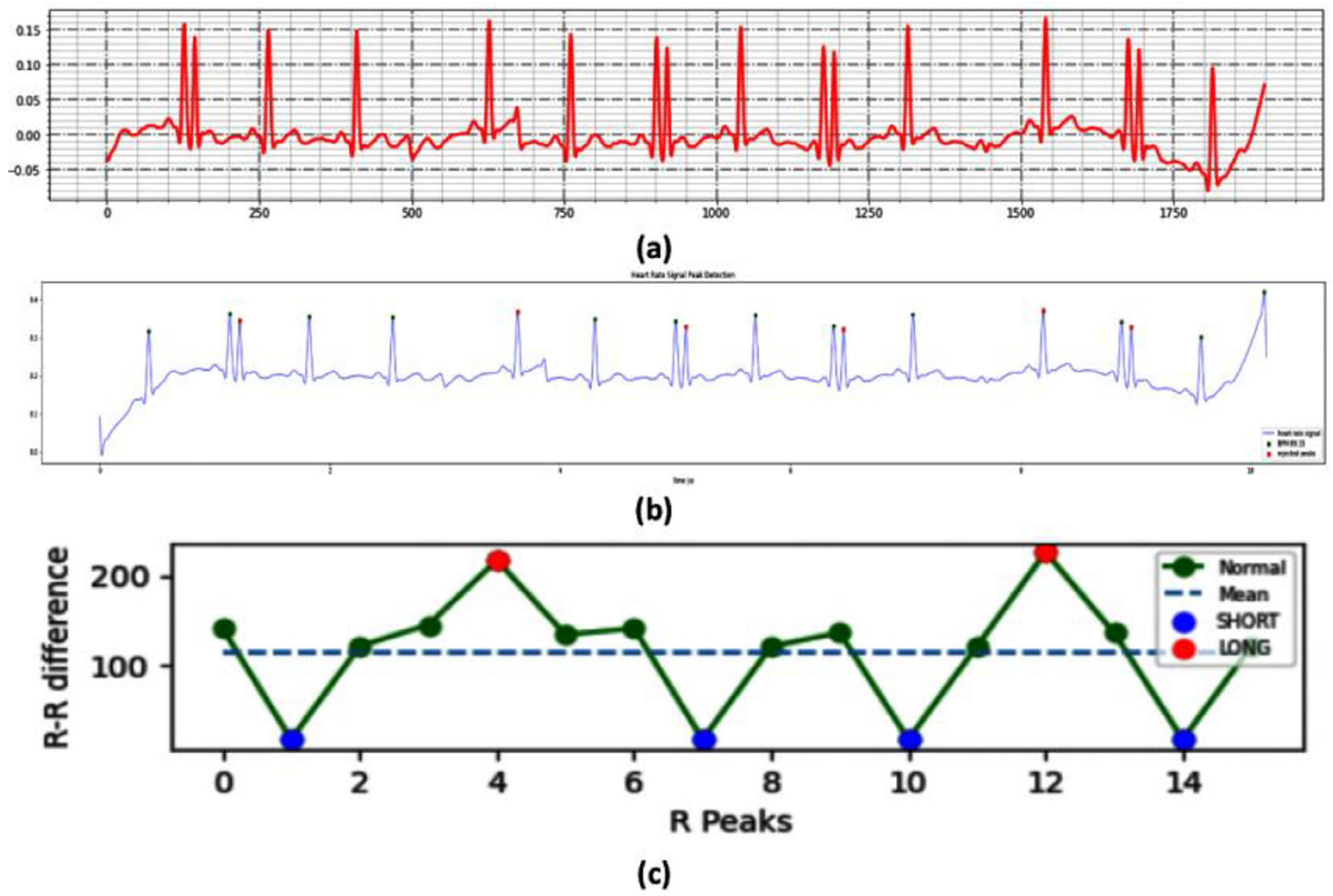


FIGURE 21 | Abnormal ECG with long and short R–R interval combination. (a) Filtered ECG signal. (b) Detected R peaks. (c) Irregular R-R interval identification.

consideration for early detection of abnormality if any. Below the information section, there is a vital sign section. It shows ECG, oxygen saturation, heart rate, and body temperature values on interactive progress bars, where the ECG graph can be scrolled left/ right and can also be zoomed in/out to have better insights. The ECG recorded date and time are also mentioned with the ECG. Moreover, there is a navigation bar at the bottom of the main screen with 5 buttons: the first four buttons (left to right) are vital signs buttons that show general information about vital signs; the fifth button on the bottom navigation bar is the setting button. When the user presses this button, a new activity opens as shown in Figure 12b. In this activity, the user can enter the contact number of the caretaker and physician to whom the emergency message needs to be sent. They can save and edit any contact details later on as needed. Below this section, there are configuration toggle buttons to enable and disable the emergency alert, alert notification, alert background service, location (GPS), and emergency SMS. The driver can also enable and disable any vital sign tracking for emergency alerts. For example, they can disable the temperature sensor to avoid false alerts due to surrounding temperature or sensor malfunction. The application configuration feature provides an easy to customize application features. There is also a voice prompt emergency activity that pops up (see Figure 12c to get confirmation feedback from the user to send an emergency message. If the user says ‘yes’, the emergency message and notification are sent to the caretaker and doctor.

The background service is something that does not have a user interface, but it runs in the background all the time as it gets started (enabled). In this application background service is used for background vital sign tracking and emergency alert. Even if the application is not launched, background service will keep tracking vital signs and trigger an emergency alert through SMS if vital sign exceeds the abnormal threshold. In case of a medical emergency, a driver can also trigger a manual alert by pressing and holding the emergency button for two seconds (see Figure 12a). An emergency message will be compiled by including recent vital signs data along with the current location and sent to the caretaker and doctor, as depicted in Figure 13a. Doctors and caretakers can track the driver’s location by pressing on the link in the received SMS for quick emergency response. As the driver/caretaker clicks on the link, Google Maps will open up and get the current location of the caretaker/ driver and draw a path toward the driver’s location automatically, as shown in Figure 13b. Hence, it is a user-friendly and customizable application for a driver to visualize vital signs on an interactive mobile interface along with other necessary features.

3.4.2 | Doctor’s App Features

As a doctor launches the application, the first activity that shows after the splash screen is login activity, where a doctor can either

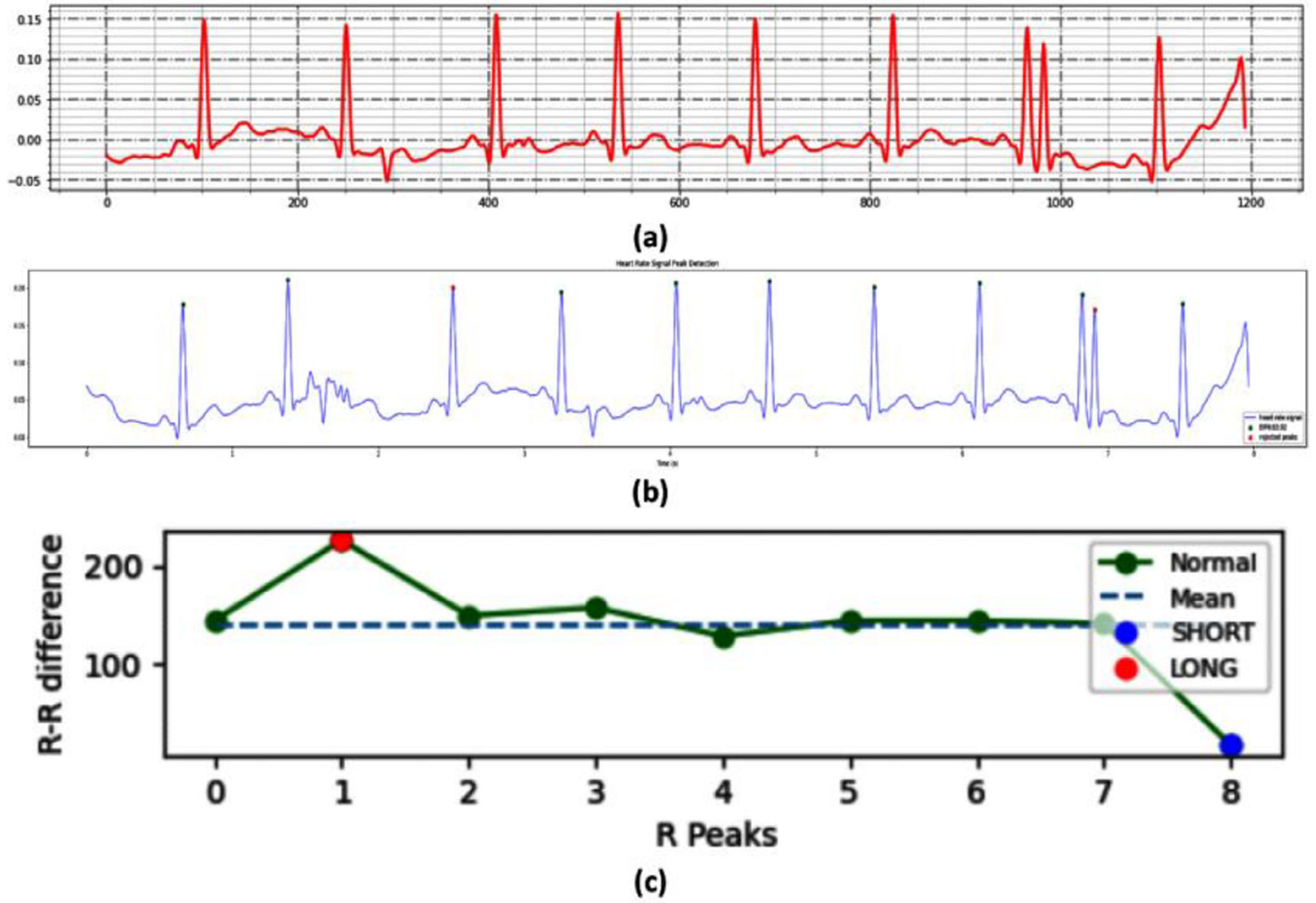


FIGURE 22 | Abnormal ECG with one long and one short R–R interval. (a) Filtered ECG signal. (b) Detected R peaks. (c) Irregular R–R interval identification.

log in by selecting 'login as a doctor' along with their email ID and password or they can sign up by filling in the required information. The initial login, sign-up, remember, and forget password procedure is the same for both driver and doctor, as aforementioned in Figure 11a–c. After registration, when the doctor enters the credential into the login activity and selects login as a doctor, the authentication is performed by using Firebase authentication. If it is a legitimate user, the main activity will open for a doctor with related functionalities. The main activity can be divided into four sections as shown in Figure 14a. Top to down, there is an action bar containing the sync and add driver button, followed by the driver profile section that contains their profile picture and name with the edit profile button on the top left corner. Here they can add their details further details like specialization, qualification, experience, hospital name, languages they understand, their location, and contact details. Below this section, there is a registered drivers list with a scroll bar to scroll up and down to navigate drivers followed by a vital sign section. As the doctor clicks on any driver in the list, vital signs and details of that driver are fetched from the cloud database and displayed in this section, which includes an ECG picture with data and time, heart rate, oxygen saturation level, and body temperature. Here the doctor can scroll left/right and also zoom in/out the ECG to have better insights for investigation. Moreover, the sync button (on the action bar) is used to refresh/synchronize data from the cloud database in case of a lost network connection.

Moreover, the action bar contains a sync button to fetch updated data from a cloud database and add a button to add a doctor by searching their email or name, as shown in Figure 14b,c, where a driver can add a doctor. So, they can visualize the driver's vital signs in the main activity. A doctor can add multiple drivers using the same process and in case of a medical emergency, they can monitor the registered driver's health status remotely to visualize vital signs on a mobile application for quick response. Moreover, the doctor can also delete drivers by using the same process to search drivers in this activity, and by pressing the remove button (if already added), the driver will be removed. Doctor application provides necessary features to remotely monitor a driver's health status for early detection of abnormalities based on vital signs.

3.4.3 | Alert System

The proposed system detects abnormal health conditions based on vital signs that act as early detection of abnormality that might lead to road accidents. The system warns the driver not to drive if the vital sign value exceeds the abnormal/critical threshold (medical standard values) and early detection of abnormality reduces health complications by seeking medical attention before getting into the critical stage. The alert system is categorized into two main types automated and manual, as shown in Figure 15. The automated alert is triggered when vital sign values exceed the medical standard threshold values, while the manual is triggered by the driver himself when they want to seek help in a medical emergency or accident. Vital sign values (such as ECG, SpO2, heart rate, and temperature) are categorized into normal, abnormal, and critical based on pre-defined medical standard threshold values. In an automated alert system, if a vital sign value is abnormal, an in-vehicle alert will be triggered to inform the driver, to avoid driving, which might lead to an accident or medical emergency. For critical vital sign values, an alert gets triggered automatically by binding an emergency message with location (using mobile GPS, GSM) and vital signs information to caretakers and physicians to take timely action in case of a medical emergency. The doctor/caretaker can track the location of the driver to reach for quick aid. Moreover, a doctor can also consult the driver and visualize their vital signs information, especially ECG, remotely. On manual emergency alert, the emergency SMS will be sent to the caretaker and doctor with the driver's current location and recent vital signs values. In the Android application, a driver can customize alert settings by enabling or disabling notification alerts, GPS, and SMS.

4 | Results and Analysis

In this section, the experimental results of DHMS are analysed and evaluated. Different biosensors such as ECG, oxygen saturation, heart rate, and temperature are tested, and their results are compared with medical standard devices on ten different subjects. Note that informed consent has been taken from the subjects regarding the usage of the data for this study. First, we analyse the ECG signal for normal and abnormal data (Section 4.1), which is followed by testing and evaluation of the oxygen saturation, heart rate, and body temperature analysis (Section 4.2), alert system (Section 4.3), and android application (Section 4.4).

4.1 | ECG Analysis

Heart arrhythmia is an irregular heartbeat pattern that can be identified by analysing the R–R interval on an ECG graph [55]. Heart rhythm occurs when the electrical signals that coordinate the heart's beats do not work properly. The faulty signal causes the heart to beat too fast (tachycardia), too slow (bradycardia), or irregularly (arrhythmia) [56]. Figure 16 shows the heartbeat cycle (polarization, depolarization, and repolarization) along with normal, slow, fast, and irregular ECG patterns. The heart rhythm (normal, slow, fast, irregular) can be identified by analysing the R–R peak interval. For normal, slow, and fast heart rhythms, the R–R peaks have approximately the same interval. In the case of irregular heart rhythms, R–R peaks do not have the same ratio. Based on heart rate, we can identify bradycardia (if heartbeat < 60) and tachycardia (if heartbeat > 100). But if the heart rate is in the normal range and there is an irregular heartbeat rhythm, which cannot be identified by heartbeat count. For that, we developed the aforementioned algorithm (see Sec. III-B-1) for detecting irregular R–R intervals (also called arrhythmia) based on ECG R–R interval analysis.

We examined both normal and abnormal ECG data to test the proposed method for detecting irregular rhythm (arrhythmia). The experiments were conducted on five healthy people (male/female, age range 27–56 years) with no history of heart diseases by using a DHMS device. Note that informed consent was taken from the subjects for data usage in this study. The results are analysed by using an arrhythmia detection algorithm to find irregular heart rhythms if any. Figure 17a is the ECG of a 27-year-old male subject, in which no irregular heart rhythm is detected. Hence, it is marked as a normal ECG by the proposed algorithm. From the qualitative results, we can analyse where all the R–R intervals have the same ratio in the ECG graph. Furthermore, Figure 17b is the representation of 30-year-old male with no abnormality, so it is marked as a normal ECG. Figure 17c is the ECG of a 55-year-old female in which no abnormality is detected, which is a normal ECG. Figure 17d is the ECG of 25-year-old male in which no abnormality is detected. Figure 17e is the ECG of 56-year-old male and is marked as a normal ECG. Hence, the proposed algorithm tested with normal ECG data did not give any misclassification.

Irregular heart rhythm (also known as arrhythmia) occurs when the heart's electrical signals do not work properly and it is detected by processing raw ECG signal to remove noise by applying the Butterworth band-pass filter followed by R peaks detection using the heartpy library, where R peaks are identified and processed through the aforementioned proposed algorithm (see Section 3.2.1) to detect arrhythmias.

The irregular heartbeat rhythm is tested by using **3**. We recorded the ECG of a normal person and manually introduced long and short R–R intervals to make it irregular (arrhythmia). We generated five different combinations of ECG patterns from normal ECG data. That includes short, long, and a combination of the short-long R–R interval. Our algorithm calculates the average mean of R peaks to find a mean value. Afterwards, every R–R interval is compared with a threshold value to detect short and long R–R intervals. If the R–R interval of the ECG graph is less than 50% (set empirically) of the threshold value, it will be considered a short R–R interval; whereas, if the R–R interval is greater than 50% of the average mean value, it is marked as a long R–R interval. Our Python script reads raw ECG signal data from sensors for 15 s, then pre-processing is performed to remove noise by using the Butterworth band-pass filter to get smooth ECG, and then the filtered signal is used to detect R peaks. At this point, we get the R peaks values and then the R–R peaks difference is accordingly calculated. Based on the R–R difference value, the average mean value is calculated, and a threshold value is formulated to check the irregular rhythm of the heart. Figure 18a is the representation of an abnormal heart rhythm in which a short R–R interval is detected. We can notice in Figure 18b that R peaks are correctly detected. The R peaks that have been detected are utilized to calculate the R–R interval values, which are then utilized to determine the mean threshold value to detect short and long R–R intervals (see Figure 18c).

$$x = \left(\sum_{i=1}^{n-1} (\mathrm{peak}[i+1] - \mathrm{peak}[i]) \div \text{total peaks } [n] \right) /2 \qquad (3)$$

Another representation of an irregular heart rhythm is depicted in Figure 19a, where all the R peaks are correctly detected (see Figure 19b**),** and based on the R–R interval, two long R–R intervals are detected (see Figure 19c).

Figure 20a is the representation of another irregular heart rhythm in which one short R–R interval and one long R–R interval are detected (see Figure 20b) and classified as irregular heart rhythm. Irregular heartbeats are correctly classified as long and short beats (see Figure 20c).

Figure 21a,b is the representation of another irregular heart rhythm in which four short R–R intervals and two long R–R intervals are detected and classified as irregular heart rhythm (see Figure 21c).

Figure 22a,b is the representation of another irregular heart rhythm in which one long R–R interval and one short R–R interval are detected and classified as irregular heart rhythm (see Figure 22c).

4.2 | Oxygen Saturation, Heart Rate, and Body Temperature Analysis

The experiments were conducted on ten different subjects (P1–P10), both male and female, with ages ranging from 25 to 56 and no prior history of lung or heart illness. An oxygen saturation test was performed, and readings were analysed on these subjects by both a medical standard device and the proposed DHMS, as shown in Table 3. The results of the medical standard device are taken as true values and compared with DHMS results to find the difference between measured values and actual values, the mean absolute error is calculated, and accuracy is analysed. Mean absolute error (MAE) was calculated using the given Formula (4), where yi is the prediction, xi is a true value, and n is the total number of data points. For oxygen saturation analysis on ten subjects (P1–P10), MAE = 1.3 is calculated, which shows results are approximately close to a medical standard device.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |yi - xi| \tag{4}$$

The normal heart rate is between 60–100 beats per minute. The heart rate of ten subjects (P1–P10) is tested by using a medical standard device, DHMS pulse sensor, and DHMS ECG sensor, and the results are provided in Table 3. The results of the medical standard device are taken as true values and compared with the DHMS pulse sensor and ECG sensor values. MAE of the ECG sensor reading is 1.5 and that of the pulse sensor is 2.2.

The LM35 temperature sensor of DHMS and medical standard devices (infrared, thermometer) is used to determine the axillary temperature. In this experiment, ten different people are chosen as the test subjects to measure temperature. The measurement was repeated three times, and the obtained average results are given in Table 3. As the temperature of different body parts is slightly different. Generally, a temperature rise of 2°F above the normal body temperature is regarded as a sign of fever. Usually, a mercury thermometer is used under the armpit or in the mouth and an infrared thermometer is used to measure from the hand and forehead. We used the LM35 sensor to measure temperature from the hand palm which shows 1.6 to 2.3°F less than the temperature measured with a mercury thermometer under the armpit. So, we added a mean difference value of 1.95°F to normalize the temperature measured from the hand palm. The results of the medical standard device are taken as true values and compared with infrared and DHMS readings and MAE is accordingly calculated. MAE of 0.58 and 2.3°F is detected on infrared and DHMS LM35 sensors, respectively. The results are approximately close with few variations with the medical standard device. Moreover, an Infrared thermometer gives stable readings more quickly as compared to mercury and DHMS devices, and the results of infrared and mercury were more stable as compared to LM35 because the voltage output causes the inaccuracy of the LM35, resulting in the fluctuation in the body temperature reading (MAE = 2.3°F). Thus, a better temperature sensor with IoT infrastructure could be used to enhance the reliability of the system.

4.3 | Alert System Analysis

Vital sign values are categorized depending on the severity into three different categories such as normal, abnormal, and critical, as shown in Table 4. Oxygen saturation's normal range is between 96% and 100%, the abnormal range is between 85% and 95%, and the critical range is below 85% [58], which is a medical emergency and indicates lungs might not be functioning well and might lead to unconsciousness.

While the ECG and heart rate normal range is between 60–100 BPM, the abnormal range is between 55 and 60 BPM and 100 and 110 BPM, and critical values above 110 BPM and below 55 BPM show tachycardia and bradycardia [59, 60] respectively. Moreover, irregular heart rhythm is also a medical emergency and is taken into the critical category to seek medical attention. Furthermore, the temperature normal range is between 97.7 and 99.5°F, the abnormal range is between 99.5 and 100.9°F, and the critical range is between 104.0–106°F [61], which indicates the abnormal function of the human body. Thus, based on these standard threshold values, alerts or warnings are triggered to prevent road accidents by seeking medical attention early.

The emergency alert system is categorized into abnormal and critical alerts depending on the medical standard vital sign values range (see Table 5). An abnormal alert triggers an in-vehicle warning by using a buzzer sound and LED blinking, which informs the driver to not drive and to seek medical attention to avoid further medical complications.

Critical alert triggers app notification and sends an emergency message along with GPS location and vital sign values to care-takers and physicians to get immediate medical attention. This could potentially avoid road accidents due to medical conditions and would save human life by seeking immediate health care attention. There is also a manual alert (that also works like a critical alert) feature. It can be used by a driver to trigger an alert if they intend to seek help. To trigger this alert, the driver needs to press the emergency button for two seconds on the main activity of the application.

The alert system was tested several times by using the DHMS device on normal people and abnormal data was given manually for testing abnormal and critical values to trigger warning and alert, respectively. The alert system gives us accurate results by

TABLE 3 | Oxygen saturation, heart rate, and body temperature analysis between the medical standard device and DHMS.

Person	**Oxygen saturation**		**Heart rate**			**Body temperature**		
Male/female	**Medical devices**	**DHMS Sensor**	**Medical devices**	**DHMS ECG sensor**	**DHMS heart rate sensor**	**Mercury (°F)**	**Infrared (°F)**	**DHMS LM35 (°F)**
P1	**93**	93	**62**	63	64	**98**	98.3	99
P2	**94**	95	**71**	69	72	**97**	97.3	98
P3	**94**	92	**57**	58	59	**98**	98.7	94
P4	**95**	93	**74**	72	74	**97**	98.2	94
P5	**94**	96	**68**	66	64	**99**	98.0	97
P6	**94**	95	**64**	66	67	**95**	96.0	98
P7	**95**	95	**78**	80	79	**97**	97.5	94
P8	**96**	97	**72**	74	75	**97**	97.0	95
P9	**94**	97	**68**	68	71	**95**	95.5	97
P10	**95**	96	**71**	73	74	**98**	98.3	96
Mean absolute error		1.3	—	1.5	2.2		0.58	2.3

TABLE 4 | Vital signs—normal, abnormal, and critical values along with their indicators.

Vital sign	Indicator	Range		Status
Oxygen saturation	Normal	96%–100%		Normal
	Concerning blood oxygen saturation level	91%–95%		Abnormal
	The low oxygen saturation level	86%–90%		Abnormal
	Low oxygen saturation levels might affect the brain	80%–85%		Critical
	Cyanosis	≤67		Critical
Temperature		Celsius	Fahrenheit	
	Hypothermia	<35°C	<95.0°F	Abnormal
	Normal	36.5–37.5°C	97.7–99.5°F	Normal
	Fever/Hyperthermia	>37.5 or 38.3°C	>99.5–100.9°F	Abnormal
	Hyperpyrexia	>40.0 or 41.5°C	>104.0–106°F	Critical
ECG and heart rate		Heart rate (hr)		
	Normal	60–100		Normal
	Bradycardia	55 ≥ hr ≤ 60		Abnormal
	Bradycardia	<55		Critical
	Tachycardia	100 ≥ hr ≤ 110		Abnormal
	Tachycardia	>110		Critical
		Irregular rhythm		Critical

TABLE 5 | Alert system categorization based on abnormal and critical threshold values.

Indicator	Vital sign	Range
Normal	Oxygen saturation	96–100%
	Temperature	97.7–99.5°F
	ECG and heart rate	60–100
Abnormal	Oxygen saturation	91%–95%
	Temperature	<95.0°F and >99.5–100.9°F
	ECG and heart rate	55 ≥ hr ≤ 60 and 100 ≥ hr ≤ 110
Critical	Oxygen saturation	≤85
	Temperature	>104.0–106°F
	ECG and heart rate	hr < 55 and hr > 110 and irregular rhythm
Critical	Triggered manually by pressing the emergency button on the Android application to seek medical attention	

triggering warnings on abnormal values and alerts on critical values. Figure 12a shows an emergency message along with vital sign values and the current location that caretakers and physicians received as an emergency message, where they could track location on Google Maps by pressing the link in the received message. As the doctor or caretaker presses the location link, the Google Maps application opens and gets the current location to draw a path toward the driver's location. Hence, the alert system works well in real time. To avoid the false alert on critical vital signs detection, there is a confirmation through voice command that asks the driver: 'Critical state detected. Do you want to trigger an alert?' If a person replies 'yes' via voice prompt, it triggers an emergency alert within, or the emergency button on the Android application can be used. In this way, we can avoid false alerts.

4.4 | Mobile Application Analysis

Mobile applications have three main modules: (1) registration module, (2) vital sign module, and (3) alert module, which perform a set of functionalities. Android application is developed by using Android studio IDE, where different libraries were used for implementation of Firebase, GPS, SMS, etc., and background service that allows the application to read data from a cloud database even if the application is not active. The following are the main modules: The registration module allows the driver and doctor to register on the application and by using the same credentials, the user can log in and authentication is done by Firebase authentication which is a service by Google's Firebase platform enabling easy integration of secure user sign-up and sign-in functionalities, supporting various methods like email/password, phone number, and third-party providers for web, iOS, and Android applications. The registration details are stored in Firebase's real-time database. Moreover, the users can save the password to avoid typing it again and again, and they can also recover the password using the 'forgot password' option, when needed. Several accounts have been created and tested that only allow legitimate users to log in. Other application functionalities are tested to perform required operations seamlessly in real time. The vital sign module enables a driver to visualize their vital signs on the application and it also enables a doctor to visualize the vital signs of registered drivers. This module fetches vital sign data in real time and displays it in graphical form on the main screen that displays ECG with horizontal sliding functionality along with ECG signal and time. It also allows zooming in/out by pinching on the screen to visualize ECG more clearly within a region of interest. The heart rate and oxygen saturation data are displayed in a round progress bar along with values, and the temperature data (in Fahrenheit) is displayed in a linear progress bar. The real-time vital sign values are displayed and refreshed as the control enters the main screen. Meanwhile, users can refresh by clicking on the sync button to get real-time data from the cloud database in case of a network interruption. Moreover, the bottom navigation bar is implemented that shows necessary information about every individual's vital signs that a driver should know for taking preventive measures in case of emergency.

The alert system module continuously checks for abnormal and critical values of vital signs. It works both in the foreground (when a user launches the application) as well as in the background even if the application is not launched. Moreover, users can customize settings to enable and disable SMS, GPS, background service, mobile alerts, and notifications, and also customize vital signs' critical value tracking. Thus, the user can enable and disable any vital sign tracking to avoid alerts; for example, if the temperature sensor is malfunctioning due to the vehicle's internal temperature in winter or summer when using the heater and air-conditioning, respectively, the driver can customize the setting to avoid false alert. Alert system modules provide a fully customizable function that plays an important role in triggering alerts on predefined threshold values for every individual model.

5 | Conclusions

This paper presented the design and validation of a holistic end-to-end IoMT-based non-invasive DHMS, to minimize health-related accidents by considering the important vital signs such as ECG/EKG, oxygen saturation, heart rate, and body temperature to detect abnormal health conditions such as bradycardia, tachycardia, arrhythmia, hypoxia, and hyperthermia, with appropriate sensor placement on the steering wheel. The system is categorized into four key building blocks, including embedded system, edge computing, cloud computing, and user interface to visualize vital sign information interactively with the alert system.

In contrast to previous work, the proposed solution uses Internet of Things infrastructure to provide a more comprehensive and efficient end-to-end framework that includes alert systems, and remote monitoring. We performed edge computing utilizing a commercial off-the-shelf board to reduce the effects of throughput, latency, and packet loss issues. This work relies on vital signs monitoring and it is particularly suited for elderly people and people with medical conditions and can also be used for public transport to ensure the safety of passengers.

The DHMS's experimental results, validated against standard medical devices, demonstrate its promising performance. It achieved MAE values of 0.58°F (infrared) and 2.3°F (LM35) for temperature, 1.3 for oxygen saturation, 1.5 (ECG sensor), and 2.2 (heart rate sensor) for heart rate, closely matching those of the medical standard device with slight variations.

We identified a limitation in the proposed design regarding inaccurate ECG electrode positioning with different steering holding styles, which could be addressed in future work in terms of designing an electrode array or integrating the framework with an ECG wristband.

Future work could also focus on designing a hybrid model based on a fusion of the physiological (ECG, heart rate, etc.) and visual cues [62] by employing deep-learning models. Moreover, we aim to focus on developing data protection mechanisms by using data encryption techniques at the data level and the deployment of federated learning and fog computing at the framework level.

AUTHOR CONTRIBUTIONS

Muhammad Adil Khan: conceptualization, formal analysis, investigation, methodology, software, validation, visualization, writing – original draft. **Mu Chen**: conceptualization, methodology, project administration, resources, supervision, writing – review and editing. **Tahir Nawaz**: supervision, validation, visualization, writing – review and editing. **Mohamed Sedky**: formal analysis; supervision; writing – review and editing. **Muhammad Sheikh**: supervision; writing – review and editing. **Ali Kashif Bashir**: methodology, supervision, writing – review and editing. **Sohail Hassan**: formal analysis, supervision, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Research data are not shared.

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