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IoT-based emergency cardiac death risk rescue alert system

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A R T I C L E I N F O

Method name:
ECG-Based Alert System for Cardiac Death Risk Rescue

Keywords:
Electrocardiogram
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Wearables
Edge computing

A B S T R A C T

The use of technology in healthcare is one of the most critical application areas today. With the development of medical applications, people's quality of life has improved. However, it is impractical and unnecessary for medium-risk people to receive specialized daily hospital monitoring. Due to their health status, they will be exposed to a high risk of severe health damage or even life-threatening conditions without monitoring. Therefore, remote, real-time, low-cost, wearable, and effective monitoring is ideal for this problem. Many researchers mentioned that their studies could use electrocardiogram (ECG) detection to discover emergencies. However, how to respond to discovered emergencies in household life is still a research gap in this field.

- This paper proposes a real-time monitoring of ECG signals and sending them to the cloud for Sudden Cardiac Death (SCD) prediction.
- Unlike previous studies, the proposed system has an additional emergency response mechanism to alert nearby community healthcare workers when SCD is predicted to occur.

Specifications table

Subject area:	*Engineering*
More specific subject area:	*Healthcare*
Name of your method:	ECG-Based Alert System for Cardiac Death Risk Rescue
Name and reference of original method:	NA
Resource availability:	The authors can make the data available upon a reasonable request

Background

The occurrence of Sudden Cardiac Death (SCD) among adults in the general population varies between 40 and 100 out of every 100,000 individuals [1]. SCD causes the deaths of approximately 4.25 million people worldwide yearly, and about 250,000 to 300,000 humans die each year in the United States because of SCD [2].

SCD can cause the death of people within minutes [2], and if there are no paramedics or Automated External Defibrillator (AED) devices around when SCD occurs, a life that should have been saved is lost. However, there are traces of SCD before it happens, such as myocardial injury marker tests, serum plum tests, genetic screening, and electrocardiograms. The first two are biochemical methods that are slow and difficult to track, and genetic processes are even more complex and expensive. The one that can be directly and

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effectively followed in real-time is the electrocardiogram (ECG) test. Below, we provide several examples demonstrating the effective use of ECG in diagnosing cardiac issues.

Shen et al. achieved a correct detection rate of 87.5 % using wavelet analysis, which was higher compared to the accuracy rates of decision neural networks at 67.44 % and back-propagation neural networks at 58.14 % [3]. Sanchez et al. proposed a method for analyzing ECG signals that can predict the probability of sudden cardiac death (SCD) 20 min in advance, achieving an accuracy of 95.8 % [4]. However, these life-saving prediction algorithms are not applied to real-time monitoring scenarios. Recently, there have been several research studies focused on the combination of ECG diagnosis techniques with Internet of Things (IoT) technologies. These studies explore how integrating IoT devices can enhance the real-time monitoring and analysis of ECG signals, potentially leading to improved detection and prevention of cardiac events. The research aims to leverage the connectivity and data processing capabilities of IoT systems to create more responsive and efficient healthcare solutions. For example, Xu et al. provided an IoT-Assisted ECG monitoring framework for analysis and diagnosis [5], and Huang et al. developed a privacy-preserving ECG-based IoT practice [6]. Raheja et al. explored an ECG monitoring system combined with IoT and encrypted data for continuous remote heart health monitoring using deep learning [7]. Furthermore, Rahman et al. presented an intelligent IoT-based health system for monitoring and diagnosing critical cardiac arrhythmias in COVID-19 patients [8], and Khanna et al. introduced a new IoT, and deep learning (DL) enabled healthcare disease diagnosis model using ECG signals [9]. Similarly, Wu et al. presented a deep learning-based IoT-enabled real-time health monitoring system, using wearable medical devices to measure vital signs [10], and Ali et al. introduced an IoT-assisted ECG monitoring system for Arrhythmia detection [11,12].

Alongside these advancements, smart gloves have emerged as a promising wearable technology for a wide range of applications including healthcare, rehabilitation, gaming, and industrial settings. These gloves incorporate various sensors and electronics to monitor and interact with the user's hands and fingers.

To start with, Iqbal et al. developed a wearable health monitoring glove that tracks vital physiological indicators such as blood pressure, body temperature, glucose level, blood oxygen saturation, hemoglobin level, ECG, room temperature, humidity, and motion [13]. Guridi et al. proposed a prototype of smart gloves equipped with pressure sensors and inertial measurement units to monitor the quality of adult cardiopulmonary resuscitation in real-time. [14]. Similarly, Zhang et al. designed a wearable, self-powered toroidal triboelectric sensor (STTS) with a simplified pyramidal structure to enable self-powered human-machine interactions [15].

Smart gloves have also found applications in object recognition [16], sign language classification [17], and monitoring drivers' biological factors and behavioral changes [18]. Ozioko et al. further explore the diverse applications of smart gloves in interaction, rehabilitation, virtual and augmented reality, and augmentative and alternative communication [19]. Despite the promising potential of smart gloves for SCD monitoring and emergency detection, the specific methods for locating these emergencies and implementing the system remain a research gap in this field.

Based on this research gap, this paper proposes a low-cost ECG detection device that connects to an edge computer via Bluetooth and uses IoT to connect patients and doctors for life-saving in emergencies. The hardware and its signal displays in the mobile phone, the edge computer, and raw ECG data are shown in Fig. 1. This paper proposes a framework to combine wearable gloves, ECG devices, IoT, and artificial intelligence to build a life-saving system that automatically analyzes predictions and reacts in time to send distress signals before SCD occurs. ECG data is collected in real-time and uploaded to a higher-level network node for risk analysis. Data with possible SCD risk is uploaded to the cloud for highly accurate predictions using oversized models. Alerts are sent to hospitals and communities to request the nearest personnel. The contributions of this work can be summarized as follows.

- We propose a framework to achieve a wearable device that can monitor and evaluate the risk of SCD and ask for help when an emergency is detected.
- We build a system that implements a part of the proposed framework, including an edge service and a wearable ECG detection device with Bluetooth connectivity.
- The proposed smart gloves provide a comfortable, unobtrusive form factor enabling continuous, long-term wear, unlike chest strap or wrist-worn ECG devices, which can be bulky and uncomfortable for extended use.
- The framework is equipped with a sensor that captures high-quality electrocardiogram (ECG) signals directly from the palms and fingertips, which are prime locations for detecting heart rhythm irregularities.
- The framework enables continuous, real-time heart rate monitoring, allowing for extensive fitness and wellness tracking over long periods.
- The framework includes Bluetooth to enable wireless data transmission to connected devices for remote and real-time heart health monitoring, which is particularly valuable for early intervention in individuals with known cardiovascular conditions.
- Data from smart gloves can be integrated with other wearable technologies, providing a more comprehensive view of an individual's overall health and well-being.

Method details

The proposed system consists of three main modules (as shown in Fig. 2): publisher, subscriber, and broker. The publisher is the patient and the subscriber is the community physician. The patient wears a wearable ECG detection device that sends the data to the edge computing or fog computing terminal (as a broker) through the Bluetooth module. The edge computing or fog computing terminal information can be subscribed, but there will be no alerts. Therefore, we design multiple topics (as Table 1 shows). Topic 1 is ECG Data, and each patient is a publisher. These topics publish ECG Data and upload it to the edge computing terminal without interruption. At the same time, the cloud server subscribes to ECG Data once every minute, which can effectively reduce the pressure

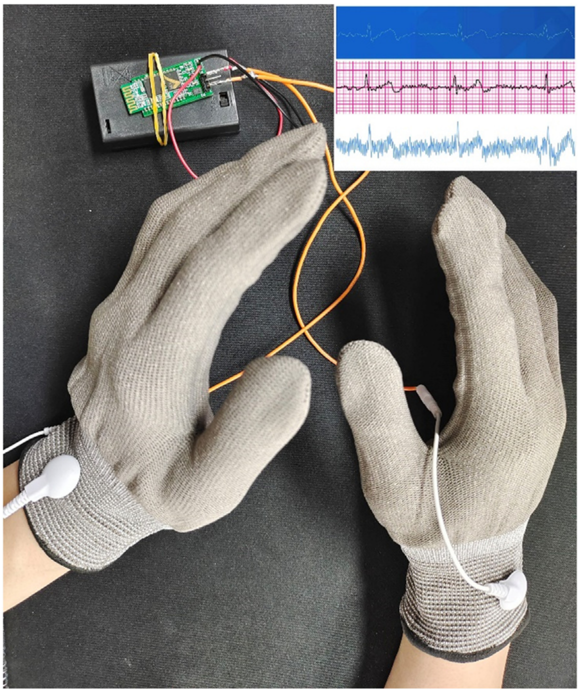

Fig. 1. The wearable device can detect ECG signals without special electrodes attached to the chest and upload signals to edge-computing services and mobile phones.

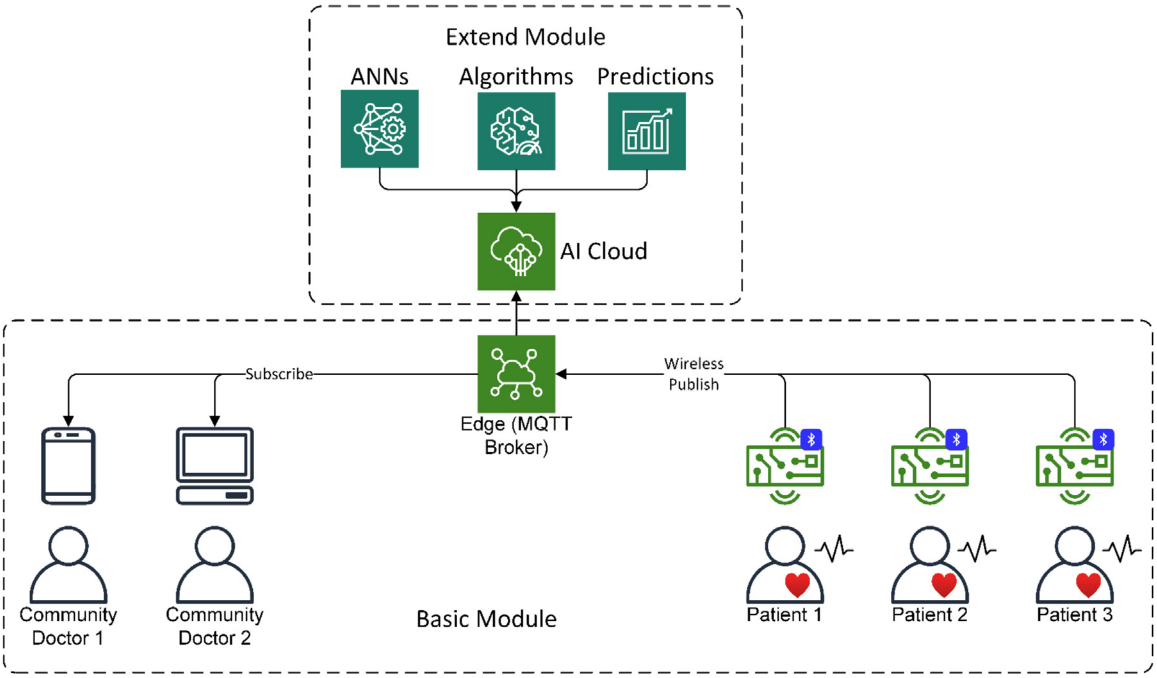

Fig. 2. The whole architecture of the emergency aid system. The extended module is proposed but not implemented. The system consists of wearable ECG detectors with Bluetooth modules for patients, edge services, and software for information users (doctors).

Table 1
The Topic And Message Content.

Topic	Message Content
Patient1 ECG Data	ECG Data
Patient2 ECG Data	ECG Data
Patient3 ECG Data	ECG Data
…	…
Patient1 Location	GPS Location/None
Patient2 Location	GPS Location/None
Patient3 Location	GPS Location/None
…	…
Emergency	Patient Number

on the network and cloud. This can effectively reduce the pressure on the network and the cloud server. After receiving the subscribed data, the cloud server will use AI algorithms to process and predict the data. If an emergency is predicted to occur, it will act as a publisher to publish the patient number corresponding to the data into the Emergency topic, and the community doctors can receive the alert and go to treat the patient.

The map service interface API can also display the location of nearby AED devices on the map. This design is expected to be worn by the patient all day long.

The energy consumption of the functional module needs to be as small as possible to prevent the battery from being replaced frequently. Some researchers have compared the energy usage between Bluetooth and Wi-Fi and pointed out that the power consumption of Bluetooth is usually 1–35 mA, while Wi-Fi generally requires 100–350 mA [20]. For this case, the Bluetooth MQTT gateway technology is used. In the configuration parameters, we need to turn off UDP push and turn on MQTT push, turn on broadcast transmissions and Bluetooth reception, and set the time to transmit tone scale configuration and broadcast interval configuration, as well as the restart interval configuration of the base station. Then, configure the MQTT server address and MQTT server port, as well as the MQTT client ID and MQTT username and password.

Table 1 shows the subscribed topic and messages. Each patient (publisher) creates a different topic and uploads ECG information and location information to those created topics each time. The edge computing server saves the data, and the community doctors (subscribers) subscribe to those messages. The cloud server also subscribes to the ECG information as a subscriber and uses its powerful computational capability to predict the SCD situation. Suppose the cloud server predicts that the risk factor of the SCD situation increases to a threshold. In that case, it creates an emergency topic as a publisher, and the community physician will know which patient is at risk by subscribing to this emergency topic.

The ECG signal acquisition module uses a highly integrated NeuroSky-BMD101 signal acquisition chip, and the communication module uses a Bluetooth module. Both the BMD101 and the Bluetooth communication module operate at 3.3 V, so a DC-DC power supply module is designed on the board to provide a stable power supply to the ECG and communication modules. The BMD101 has a low-power feature, with a working power supply of 870 mA in the active form and dropping to 225 mA in the standby state. The Bluetooth chip also operates at around 400 mA. This ensures continuous runtime without the patient needing frequent battery changes.

Fig. 3 depicts the circuit diagram. The communication between the Bluetooth module and the BMD101 ECG module is a serial communication with a baud rate of 57,600, and the ECG data is received by sending the corresponding command.

Fig. 4 shows that the hardware contains an ECG and Bluetooth module, gloves, wires, and electrodes. The gloves are made of silver fiber. Its resistance is 50 Ω from fingertip to wrist. The Bluetooth module and the ECG SOC module are soldered together. There is an onboard DC-DC power supply regulator module.

Two wires from the onboard are soldered into two electrodes with snap buttons. The snap button on the gloves can be easily removed and inserted. Three AAA batteries power the module. It cannot use an external active power supply because the industrial frequency noise cannot be completely filtered out and will affect the accuracy of the test. Fig. 5 shows the operation logic of cloud computing. That said, an additional filtering component can be incorporated into the front end to help reduce noise in the captured signals.

Cloud computing is mainly responsible for reading patients' ECG data at regular intervals and then using a mixture of AI algorithms to improve the prediction accuracy and achieve an accurate prediction of the probability of SCD occurrence. When the predicted result is a greater probability, it is defined as an emergency state and will publish the signal of the emergency state to the broker. Fig. 6 shows the logic flow diagram of the subscriber's program. This being turned on and initialized, the device connects to the broker and subscribes to the relevant messages. Then, it keeps repeating whether there is an emergency (the cloud provides the emergency judgment). If an emergency happens, the edge-computing service will locate the patient using GPS data uploaded by the patient (publisher). The patient will be saved as soon as possible.

The communication between the Bluetooth module and the BMD101 ECG module is serial. The BMD101 is the third generation of NeuroSky's Signal Detection and Processing System on Chip (SoC), which has all the components needed for signal acquisition, such as a front-end amplifier, signal follower, multi-stage amplifier circuit, Analog-to-Digital Converter (ADC), and digital filter. As Table 2 shows, The output signal of the BMD101 is digital. It uses the serial port Universal Asynchronous Receiver/Transmitter (UART) for data control with a 1-bit start, 8-bit data, 1-bit stop, and a baud rate of 57,600.

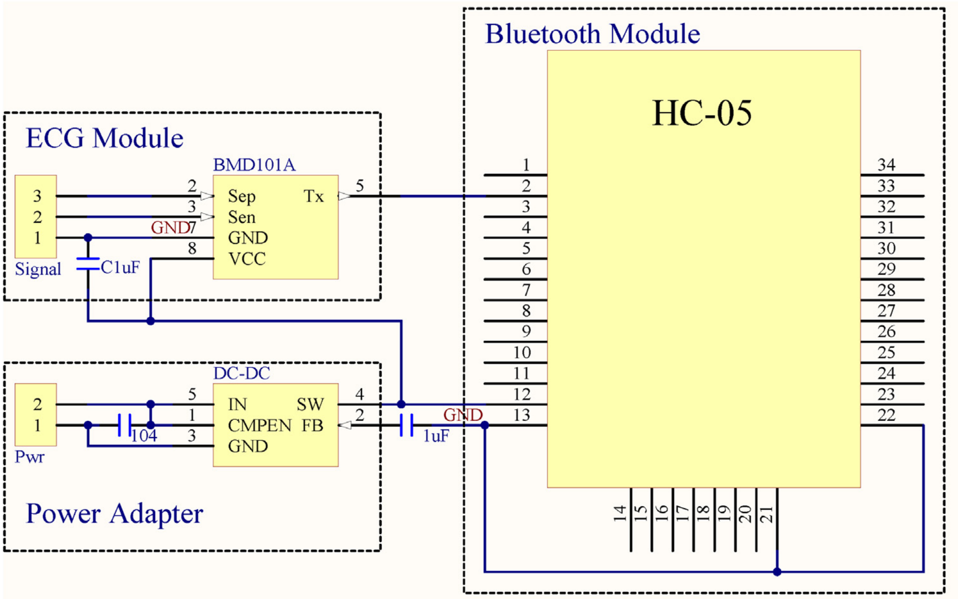

Fig. 3. Circuit diagram. There are three modules: the ECG module using a BMD101 System on Chip (SoC), the power adapter module, and the Bluetooth module.

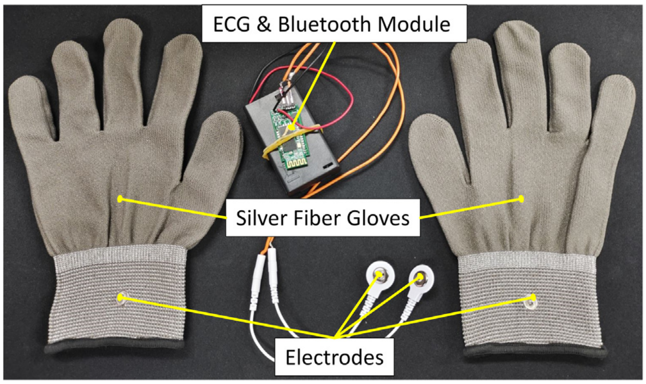

Fig. 4. The hardware includes an ECG, a Bluetooth module, gloves made of silver fiber, and electrodes. The electrodes are a snap that can easily snap together.

Table 2
Digital Output Packets Format.

Header			Data Payload			CRC
			Data Row			
SYNC 0xAA	SYNC 0xAA	pLenth 0–255	CODE \	vLength \	value \	chksum CRC

The first two bytes of SYNC represent a consecutive pair of synchronization bytes to mark the beginning of the packet. The third-byte pLength indicates the payload length in the range of 0–255. These three bytes form the data header; the next four are the data payload containing the data content. The last byte is the CRC check digit, which must be calculated correctly for the value of the check digit to be valid.

Method validation

The interface test was done before the system was built, and after the system was built, the system and dynamic tests were done. After confirming that the system works appropriately through system testing, to test the system's network transmission performance

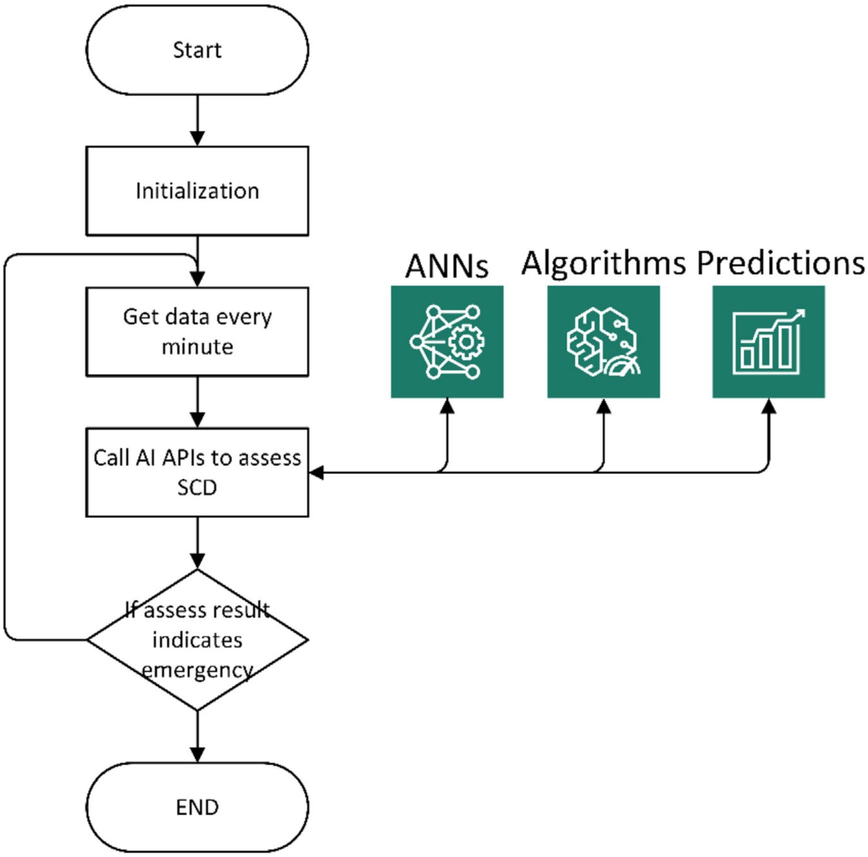

Fig. 5. Cloud computing logic flow.

bottleneck, we use the method of separate testing of publisher and subscriber to test the performance of each separately. As shown in Fig. 7(a), the performance of publisher upload data is tested in terms of active distance (i.e., from the device receiving the signal). The sampling point interval used in the experiment was 2 m because previous tests found that the signal did not change much at 1 meter or 0.5 m. As Fig. 7(b) shows, Use a subscriber to see if the signal is expected and how long the delay will be when there is an emergency assistance signal. Fig. 7(c) shows the data transmission test between ECG and its communication module and broker.

Finally, the signals received by the three devices were tested separately, which are Test 1, Test 2, and Test 3 in Fig. 7(c). During the test, human body-worn devices were required to collect data. We calculated the transmission speed by spying on the Bluetooth transmission packets and recording the spy time (accurate to 1 millisecond) by dividing the total number of packets by the spy time. The test is carried out at a distance of two meters, and each is a control group. Each control group is collected for one minute. The error is calculated as follows:

$$\text{error} \;=\frac{57,600,\ \text{bp, s}}{6,0\ \text{s},*10,00\ ,\text{ms}}=0.96\ \text{bit}$$

In addition, We propose an experiment for simulating actual usage. Fig. 8 shows the three typical patient position scenarios relative to the house's signal collector.

The information depicted in Fig. 9 illustrates the process of uploading the results of a data distance performance test by the publisher. The outcomes demonstrate that the signal transmission distance can attain a comparable rate until it reaches a distance of 27 m. Subsequently, the data transmission speed exhibits a sharp decline. Beyond a distance of 29 m, the connection is wholly disrupted and cannot be restored. The simulation test of the application scenario reveals that a room measuring 5×5 m was found to be separated in scenario A, leading to signal loss. Typically, signal transmission is possible through a solid wall measuring 5 m or a right-angle wall measuring 5×5 m. However, a data comparison shows that transmission speed through a right-angled wall is marginally higher than direct blockage by a solid wall, as illustrated in Fig. 10.

The assessment indicates that the system's power consumption during the signal search operation falls from 44 to 47 mA. Subsequently, upon establishing a connection, the power consumption during standard data transmission ranges from 30 mA to 33 mA.

Fig. 11(a) depicts an experimental sample of the heart rate waveform after signal processing. The graph in Fig. 11(a) constitutes a screen crop obtained from a mobile phone, with the APP being a specialty software designed for detecting ECG signals from the NeuroSky BMD101 SOC. The graph displays three heartbeat signals, and the mobile view for the subscriber simulation employs

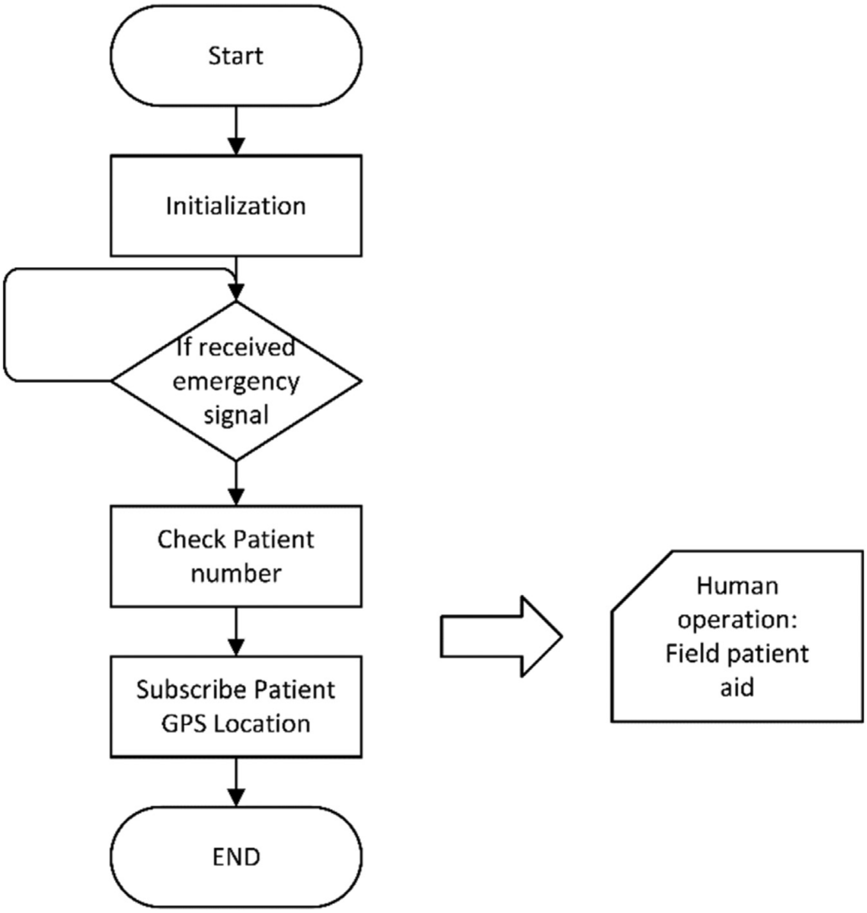

Fig. 6. Subscriber software logic flow.

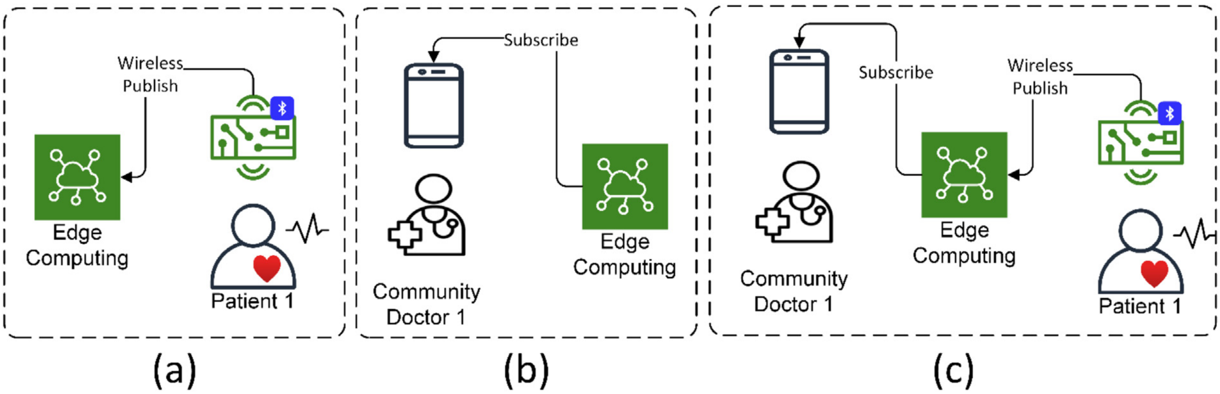

Fig. 7. The experiment of upload performance. (a) The connection diagram of the speed test of ECG data uploaded by Bluetooth at various distances. (b) The link test diagram of a community doctor's device connecting to an edge computing service. (c) Combine (a) and (b) for test.

the phone to receive the signal. Fig. 11(b) illustrates the signal seen in the broker (computer view), indicating that the broker has successfully received the wireless signal. In contrast, Fig. 11(c) displays the raw data saved in storage before processing. Although the unprocessed raw data waveform appears extremely noisy, the three pulse beats remain distinguishable. The edge computing service denoises the displayed data on the mobile and the computer. Fig. 11(a) and (b) demonstrate the denoised ECG signal on the mobile phone and the edge computer, respectively. he present study investigates the feasibility of implementing an ECG monitoring system for complete process monitoring of in-home activities. The results reveal that the communication distance of the system is sufficient for the purpose. However, in the case of larger homes, the number of receivers needs to be increased for effective monitoring. The

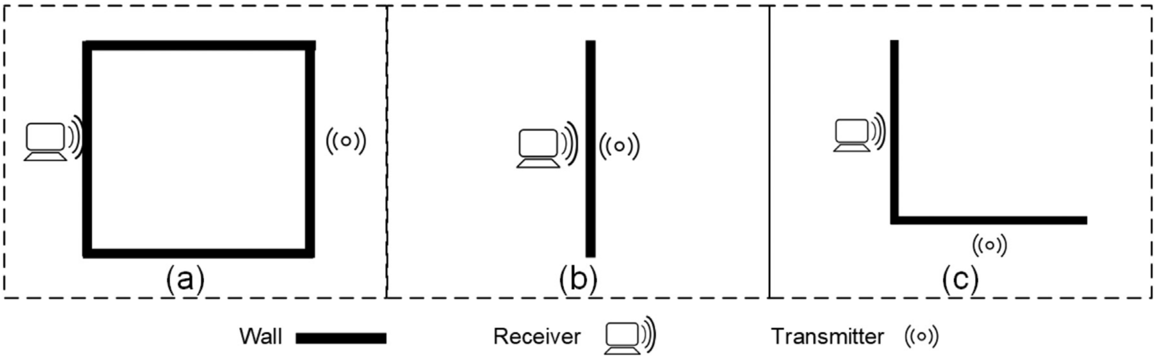

Fig. 8. Simulates connections of scenarios: (a) Case A experiments that a room obstacle the signal between transmitter and receiver. (b) Case B shows that a solid wall obstructs the transmitter and receiver signal. (c) Case C experiments with a right-angle wall obstacle to the signal between the transmitter and receiver.

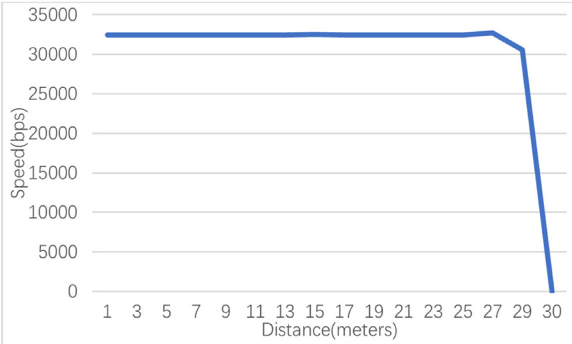

Fig. 9. Upload performance data.

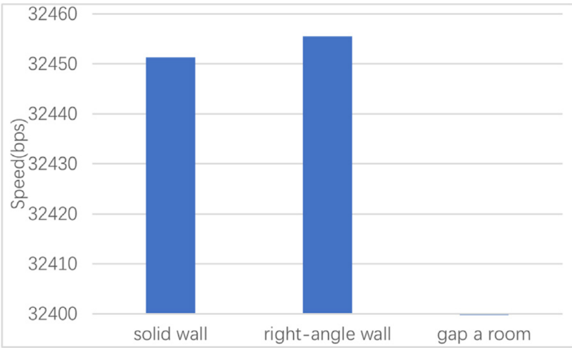

Fig. 10. Scenario simulation results from the transmission speed through a right-angled and solid wall.

study demonstrates that the ECG monitoring system can be monitored on multiple platforms, such as cell phones and electricity, and that the subscription form is convenient for obtaining data. The proposed method offers the advantage of lower costs, making it easier to popularize the application. The critical contribution of the study is introducing a fully automated cardiac death rescue system with emergency response capabilities implemented at the edge. Compared to previous research, the study proposes an emergency response concept that can report emergencies to community doctors through IoT for timely life-saving interventions. Table 3 compares our design with related work, highlighting the most significant features.

Most previous ECG-related designs have a single function, such as uploading data to a server or cloud computing based on IoT [3,26], SCD prediction [21-23], IoT-based patient identification [22,24], and wearability. However, these designs only monitor the ECG and lack emergency response capabilities. Although some recent studies have introduced artificial intelligence and machine learning methods to utilize ECG signals for disease prediction, they do not simultaneously provide wearable patient identification, SCD prediction, and emergency response features [25-27]. In contrast, our proposed IoT-based SCD predictive rescue system includes all

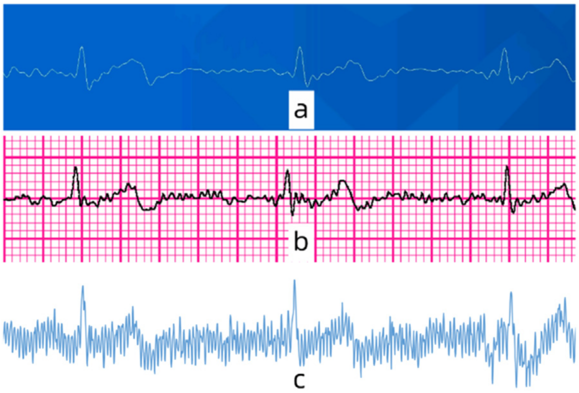

Fig. 11. ECG signal displayed on a mobile phone (subscriber).

Table 3
A comparison between related works and our proposed work. Y, N, and P refer to Yes, No, and Work in Progress, respectively.

Solution	SCD Prediction	IoT Based	Patient Identity	Wearable	Emergency Response
Shanin et al. [3]	N	Y	Y	N	N
Venkatesan et al. [21]	Y	N	N	N	N
Mena et al. [22]	Y	N	N	Y	N
Peris-Lopez et al. [23]	N	N	Y	N	N
Liu et al. [24]	Y	Y	N	Y	N
Iskandar et al. [25]	N	Y	N	N	N
Rahman et al. [26]	N	Y	N	N	N
Big-ECG [27]	N	Y	N	N	N
Proposed work	P	Y	P	Y	Y

these features, making it a comprehensive and effective solution for cardiac death rescue. Various integrated and efficient algorithms exist in the domain of noise removal algorithms. The algorithm utilized in this paper is one of the integrated algorithms.

The direct application of these algorithms offers multiple advantages, including fewer bugs, faster operation, and more stability. This paper presents a simple publisher-broker-subscriber model of the Internet of Things (IoT) and a basic application of electrocardiogram (ECG) signals. Artificial intelligence (AI) algorithms are yet to be developed due to limited patient experiments. Therefore, this work must implement sudden cardiac death (SCD) prediction and patient identity confirmation. Future research recommendations can include AI algorithms to predict the risk status of ECG signals and patient identity to ensure the actual rescue of individuals at risk of SCD. Although this paper proposes a system that covers monitoring and real-time transmission to cloud prediction and emergency response, it currently implements an IoT-based wearable ECG monitoring system with emergency response only, without cloud involvement. Due to the absence of SCD data, only the edge part is implemented in this paper's proposed approach. Future work can continue to increase the cloud service and complete the whole system.

Conclusion and future works

We have developed an Internet of Things (IoT)-based wearable electrocardiogram (ECG) risk response system that comprises an ECG detection and communication device, an edge server, and an Android mobile. This system enables the Android mobile to receive a risk alarm in an emergency, and the emergency prediction is based on ECG signals analyzed by an artificial intelligence (AI) model. The three terminals can be successfully linked, and ECG signals can be transmitted or received between them. The ECG monitoring terminal has a power consumption of as low as 33 mA when connected, making it suitable for long-term wear without battery replacement. The Bluetooth performance shows that it can transmit ECG signals up to a distance of 27 m in a straight line and even through walls, but the signal is lost when a room blocks the transmission route. Therefore, the system is more suitable for open spaces or minor suite use. Future research can improve the system by establishing an AI prediction model to enhance the emergency response system's accuracy. The patient identification function can be enhanced using ECG signal authorization technology to achieve individual patient identification. Another potential improvement is to extend the transmission distance without increasing power consumption.

Ethics statements

Ethics approval: The study followed the Declaration of Helsinki and was approved by the Universiti Sains Malaysia Ethics Committee. The institutional review body explicitly approved all aspects of the study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The author can make the code available upon a reasonable request.

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