

Introduction to Algorithmic Health: Exploring Healthcare Through Digital Twins

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Abstract

Components from several industries can be connected over the Internet thanks to a new communication paradigm called the Internet of Things (IoT). One of the most exciting applications of IoT technology is in contemporary healthcare as the social resource requirements, such as physicians, hospital, and health monitoring devices, in the traditional healthcare system are increasing. This paper covers the development of a tiny, wearable sensor that may be used to monitor electrocardiograms, photo plethysmography, and body temperature. The anticipated sensor can constantly evaluate blood pressure (BP) and relies on the pulse arrival time devoid of needing excess devices/wires as the PPG and ECG sensors are merged into a single device. Vital sign monitoring is done using the three sensors on the sensor. A power board handles battery charging and energy supply, and a centerboard handles signal processing and acquisition. For remote health monitoring applications, affixing all components to the human body is simple, thanks to its rigid-flex structure. The centerboard's sensors can be taken out to save energy and be used

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for specialized physiological signal assessments such as the ECG. The usefulness of the suggested sensor is tested through experiments, and performance is compared to a commercial reference device.

Keywords: Healthcare, Internet of Things, remote sensing, sensors, human body

1.1 Introduction

Many scientific fields have shown great interest in the Internet of Things (IoT). IoT technologies allow many components from many locations to be connected so that resources and information can be shared without being limited by time or space. The current healthcare industry is one of the most enticing uses of IoT [1]. Chronic illnesses are one of the leading global health concerns for people as life expectancy rises. Early detection and management of chronic diseases and improving people's health depend on continuously monitoring human vital indicators such as body temperature for an extended period, breathing rate, heart rate, and blood pressure. When considering hospital beds, medical equipment, physicians, and nurses, the traditional healthcare system has fewer social resources than the aging population. One intriguing answer to the need for ongoing health monitoring is the creation of wearable technology, which is a project for the future incorporating IoT technologies [2].

A tiny, low-power, wearable sensor is suggested for vital sign monitoring with Internet of Things-connected healthcare applications. The sensor comprises three sensors, a power board, and a centerboard. Flexible, flat cables connect the sensors to the boards. Consequently, removing any unnecessary sensors from the system is simple to minimize its overall size and power usage. To measure physiological parameters, including body temperature, PPG, and ECG, the sensor rigid-flex construction makes using biocompatible tapes to secure it to the chest simple. Without additional preparations, continuous blood pressure calculation on the suggested sensor is possible with the combination of PPG and ECG sensors [3]. The sensor data will be sent to a gateway, desktop computers, or mobile through a Bluetooth module. To safeguard subjects' confidentiality and privacy during transmission, AES-128 encryption is used. Each health data set will have a timestamp added before the gateway transfer data to a cloud server for further processing and preservation. The trade-off approach for monitoring users with movement requirements is to use a smartphone as a mobile gateway, although mobility is not the main emphasis of this study.

1.2 Related Works

Generally, three primary components are typically found in an IoT-connected healthcare system as follows: (1) wearable sensors to monitor health indicators, (2) an Internet gateway to link wearables to wearables, and (3) a cloud server for storing and processing data after they have been collected. Wearable sensors are essential for a healthcare platform with Internet of Things connectivity for remote health monitoring [4]. At the same time, gateways and cloud servers comprise the fundamental IoT infrastructure. The body's vital signs can provide insight into an individual's health. Scientists have suggested numerous wearable sensors to measure health data. Comprehensive wearable sensor reviews for remote healthcare applications, comprising Galvanic Skin Response (GSR), body temperature and activity, blood oxygen saturation (SpO₂), and cardiovascular monitoring are described. For instance, a ring-shaped wearable sensor that measures heart rate is proposed. It is based on photoplethysmography (PPG), which examines clinical and technological problems during long-term continuous HR monitoring. In an intelligent assisted living home, wearable motion sensors identify behavioral anomalies in senior citizens. The suggested probabilistic framework is designed to enhance the quality of life for senior citizens by utilizing wearable sensors to detect abnormalities in their everyday routines. In ref. [5], RR and the duration of apnea during sleep are measured using a tiny magnetometer-based sensor. They are transferring the sensor data to a smartphone gateway to contrast it to an airflow sensor sold commercially. As for blood pressure readings, the wearable BP-monitoring system cannot use the bulky, cuff-equipped standard sphygmomanometer because of its short measurement intervals. Several intriguing wearable blood pressure monitoring techniques have recently been developed, all based on pulse transit time (PTT) and pulse arrival time (PAT) [6].

Most wearable BP estimation systems in long-term monitoring cases could be more user friendly since they use separate devices to measure PPG (finger/earlobe) and ECG (on the body). A wristwatch design for blood pressure readings is proposed. To acquire the ECG and PPG signals, the user must wear a watch on his left wrist and contact the electrode over the right hand [7]. A suitable regression model built using the PAT's collected ECG and PPG data can be used to determine the related BP values. Even though the bio-watch's hardware design is more straightforward because it requires two hands to take a reading, it cannot continuously measure long-term blood pressure numbers. Since the given work integrates PPG

and ECG sensors, it can be applied to a chest-based sensor for continuous, long-term blood pressure estimation. In contrast to conventional wearables based on the wrist and finger, the suggested chest-based sensor is covert enough to be worn under clothing without interfering with daily activities [8].

1.2.1 Reviews on Wearable Sensors

One important method for tying wearable sensors and IoT gateways together is wireless communication. Many wireless protocols, including Zigbee, 6LoWPAN, BLE, and others, have been proposed for short- and long-range data transmission (LoRaWan, Sigfox, etc.). For IoT-connected healthcare applications, researchers have put forth several wearable health monitoring devices. For example, the Health-IoT platform incorporates an intelligent medication box and non-intrusive bio-sensors [9]. Developing a wearable biosensor for body temperature and ECG monitoring coexists with integrating RFID technology into the medicine box to facilitate patient identification and prescription reminders. The author in ref. [10] describes an inexpensive wearable SN for the IoT healthcare system. The SN can gather and send body temperature, respiration rate, and ECG data to a gateway that can send emergency alerts. A wearable ECG monitor that may be customized is displayed next to an IoT architecture. The heart rate variability (HRV) and heart rate (HR) can be evaluated when ECG data are transferred to the smartphone using a Bluetooth module. The author used mobile phone accessories to set up a wireless health-monitoring system. The ECG signals are recorded and collected using the dry electrodes. A smartphone application can then analyze and predict a patient using these data. Unfortunately, it cannot record continuous ECG data because both hands are needed to record the signal. A wearable medical gadget with IoT capabilities for measuring several physiological parameters, including HR, HRV, and RR, is presented [11]. The primary gateway for storing local data and sending it to the Internet cloud is chosen to be an Android phone. However, since the smartphone could be needed for other everyday tasks, there are better options than utilizing it as the only gateway. To obtain physiological measurements, health data can be transferred via the Internet to a cloud and kept in a local database; this work uses both a mobile and a fixed gateway.

Because of the widespread use of IoT platforms and devices, security concerns about IoT today face unique obstacles outside of the conventional information technology framework. A comprehensive analysis of IoT security, including several security tiers, protocols, standards, solutions,

Table 1.1 Comparison of various existing approaches.

Ref	[4]	[6]	[8]
Sensors	Heart pulse and temperature sensor	Pulse oximeter and temperature sensor	Accelerometer, pulse oximeter, temperature sensor
Data	Heart rate and temperature sensor	Oxygen, blood, heart rate, and temperature level	Acceleration, blood oxygen level, heart rate, and temperature
Battery	Li ion	Li ion	Super-capacitors
Energy consumption	PVC controller	Two PVC controllers	PVC, DC–DC boost converter
Power consumption (mW)	4.9	20.2	2.1
Lifetime	137	33.2	1.9
Sensor charging time	14.6	11.7	0.04
Times/h	15	60	3
Sleep and wake up	15	1	20
Active time/day	880	5	10
Sleep time/period	9.3	50	1190
Sustainability factor	Bluetooth 100 m	2.8	Bluetooth 100 m
Wireless technology	Wrist sensor	Wi-Fi	Wrist
Wear ability	Finger	Upper arm	Fingers
Data monitoring	Android phone	Server	Android phone

and potential blockchain applications, is provided. A variety of lightweight encryption algorithms, including BCC, LEA, Twine, Skipjack, and AES, are invented or upgraded to meet new needs as a result of resource limits on IoT sensor nodes (energy, latency, and processing power). Owing to its minimal processing needs, low latency, and inexpensive electricity, the BLE module's integrated AES-128 encryption engine is used in ref. [12]. Moreover, as the suggested sensor measures ECG, biometric ECG authentication may help maintain privacy. The movement of the user must be considered by a wearable healthcare infrastructure connected to the IoT to allow for ongoing health monitoring.

A framework for the design of a wearable health-monitoring system that supports mobility is detailed. There is a comparison and discussion of several conceptual and technological approaches. Mobility-supported healthcare systems are described with two examples of needs and solutions being a handover mechanism and a coordinator node. Since the suggested wearable healthcare system is outside this article's purview, it uses a smartphone or mobile gateway as a workaround to satisfy the mobility criterion. The health data are stored in an intermittent buffer to maintain the connection when the mobile gateway's sensor is removed and put back on the stationary gateway. The wearable sensor will be connected to many mobility-supported gateways via the received signal strength index (RSSI) [13] allowing researchers to investigate possible localization applications. Table 1.1 depicts the comparison of diverse existing wearable sensor systems.

1.3 Hardware Description

Wearable biomedical sensors are flexible and lightweight to painlessly cling to the human body. Given the challenges associated with cable-based wearable sensor connections to external healthcare devices, wireless data transmission is a fundamental necessity. Power usage must also be considered when long-term health monitoring is required. A wearable wireless sensor that is presented in this study for monitoring vital signs is shown in ref. [14]. Flexible, flat wires link the centerboard to other sensor boards. The biocompatible tapes, which can easily adhere to the sensor's architecture, are rigid-flexible and attached to the chest. The suggested wearable sensor consists of three sensors for body temperature, PPG, and ECG readings, power board for the energy supply, and a centerboard for signal processing and transmission [15].

1.3.1 Sensor Board

The centerboard's design is depicted in Figure 1.1, which links the other sensor boards to process and acquire signals. The Simblee® RFD77101, a professional-grade, high-performance Bluetooth 4.0 transceiver, also known as a BLE module, is the central component of the center board. It has an inbuilt antenna and an ARM Cortex M0 processor in a small volume measuring (11 mm × 8 mm × 3 mm). First, signal processing, which includes low-pass filtering, real-time DC removal, and band-pass filtering, will be carried out by the integrated microcontroller (MCU) on the physiological data that has been acquired [16]. The BLE module transmits the measured vital signs to a gateway to store the data for remote health monitoring and additional analysis. Because of its tiny form factor and low power requirements, the chosen BLE module is appropriate for wearable technology. Its ultra-low-power sleep mode uses less than 4 μ A of current, whereas 8 mA is its maximum transmission current. An integrated circuit for the analog front end (AFE), called AD8232, and a buck-boost converter for voltage control, called RT6150A, and ECG signal acquisition make up the remaining portion of the centerboard.

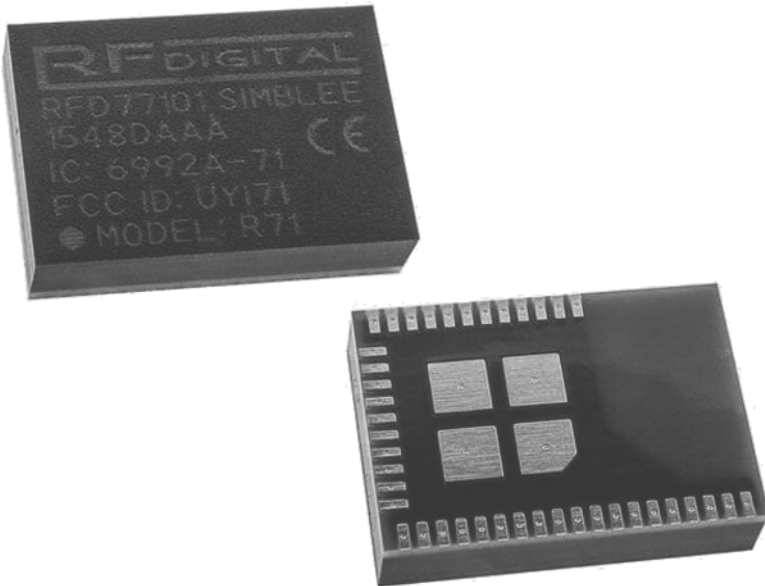


Figure 1.1 Simblee® RFD77101.

1.3.2 Power Requirements

A separate board is constructed to power the wearable sensor. An LIR2450 (Multicomp®) 120-mAh rechargeable battery can be installed on the back side of the power board. An economical, effective buck-boost converter, the Richtek® RT6150A, maintains a steady voltage of 3.3 V. Rechargeable batteries are designed to last longer when a Microchip® linear charge controller, product number MCP73831, is used to control the battery's charging state. When the battery's capacity is nearly depleted, it starts with a constant current quick charging mode. At a preset time, the controller will begin charging the battery with a variable current at a fixed voltage. On the middle board, the MCU analog-to-digital converter (ADC) is connected to the battery to monitor its voltage. Given that there's a chance the battery voltage will exceed the 3.3-V MCU reference value, this low-power voltage divider circuit is employed [17]. This voltage divider is not like the traditional two-resistor voltage divider in that it is only functional when the "enable" signal (Bat-EN) is sent by the MCU, which helps protect you from accidentally draining the battery. After reading the battery voltage, the MCU will activate the P-channel MOSFET using the conventional voltage divider's output (Bat-ADC). When a battery measurement is unnecessary, the resistors usually never drain current because of the P-MOSFET's high impedance (open circuit) state when the MCU pulls down the Bat-EN [18].

1.3.3 ECG Sensor Measurements

The ECG sensor cannot function without the AFE circuit, which collects ECG data. ECG data are recorded in this work using an off-the-shelf Analog Devices® AD8232 ECG AFE chip. A wholly integrated signal conditioning block for ECG and other physiological measurements is called AD8232. It gathers, enhances, and filters tiny bio-potential signals [19]. Its low current is 170 μ A, and it can work between 2 and 3.5 V. It is appropriate for wearable healthcare applications because of its inexpensive cost, small size, and low power consumption. To reduce the distortion of the ECG signal, some filters are 0.5-Hz high pass and 40-Hz low pass. To improve the display of the ECG waveform, the integrated operational amplifier is used to amplify further the biopotential signals collected from electrodes.

Three flexible PCB-based dry copper electrodes are made and mounted for ECG biopotential capture rather than conventional wet gel electrodes. Printed copper that is dried electrodes are more economical and environmentally beneficial than throwaway wet electrodes because they may

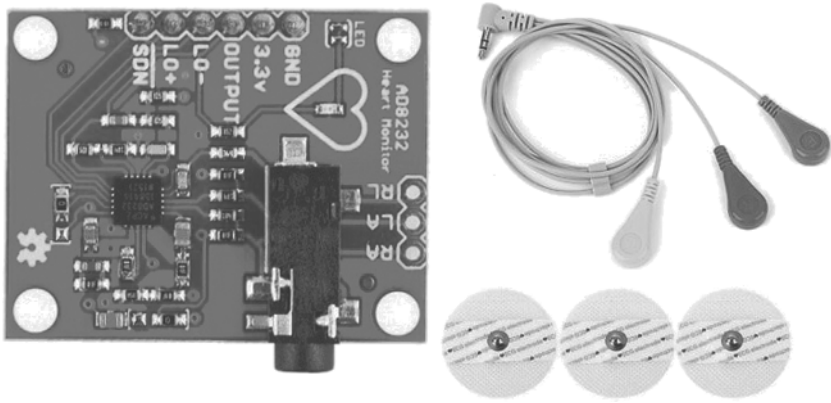


Figure 1.2 ECG sensor measurements using an AD8232 AFE chip.

be reused several times. Weak ECG signals can be sufficiently gathered thanks to the dry copper electrodes in the ECG AFE circuit [20]. Using a Tektronix® DPO7104 oscilloscope, a 28-year-old male participant's raw ECG sensor measurement data are shown in Figure 1.2. The T and P waves in the ST segment and the QRS complex are among the essential components of ECG signals that are easily recognizable, as shown in Figure 1.2. Upon gathering the ECG signal, it undergoes additional processing before being wirelessly sent and seen in real time. Data are stored on the IoT-cloud for future analysis.

1.3.4 PPG Sensor

Another popular wearable application involves the PPG sensor, which monitors human health, and the ECG sensor. A non-invasive optical method called photoplethysmography measures fluctuations in the amount of blood at the tissues' subcutaneous microvascular bed. A PPG sensor's fundamental idea is to highlight skin tissues using a light source. Subcutaneous tissues and blood vessels reflect light, and a photodiode (PD) is used to measure changes in light intensity that are transmitted through or reflected. Several chemicals found in skin tissues can alter the intensity of light that is transmitted or reflected, but periodic blood flows are the source of the most dynamic variation. The variation in light intensity picked up by the PD coincides with the heart rate since the diastolic and systolic stages of a heartbeat cause variations in the blood volume in arteries. PPG sensors are classified as transmission or reflectance

mode depending on how light is reflected from skin tissues. Due to its ability to sense any area of human skin, reflectance mode PPG sensors are used in wearable applications more often [21]. Transmission-mode PPG sensors measure heart rate (HR) and oxygen saturation typically used to measure red and infrared light. It has been discovered recently that green light works better than other light sources for the detection of fluctuations in surface blood flows making it a superior choice for reflectance-mode PPG sensors. A tiny green LED takes measurements and lights up skin tissues. An Avago® APDS9008 surface-mounted photodiode (PD) is used to gather the reflected light. The detected PPG signals' amplitude will grow, and high-frequency noises will be eliminated. A flexible flat wire on the chest to take measurements connects the PPG sensor to the centerboard. An individual's first PPG signals are shown in Figure 1.3, where they were recorded on his chest while he was stationary for 1 min. After the DC components are eliminated, the PPG data's spectrum is examined using fast Fourier transform (FFT) [22].

The time interval between PPG peaks can be used to measure heart rate. It is also possible to compute the respiration rate since breathing causes a chest movement that acts as a DC component signal with a low frequency. The rear of the PPG board has a high-accuracy temperature sensor for measuring body temperature, the Silicon Labs® Si7051. The central board is connected to all the sensors and dry electrodes using flexible flat wires, which is a handy and comfortable way to attach the suggested sensor and its rigid-flex structure to the chest for health monitoring [23]. Furthermore, removing them from the sensor configuration is a straightforward process. When there is no need for ECG monitoring, for instance, the sensor can be made smaller by removing the electrodes. Consequently, based on the user's needs, the sensor can be tailored to measure the required physiological parameters [24].

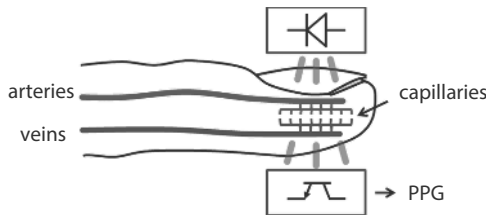


Figure 1.3 PPG working principle.

1.3.5 Power Consumption

Low power consumption is a crucial prerequisite for wearable sensor operation over an extended period. Here, low-power circuits are used to implement the suggested sensor. The individual sensor, BLE, and MCU power consumption are displayed in Table 1.2. Several operating modes for tailored healthcare applications can be set for the sensor to minimize power consumption further as follows: (1) All signals are continuously measured and transmitted, (2) cycles of computed vital sign transmission and continuous observations of specific signals, and (3) cycles of physiological parameter readings and transmission [25]. For continuous collection and transmission of the stated sensor, it is advised to use a maximum power of 44.57 mW (average current: 13.51 mA) for all sensor signals used for the BP estimate over the gateway. The sensor has an 8.88-h operating battery life in this mode when using a 120-mAh cell. The consumption of electricity will be lower when only one sensor is necessary. Assuming PPG is the sole HR monitoring tool, HR data are transmitted to the gateway once every minute. If so, the average current of 5.46 mA can lower the power consumption to 18.03 mW, for instance (BLE data transfer takes less than a second). Consequently, when powered, the sensor may run for 21.98 h on the same battery. The sensor may be set to operate in two cycles, lasting 1 min each for regular operation and 4 min for sleep (which can be adjusted based on various needs). This will further extend its lifespan [26]. In this 5-min cycled operation mode, the sensor can run on the 120-mAh battery for over 100 h. Table 1.2 shows the power consumed by sensor nodes.

Table 1.2 Power consumed by sensor nodes.

Item	Current	Power
PPG sensor	1.3 mA	4..3 mW
ECG sensor	176 μ A	0.58 mW
Temperature sensor (1 Hz sample rate)	195 nA	0.64 μ W
BLE transmission @ dBm	8 mA	26 mW
Micro-controller	4 mA	13 mW
Micro-controller at sleeping mode	7 μ A	23 μ W

1.4 Methodology

1.4.1 Healthcare Monitoring System

The various physiological markers of the human body serve as fundamental indicators of an individual's state of health. Periodically recording physiological data is essential mainly targeting the elderly demographic. The development of wireless communication and low-power miniature electronics capabilities has led to the proposal of numerous wearable or implantable biomedical sensors to monitor people's health for medical reasons. This study suggests that wearable sensors can measure body temperature, PPG, and ECG [27]. The appropriate signal-processing algorithms are utilized to determine blood pressure and pulse rate in light of the PPG and ECG readings.

1.4.2 Heart Rate Monitoring with ECG

Since cardiovascular diseases (CVDs) account for a large portion of catastrophic mortality, the ECG signal is one of the physiological characteristics that is monitored the most frequently among the other parameters. Enhancing patients' health condition can be significantly aided by early detection and management of CVDs. To prevent CVDs, it is crucial to monitor ECG in real time and over an extended period. Through wireless data transmission to Internet cloud healthcare centers, remote ECG monitoring has become possible with the advent of IoT technology. The recommended sensor collects ECG signals by attaching dry electrodes to the subject's chest and using them to power the AFE circuit. The ECG data will be sent through the gateway and the wireless network to an Internet cloud after the ECG signals have been sent to the center board's BLE module. The wireless network and gateway deployment will be the primary subjects of discussion during the presentation [28].

Future analysis will be facilitated by having the ECG data saved in the cloud center. The cloud center enables medical practitioners to review patients' ECG data remotely. The wearable sensor system is depicted in Figure 1.4, where the ECG waveform can be accessed online. The gateway receives data from the BLE module shown on the real-time ECG display. Python/MATLAB 2020a can construct a graphical user interface (GUI) on a computer that displays ECG signals. A PC linked to a BLE network can serve as the gateway. A different gateway concept is based on a smart-phone that uses an app created on the Evthings® platform to display the

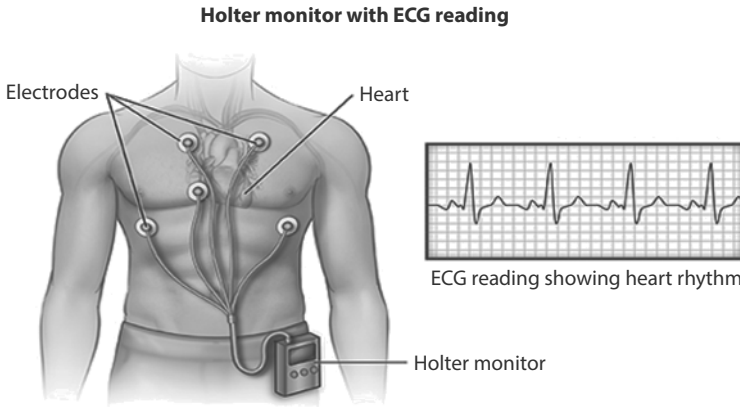


Figure 1.4 ECG signal monitoring using a Holter monitor.

ECG waveform. A smartphone app screenshot for real-time tracking of ECG waveforms is shown in ref. [29].

1.4.3 Heart Rate Analysis

One of the most crucial organs is the heart because it pumps blood filled with oxygen and other nutrients throughout the body functioning as a circulatory system pump. Heart rate refers to the speed at which the heart contracts and relaxes. As a standalone risk factor for CVDs, HR is one of the body's key indicators. The duration of the PPG signal between its peaks or the R-R intervals found in ECG data can be used to compute HR. A three-lead ECG module on the Finapres[®] NOVA, HR data from the suggested wearable sensor are compared with HR data from a commercial health-monitoring gadget [30]. The wearable PPG and ECG sensors are used to assess heart rate. Table 1.3 compares the HR readings from the PPG, ECG, and reference gadgets. The identical patient uses the reference device and related sensor for 10 min.

The individual works up a sweat for 3 min while seated on a stationary bike. The table illustrates a significant correlation (more than 98%) between the HR readings on the sensor of the PPG and ECG sensors and the reference device's HR. Two male participants (S1 and S2) undergo the same experiment twice. A comparison between the reference HR and the calculated HR from the sensor is shown in Table 1.3. The experiment's outcomes show that the suggested wearable sensor ECG and PPG can produce

Table 1.3 HR computation based on PPG and ECG signal.

		HR based on ECG			HR based on PPG		
		Mean	SD	CI	Mean	SD	CI
S1	Test_1	-0.01	0.045	[-0.87, 0.87]	0.05	1.37	[-2.67, 2.74]
	Test_2	-0.01	0.45	[-0.92, 0.92]	0.04	1.47	[-2.87, 2.93]
S2	Test_1	0.1	1.26	[-2.37, 2.60]	0.15	2.35	[-4.45, 4.75]
	Test_2	0.01	0.39	[0.75, 0.76]	0.03	1.90	[-3.66, 3.75]

accurate and dependable HR values, which will be tracked in the Internet of Medical Devices system.

1.4.4 BP Analysis

The blood flowing force through a blood vessel pressing against its walls is called blood pressure, another essential bodily indicator. The two numbers used to express blood pressure are two blood pressure readings: the systolic (SBP), which is the peak value recorded, and the diastolic (DBP), which is the lowest number detected during a pulse. One of the main risk factors for CVDs, which can result in impairment or even death, is persistently high blood pressure or hypertension. Regretfully, less than 46% of cases of hypertension are diagnosed since the early signs are no always evident. The sphygmomanometer uses an arm cuff to take traditional blood pressure readings [31]. Because of its enormous bulk and low measurement frequency, long-term, constant BP monitoring is a better option than this. In situations where long-term, constant BP monitoring is required, researchers have recently developed several noninvasive blood pressure estimate techniques. One of the possible methods relies on the PAT, which has an inverse connection with blood pressure (BP). The pulse wave propagation time from the heart to the peripheral arteries via the arterial tree is measured, which is the time interval between the PPG signals’ maximum inclination point. It can be computed using the ECG signals’ R peak. Applying the ECG data from the recommended wearable sensor yields the PAT. A regression approach is given for the real-time BP estimate to convert the PAT into BP data [32].

In addition to the PAT, there is a correlation between BP and HR since rising BP causes HR to rise in an attempt to enhance cardiac output. Consequently, the HR and PAT are combined into a linear regression model by the BP estimation methodology:

$$BP = a * PAT + b * HR + c \quad (1.1)$$

The linear least square approach can be used to calculate the model parameters that are individual to each subject, the coefficients (a , b , and c), about the reference blood pressure data obtained from commercial beat-to-beat blood pressure monitor. Two healthy male individuals are used in a 5-day experiment to ascertain the parameters of the BP estimate model in a laboratory setting with a 25°C regulated temperature. The sensor is secured to collect ECG and PPG signals on the subject's chest. The BLE module then sends these signals to the computer, where they are processed in real-time [33]. The Finarpes® NOVA noninvasive blood pressure-monitoring device is used for reference blood pressure readings. After an arm-cuff unit performs an initial BP calibration procedure, it can give you real-time, beat-to-beat blood pressure readings by employing a middle finger cuff. Five days are dedicated to gathering the subjects' data. The participant must complete two 15-min training sessions and 10-min daily validation session to adjust the coefficients of the BP estimation model.

Every session is followed by a 10-minute rest period. The training consists of two 3-min activities to raise the subject's blood pressure, while he sits on a stationary bicycle. Before and after the workout, he takes a one 3-min break to get his blood pressure to normal. The coefficients are computed and updated following the two training sessions and will be used in place of the BP estimate model. The BP estimate model's accuracy is verified in real time against the reference BP monitoring equipment through a validation session. Table 1.4 summarizes the overall RMSE for both subjects and the estimated blood pressure (BP) and blood pressure (BP) reference for every day of the experiment [34]. According to the results, the commercial gadget and the BP estimate model exhibit good agreement. Figure 1.5 displays the real-time SBP results with a significant correlation

Table 1.4 RMSE evaluation.

Sample	Pressure	Days							
		1	2	3	4	5	6	7	Overall
S1	Systolic pressure	9.1	6.0	6.1	7.4	4.4	4.3	4.1	6.6
	Diastolic pressure	3.1	2.5	2.9	5.9	5.5	5.6	5.5	4.0
S2	Systolic pressure	6.8	5.7	7.6	5.0	6.9	6.8	6.7	6.4
	Diastolic pressure	5.4	7.5	7.2	5.8	4.4	4.3	4.2	6.1

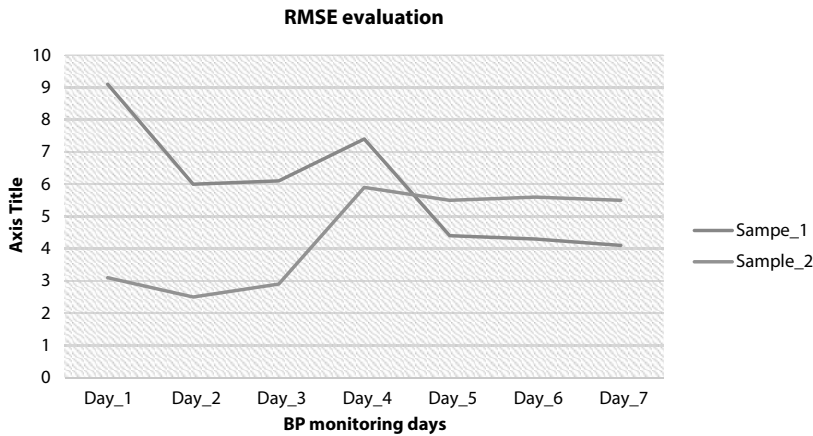


Figure 1.5 RMSE evaluation.

of 0.82 compared to the reference SBP values. The experiment results demonstrate that wearable sensors and real-time blood pressure monitoring with a reliable estimation model are possible with suitable methods for calibration. Long-term, continuous remote blood pressure monitoring throughout business operations is feasible.

1.4.5 Human Body Temperature Analysis

Body temperature, which falls between 36.2°C and 37.5°C, is typically considered the first vital sign. The body goes through a complicated series of operations to maintain a steady body temperature, which allows all other bodily functions to work as usual. A fever or illness is usually indicated by an elevated body temperature, which is the body's defensive response to disease-causing stimuli. Thus, taking your body temperature regularly is critical to identify any potential illnesses early. To periodically measure body temperature, the Si7051, the wearable sensor, makes use of a tiny Silicon Labs® digital temperature sensor. Over the whole measurement range of 36°C to 41°C, the sensor has a high accuracy of 0.1°C. It is appropriate for wearable applications because of its power consumption, which is among the lowest in the industry, with a sampling rate of 1 Hz and an average of 195 nA. The sensor measures body temperature every 30 s, and the results are relayed to, and stored on, a cloud server. The sensor system's website or a smartphone application can show real-time temperature data [35].



Figure 1.6 Generic architecture of IoT-based remote monitoring system.

1.4.6 IoT-Based Remote Monitoring System

To monitor their health state, multiple wearable sensors are applied to various subjects in IoT-connected healthcare applications. In Figure 1.6, a wireless sensor network comprises a gateway, and the information is sent over the BLE module from each sensor. The sensor data will be sent to an Internet cloud by a fixed gateway with a WiFi connection using the lightweight messaging protocol Message Queuing Telemetry Transport (MQTT). In remote healthcare settings, medical staff can review patients' health data through a cloud user interface (UI) or a local user interface (UI) on the gateway [36]. The user can utilize a smartphone as the mobile gateway and the stationary gateway linked to the sensor of each participant. A personalized smartphone application may show the user's health information, which can be transferred to a cloud server. All sensor data are visible for users to access the cloud database. The health information of several subjects will be kept on the cloud server for backup and future research needs.

1.4.7 Network Connectivity

BLE modules are used in the wireless sensor network's implementation to transfer local information to the gateway, which then uses the MQTT protocol to transport data to the Internet cloud. The Bluetooth Group is responsible for developing and marketing Bluetooth Low Energy, a new wireless technology. BLE's short-range, low-latency data transmission is its intended use (0–100 m) with efficiency and low power consumption. The use of BLE is increasing despite the existence of alternative wireless

technologies like ZigBee, 6LoWPAN, UWB, Z-Wave, WiFi, and others because it is widely used in commercial electronics (cars, laptops, smartphones, etc.) because of its low power consumption and latency. Several IoT applications may find BLE a practical solution, including smart home control, healthcare, and environmental monitoring [37]. This study retrieves health data from the wearable sensor via Bluetooth Low Energy (BLE) via a fixed gateway located in a local region (an office room). The patient can be connected to a smartphone outside the fixed gateway service area for data viewing and transfer.

Data transmission from many wearable sensors is required for the cloud using a messaging system that can run on constrained hardware, power, and bandwidth. To meet the unique needs of WSNs and IoT applications, the CoAP and MQTT protocol have been suggested. Conversely, CoAP is predicated on a protocol that facilitates a one-to-one state data exchange among the server and client. MQTT is a many-to-many communication protocol that enables data transmission between several brokers and customers at the same time. This explains why the cloud and gateway in this effort are using MQTT. TCP/IP networks are used to publish/subscribe to the MQTT messaging protocol. It is intended to be a very lightweight, low-complexity messaging protocol for sensors with little power, high latency, and bandwidth, among other applications with limited resources. Customers and brokers make up the typical MQTT; brokers oversee client relationships, and customers can publish and subscribe to communications on various subjects [38]. The deployment of the wireless network connecting the cloud, IoT gateway, and wearable sensor is depicted in Figure 1.7. The gateway can utilize the distinct MAC address of every wearable sensor to differentiate data from various predefined frame types. BLE modules are used to send the sensor health data that are sent to the IoT gateway. The gateway will acknowledge the data as soon as it receives it from the sensor. Data from various gateways can be synchronized using the timestamp attached to each piece of information after the gateway gets it. The local IoT gateway acts as a bridge to connect to a cloud MQTT broker. For data visualization, the local area network's local user interface may receive access to the health data. Similarly, remote health monitoring is possible through the cloud UI with a cloud MQTT subscription.

1.4.8 Network Gateway

As illustrated in Figure 1.7, the Simblee[®] BLE module in this study is linked to the Raspberry Pi, the fixed gateway via USB ports. The Pi's built-in BLE

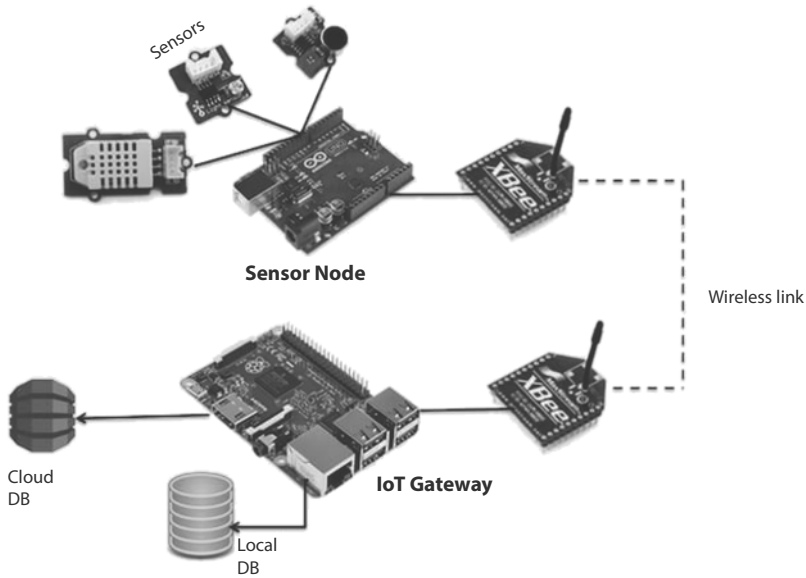


Figure 1.7 IoT gateway.

module is replaced by a standalone BLE module that gathers health data from numerous SNs, which would complicate the software programming processes needed for edge computing. The Raspbian system has a MySQL database loaded to save data on the gateway. This makes it possible to backup and retrieve health data from several subjects as needed. Data are forwarded to the cloud server over the Internet connection via the Pi's WiFi module. The Raspberry Pi is equipped with MQTT; it acts as a mechanism for messaging between the cloud and the gateway [38]. A minimal online user interface (UI) built on Node.js is set up for local users, smartphone cellphones, and local area network-connected web browsers to access. Suppose the person wearing the sensor cannot connect to it as an alternative to the fixed gateway (out of service); a smartphone's built-in mobile gateway can receive and send data to the cloud. Viewing sensor data is possible with the web-based smartphone application built on the Evothings® platform. It is used to develop mobile applications using HTML5, CSS, and JavaScript rather than the operating system's platform-specific APIs for Android and iOS. Bluetooth Low Energy (BLE) connects wearable sensors and smartphones [39]. Sensor data, such as the ID of the subject, physiological data, and battery level can be shown using the built application on a smartphone running the Evothings® Viewer installed on it.

With the mobile gateway in addition to the stationary gateway, patients' health status can be continuously monitored without being limited by physical location [40].

1.4.9 Server

In many different IoT application domains, the Internet cloud is a crucial component. An American cloud infrastructure company called DigitalOcean is where the cloud server for this project is located. The Ubuntu 16.04.5 operating system on the cloud server has 2 GB of RAM and 25 GB of storage, which is more than enough for the needs at hand. To enable data transmission from the IoT gateway to the Ubuntu cloud server, the cloud MQTT broker needs to be deployed. Following receipt by the IoT gateway, the cloud-based MySQL database will receive data from several sensor for further examination and backup [41].

1.4.10 Database

Since two gateways—one fixed and one mobile—are used in this job, data integrity must be ensured by synchronizing the data from the two cloud gateways and keeping the local database current. As previously stated, upon receipt by the gateway, every set of RF data is accompanied by a timestamp. The cloud server and the gateway can use the timestamp to synchronize the database [42].

1.4.11 Security

By transforming data into cypher text, one of the most popular techniques for safeguarding private information is encryption. The data can only be decrypted by those who share the same key. The same information can, therefore, be ciphered and deciphered by sensors and gateways using the same key. An integrated AES encryption engine powers the advanced BLE module Simblee. The gateways and wearable data connection are encrypted in our study using the industry standard AES-128-bit encryption because security is not our main area of interest. AES-128's low memory and computational requirements make it a good choice for wearables with limited resources [43].

1.5 Performance Analysis

Multiple participants are tested using three wearable sensors to verify the functionality and viability of the IoT-connected healthcare system. A small lab room with 25°C temperature is utilized to conduct experiments. The Wi-Fi-connected Internet of Things gateway is positioned to collect data in the middle of the space. Three subjects, seated at various room corners, have sensors on their chests. This experiment removes the ECG electrodes from the sensor because blood pressure and ECG readings need active continuous data transmission to be verified. The temperature sensors and PPG record three patients' body and heart rates. The sensor data are transmitted to the cloud server from the IoT gateway. The data are validated each time it is sent from the sensor to the gateways; if not, it is sent three times. A missing counter will be created and added to the next sending cycle if the receiving acknowledgement is not received [44].

To ensure that every piece of data is successfully transferred to the cloud at least once, the quality of service is set to level 1 (at least once) for the MQTT protocol data exchanged amid the cloud server and the gateways. For remote health monitoring, each patient's temperature and heart rate can be seen in real time on the cloud-based user interface webpage. The sensor may be expanded using electrodes to monitor blood pressure and ECG when necessary for severe cases. Researchers worldwide have put out many wearable device designs with IoT applications in recent years to monitor essential indicators, including heart rate, blood pressure, temperature of the body, and respiration rate. An extensive overview and comparative analysis of current wearable healthcare systems are provided. The majority of the gadgets have attachment points on the hand or chest. On the other hand, regular movements can easily affect devices worn on hands. While the belt around the belly is not the best option because of comfort concerns, the authors of ref. [45] suggest a chest-based sensor. This study suggests a rigid-flex sensor for wearers' chests that may be quickly and readily placed without causing too much disruption to day-to-day activities. Low-power circuitry and cyclic operation loops are required in sensor design to increase wearable device operating times. A wearable device's operating duration typically ranges from a few hours to several days. A small rechargeable coin battery (120 mAh) that can run for 100 h in a 5-min operating cycle is employed as the power source for this project.

Most medical experts focus on the cardiorespiratory system regarding healthcare applications. Standard devices that are capable of measuring respiration rate, heart rate, and heart rate variability are ECG/PPG sensors, which come in many designs. The suggested sensor proven effective in earlier research is integrated with ECG and PPG sensors in this work. The PPG and ECG sensors can be quickly removed and put back together in various monitoring situations to minimize power consumption and maximize comfort. Moreover, adopting ECG and PPG yields an additional crucial insight: blood pressure is estimated using the pulse transit time. Our earlier work presents the procedures for gathering data, analyzing it, and assessing our blood pressure estimation technique [46]. Wireless communication is crucial for remote health monitoring scenarios in IoT-connected healthcare applications. Because of its ubiquitous usage in electronic products and low battery consumption, BLE is the widely used wireless technology for wearable medical devices. Since BLE can only transmit data at a distance of 100 m, several gateways are suggested for long-distance data transfer. For fixed gateways, numerous mobile computers, like the Raspberry Pi is utilized in refs. [47] and [48] select cell phones as their mobile gateways. In this work, short- and long-range data transfer on cellphones and portable PCs are accomplished via BLE and WiFi, respectively. Both gateways use the MQTT protocol, a subscribe messaging system perfect for IoT applications with low power and data rate needs [49, 50]. There is a smartphone application for medical professionals and a web application for customers to see the tracked health data.

1.6 Conclusion

This study presents a novel wearable sensor for long-term healthcare monitoring in Internet of Things contexts. Three primary parts comprise the sensor system as follows: many sensors for physiological parameter measurement; a central board for the reception, processing, and transmission of signals; and a power board for the battery charger and energy source. Because of the rigid-flex structure that connects these parts, the sensor can monitor body temperature, heart rate, PPG, and ECG. Combining the ECG and PPG on one device allows continuous blood pressure estimation using the PAT technique without needing extra connections or hardware setups. The suggested sensor effectiveness is shown through experimental findings compared to a commercial medical reference piece of equipment. In IoT-connected healthcare applications, health data are transferred from the sensor to an IoT gateway via a BLE module. The gateway sends the

data to a cloud server on the Internet for processing and archiving. The development of mobile (smartphone) and stationary (Raspberry Pi) gateways enables the sensor to function constantly indoors and outdoors. In the cloud, timestamping guarantees data integrity and synchronization, while data encryption protects privacy in both the sensor and the gateway. A cloud website can display real-time physiological information for remote healthcare applications. Future development will concentrate on creating additional edge computing features on the gateway to improve the IoT-connected healthcare platform.

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