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# Development and research of a remote patient monitoring system

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## Abstract

This paper presents an architecture design for a patient monitoring system integrated with Internet of Things (IoT) technology to detect and quantify patient stress levels. Research in remote patient prediction systems is considered one of the most important areas at present. This technology offers the potential to improve stress assessment, provide interventional treatment, and provide personalized stress management techniques. A Raspberry Pi microcontroller was used as a key controller. The unit is equipped with electroencephalography sensors, electrocardiogram sensors, glucose sensors, and electromyography sensors to record physiological signals indicative of stress, such as cardiac activity and human brain activity, a method for monitoring blood glucose levels in diabetic patients and measuring electrical activity. Muscles are collected from these four sensors and transmit information via communication channels (Wi-Fi, USB). The information obtained is transferred to a storage database, where patient data is securely stored. In the storage database, interaction between the patient and the doctor occurs via a 4G communication channel. Data is transmitted via a 4G communication channel from the storage database to the doctor's personal computer. From the doctor's personal computer, data is transferred to the doctor's control panel, and from there the data is transferred to a web server, where all data is processed and the patient is monitored. In the course of research, it was found that the proposed device has 95% reliability in measuring cardiac activity and human brain activity, a method for monitoring blood glucose levels in patients with diabetes and measuring the electrical activity of muscles.

**Keywords:** Electra myography sensor, Electrocardiogram sensor, Electroencephalography sensors, Glucose sensor, Health monitoring, Internet of things, Remote patient prognosis systems.

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## 1. Introduction

The increasing number of remote patient prognosis systems (RPMS) has become noticeable due to the emergence of highly infectious diseases like COVID-19, demographic shifts towards an ageing population, and an increase in health complication scenarios. In addition, technological advances have led to the more extensive use of Remote Patient Monitoring (RPM). RPMS is used for specific categories of patients, for example, patients with chronic diseases or contagious diseases during isolation, as well as individuals with limited mobility or other forms of disability [1]. These systems are also used for postoperative patients, newborns, and elderly patients. The goal of healthcare is to guarantee the comfort of patients in their everyday lives. Thus, patients can move freely and engage in physical activity in their own circle [2]. In the past, patient prognosis systems typically used wired sensors attached to computers inside hospitals. A limitation of these systems was that they limited patient maneuverability. The devices used were also bulky, expensive, and only suitable for a limited number of patients. RPMS was introduced when healthcare providers expanded to provide home-based care. As the traditional patient prognosis predicted, this system was not user-friendly. Over time, the method has improved, allowing researchers to create conclusions for remote patient prognosis and simulations supported by wireless communication. The healthcare division is improving significantly as more scientists and firms are using remote patient prognosis solutions to improve healthcare services, resulting in business growth [3-5]. In a remote patient prognosis system, physiological information is taken using biomedical sensors to assess the state of health of patients outside the clinic [6]. Its goal is to bring classic medical settings into people's homes, where they live, work, and play. Concentrated information is transmitted wirelessly to the healthcare provider using various forms of communication [7]. With the help of telemedicine, it is possible to reveal and broadcast physiological data such as heart rate, respiratory rate, body temperature, blood pressure, and oxygen saturation in a real-time system [8, 9]. The advantages of RPMS lie in the detection of diseases in real-time and the ability to model the patient's well-being in the long term. In cases of early disclosure of mortality, immediate action is allowed. In addition, these systems reduce healthcare costs through the use of various communication technologies. During treatment, patients can extend their daily activities. In addition, RPMS improves emergency response in road traffic accidents and improves maneuverability [10]. Wireless sensors and wireless communications are used to collect and transmit information to the hospital when monitoring patients remotely. All kinds of sensors are used to collect information, such as wearable and implantable (contact sensors), as well as non-contact sensors. The received information can be processed and converted into a suitable volume using an internal or external controller before being wirelessly transmitted to the hospital. Various forms of communication are used to transmit information to the end user, both near and far [11]. The increasing number of devices connected to the Internet has led to the emergence of the concept of today's heterogeneous networks. The Internet of Things (IoT) ensures that information from heterogeneous networks is enabled and interoperable. It also brings intelligence to many physiological objects, such as smart cars, homes, healthcare, industry, and smart grids [12]. However, there are certain issues, such as mobility, quality of service (QoS), automation concepts, and security, that have exposed the individual shortcomings of RPMS. The heterogeneous nature of RPMS, formulated in heterogeneous architectural design, network communications, locations, facts, and environments, complicates QoS characteristics. Thus, guaranteeing QoS conditions for network parameters guarantees an increase in the performance of RPMS [13].

The Internet of Vehicles (IoV) within the overall structure can be used to alleviate RPMS challenges in terms of mobility and routing protocols. First, IoV allows RPMS nodes that are either on vehicles or along the road to conduct information forwarding and computations, with vehicles intermittently entering and exiting the internet. Second, IoV significantly reduces the transmission interval between nodes, provided that the IoV mobility scheme is well-designed. Third, network delay will be reduced while bandwidth is increased simultaneously. Finally, connectivity will be maintained even in sparse or disconnected sensor networks. This article provides an exhaustive analysis and contemporary study of existing RPM systems and their characteristics. The research explores the current remote patient monitoring systems based on their applications. Additionally, an analysis of other RPMS functions and their applications has been conducted.

The development of diverse devices and the associated communication challenges have led most authors to analyze RPM from the perspective of their application areas, architectures, technologies used, and problems. Remote patient monitoring systems, as one of the applications of "smart cities," can use the IoV platform to address issues related to mobility, energy efficiency, QoS, and many others. However, numerous researchers have introduced mobile Adhoc networks (MANETs), similar to vehicular Adhoc networks (VANETs), in the context of remote patient monitoring systems to improve healthcare delivery, and this progress is significant [14]. Despite the effectiveness of these ideas, there are still several drawbacks and issues related to mobility, network uptime, and energy efficiency that need to be addressed. IoV is one of the communication models that could potentially rationalize and solve the problems encountered in RPMS [14]. The final advantages in the field of RPMS have been analyzed, starting with contact and contactless methods. Discussions have been held on contactless camera-based approaches and contact-based methods [15]. The capabilities and challenges of applying Wireless Body Area Networks (WBAN) for RPMS have been analyzed. A new multiple access protocol with time division for WBAN based on WBAN RPMS has been developed [16]. Cheap and non-invasive RPM solutions for elderly individuals have been analyzed and compared, and a few management techniques for data collection in RPMS have been developed [17]. Explore recent Internet of Things (IoT)-based RPM applications. This brings extensive research into the use of IoT in RPMS based on RPMS findings, big data, and disease forecasting [18]. Approaches to conducting surveys and the specificities of mobility modifications in RPMS have been addressed, both for individual and group RPM. Analyze existing routing and MAC protocols, and investigate and identify appropriate technologies [19, 20]. A comprehensive IoV recommendation has been made, allowing vehicles to interact with anything connected to the Internet [21]. The prediction framework primarily utilizes IoV technology for monitoring heart diseases. Recent studies on RPMS show that the global market for remote patient prognosis has been growing rapidly since 2020. This has led to an increase in the number of companies developing these facilities [22, 23].

Life activity forecasting is a routine examination where key physiological parameters such as body temperature, heart rate, blood oxygen concentration, blood pressure, and respiration rate are measured. In RPMS, forecasting is conducted outside the hospital. This is important because it enhances clinic efficiency and reduces hospitalizations since more patients can be monitored at home. Remote monitoring of patients may involve one or several physiological parameters, depending on the type of patient being monitored, and the forecasting may occur in real-time or on a regular basis. This also depends on the diagnosed condition; for example, blood pressure can be monitored to diagnose hypertension. Monitoring essential functions determines whether the patient's condition is worsening or not [24].

As a result, various experts have developed and utilized forecasting systems for essential functions to detect deteriorations or abnormalities in a patient's body. In a study by Li and Warren [25], a wearable, cost-effective pulse oximeter with a low reflectance coefficient is described as capable of providing clear photoplethysmography (PPG) information without the need for filters. The PPG signal is sent to the main computer at 240 Hz via a Zigbee transceiver or mini-USB interface. Computer processing is required to eliminate ambient noise and slow-changing distortions in the PPG signal. RPMS can track heart rate, respiration rate, blood oxygen concentration, and blood pressure. These RPMs measure more physiological variables, making them more reliable. In a study by Oğuz and Ertaş [26], the authors reported heart rate accuracy within 0.1°Cover a temperature range of 16-42°C using two digital temperature sensors to monitor the temperature of two ear canals, with data transmitted via Bluetooth for subsequent analysis. However, using ear canal rotation frequency sensors can lead to ear trauma, and sensor probes may induce small fluctuations in measurements during movement. As a result, wearable RPMs may be preferable.

For automatic screening of potential COVID-19 patients, authors Dong, et al. [27] applied XGBoost and logistic regression methods. Physiological parameters such as respiration, heart rate, body movements, and sleep patterns were assessed using an ultra-wideband radio frequency impulse radar. The study compared 140 radar images from COVID-19 patients with 144 radar image from a control group of healthy individuals. XGBoost LR showed excellent discrimination, outperforming some individual machine learning methods. However, this study had limitations, as environmental factors and certain variables can affect controlled RPMS tests. The accuracy rate in practice may be lower, considering the small sample size and lack of representation of certain age groups. Additionally, the proposed RPMS is limited to monitoring one patient at a time, reducing its suitability in a real hospital.

Systems, in previous studies, were designed to predict one or two physiological parameters, whereas the authors of Kumar, et al. [28] designed an order of prediction of some topically required functions that monitors all five physiological parameters. A microcontroller manages temperature sensor readings displayed on a liquid crystal panel. A radio frequency transmitter sends information to a radio frequency receiver, which uses a controller to display information on a liquid crystal screen. Previous RPMS systems were designed to forecast one or two physiological parameters, while authors Kumar, et al. [28] constructed a forecasting system for multiple essential functions, monitoring all five physiological parameters. An improved design using Internet of Things (IoT) sensors remotely collects these parameters from the patient. In RPMS, WBAN is used to transmit information to a doctor's smartphone. The smartphone includes an app that directs doctors to make decisions. This RPMS setup also allows for the administration of essential medications to the patient during ambulance transport. This ensures the doctor's conditional stay in the ambulance. Another study by Kumar, et al. [29] describes an RPMS for measuring blood oxygen saturation and heart rate. A unique 868 MHz wristwatch subsystem with an emphasis on optical PPG is presented. Spectra at 868 MHz and 2.45 GHz are compared. Using the investigated wrist-worn sensor platform, the design was successfully used in clinical conditions to measure SpO2 and heart rate. The researched sensor station may be used in future RPMS applications due to efficient medical testing.

## 2. Materials and Methods

The architecture of RPMS describes the system's structure, its multi-layered nature, and how the layers interact with each other. When it comes to human life, the RPMS structure resembles disorder and obstacles. Firstly, what brands of sensors are suitable for collecting clear and reliable patient information? Secondly, which processing technologies and communication protocols will be more favorable for this system, and finally, will the medical community and patients approve of this idea?

The scientific novelty of this work lies in the fact that the architecture of the patient monitoring system consists of the patient's personal medical information stored inside an authentication storage device (smartphone) and then transmitted through communication channels. There are also four sensors (an electroencephalography sensor, an electrocardiogram sensor, a glucose sensor, and an electromyography sensor). Information is collected from these four sensors, and they transmit the information through communication channels (Wi-Fi, USB). The received information is sent to secure data storage 4, where patient data is kept secure. In data storage, information is transmitted via a 4G communication channel, facilitating interaction between the patient and the doctor. Data from the storage is sent via a 4G communication channel to the doctor's personal computer 5. From the doctor's personal computer, the data is transmitted to the doctor's control panel 6, and from there, the data is sent to a web server 7, where all the data is processed and patient monitoring takes place.

Figure 1 shows the architecture of the patient monitoring system.

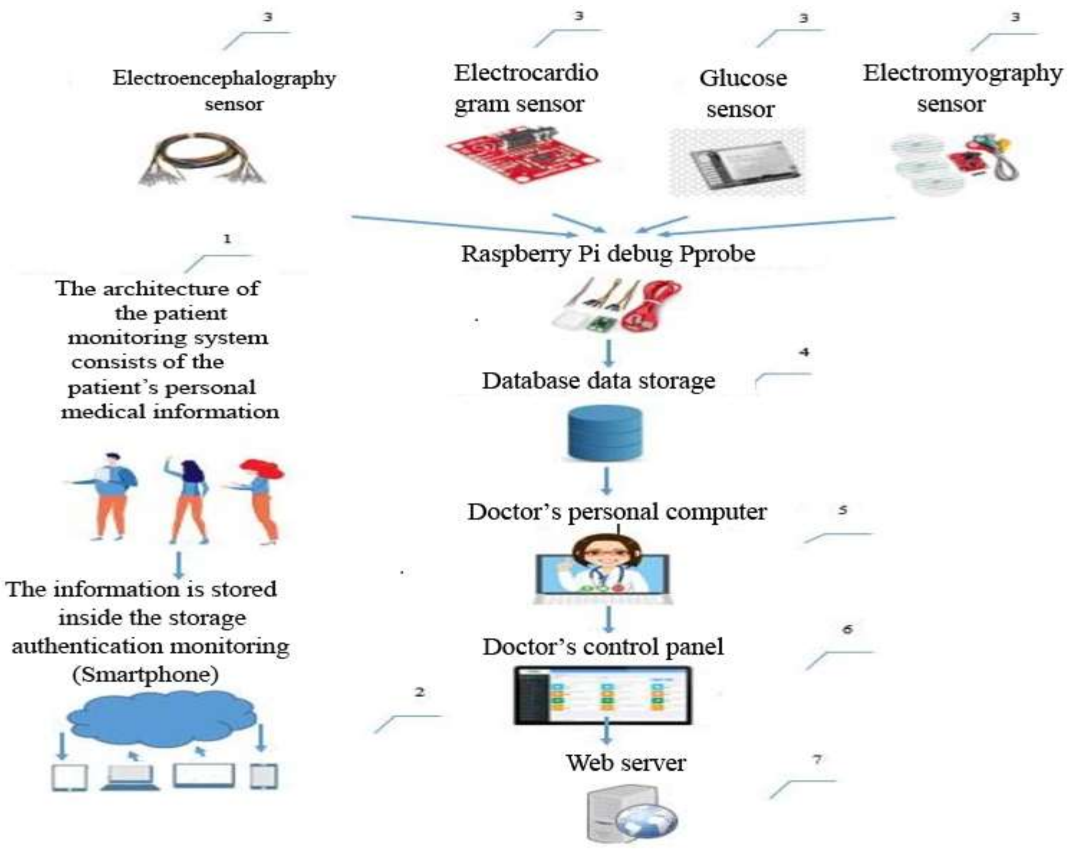


**Figure 1.**
Patient monitoring system architecture.

The operation of the proposed architecture is carried out as follows: The architecture of the patient monitoring system, consists of the patient's personal medical information 1, which is stored inside the monitoring authentication storage (smartphone) 2 and then transmitted through communication channels. There are also four sensors 3 (electroencephalography sensor, electrocardiogram sensor, glucose sensor, and electramyography sensor). Information is collected from these four sensors, and they transmit the information through communication channels (Wi-Fi, USB). The received information is transmitted to storage base 4, where the patient data is stored safely. In the storage base, the data is transmitted through a 4G communication channel where patient and doctor interactions take place. From the storage base, the data is transmitted via a 4G communication channel to the doctor's personal computer 5. From the doctor's personal computer, the data is transmitted to the doctor's control panel 6, and from there, the data is transmitted to the web server 7, where all the data is processed and the patient is monitored.

Figure 2 illustrates an electroencephalographic sensor.

**Figure 2.**
Electroencephalography sensor.

Electroencephalography, or EEG, is considered an essential tool for studying human brain activity. EEG sensors are devices that record the electrical activity of the brain, allowing scientists and doctors to study the brain's condition, detect pathologies, and diagnose various neurological and psychiatric disorders.

Electroencephalography is a research method that involves applying electrodes to the surface of a patient's head. These electrodes capture the electrical activity of neurons in the brain. Neurons that communicate vigorously with each other generate electrical signals that can be recorded with the help of EEG.

EEG sensors consist of multiple electrodes placed on the scalp. These electrodes are connected to amplifiers and a computer that analyzes the signals and visualizes them in the form of graphs, called "electroencephalograms" (EEG). EEG can capture various types of brain activity, such as alpha waves, beta waves, delta waves, and theta waves.

Figure 3 shows the electrocardiogram sensors.

**Figure 3.**
Electrocardiogram sensors.

Electrocardiogram (ECG) sensors are essential medical devices designed for measuring the electrical activity of the heart. They play a key role in diagnosing heart conditions, monitoring the cardiovascular system's status, and advancing innovative technologies in the fields of medicine and fitness.

An ECG sensor operates based on the principle of recording electrical signals generated by the heart during its contractions and relaxations. The primary components of an ECG sensor include electrodes, amplifiers, and a recording device. Typically, an ECG sensor includes multiple electrodes that are attached to the patient's skin at specific body locations, such as the chest, arms, and legs. These electrodes record the electrical signals created by the heart.

The electrical signals obtained from the electrodes are very weak. Amplifiers increase the amplitude of these signals, making them more readable and analyzable. The amplified signals are then recorded on paper or in digital form. This enables doctors and researchers to analyze the shape and characteristics of the electrical signals to detect anomalies.

Figure 4 shows a glucose sensor.

**Figure 4.**
Glucose sensor.

Glucose sensors are innovative medical devices that have revolutionized the way glucose levels in the blood are monitored in patients with diabetes. These small and convenient devices enable patients to more effectively manage their condition and prevent acute complications of diabetes.

Glucose sensors operate based on technology that allows the measurement of glucose levels in the interstitial fluid or inside cells. The primary components of a glucose sensor include the following:

- A small device typically implanted under the skin that houses a sensing element. This element responds to changes in glucose levels, often through chemical reactions.

- A transmitter that relays information about glucose levels to a receiver.
- A receiver that displays the glucose level on a screen. Some receivers also have the capability to transmit data to smartphones or computers for further analysis.

1. Glucose sensors allow patients to continuously monitor their glucose levels in real-time, regardless of the time of day. This is especially important for those with type 1 diabetes or those requiring intensive glucose level controls.
2. Glucose sensors provide more accurate and reliable data compared to traditional blood testing methods using lancets and test strips.
3. With more frequent and convenient monitoring, patients can make more informed decisions about insulin dosing, diet, and physical activity, helping to improve glycemic control and prevent complications. Glucose sensors are typically securely attached under the skin and remain in place for several days or weeks, providing convenience and reducing the need for frequent finger pricks.

Figure 5 shows the electromyography (EMG) sensors.

**Figure 5.**
Electromyography (EMG) sensors.

Electromyography (EMG) sensors are an important tool in the field of medicine and physiology designed to measure the electrical activity of muscles. This technology provides researchers, physicians, and rehabilitation therapists with information about muscle and nervous system function, which has a wide range of applications, including diagnostics, rehabilitation, and research.

EMG sensors record the electrical signals produced by muscles during contraction and relaxation. The main components of an EMG sensor include the following:

1. Electrodes are attached to the surface of the skin in the area where muscle activity needs to be measured. Typically, pairs of electrodes are used: an active electrode and a reference electrode. The electrodes record the difference in electrical potential between them;
2. The electrical signals obtained from the electrodes are very weak. An amplifier increases the amplitude of the signals, making them more readable and analyzable.
3. The amplified signals are then recorded on paper or in digital form. This allows for the analysis of the shape and characteristics of the electrical signals, such as amplitude and frequency. EMG sensors are used for the diagnosis of neuromuscular disorders such as Lou Gehrig's disease, myasthenia gravis, Parkinson's disease, and others. They also enable doctors to monitor patients' progress during treatment and rehabilitation. EMG sensors are used to assess muscle activity during physical therapy and rehabilitation after injuries or surgeries. They help patients regain control of their muscles and improve their function.

EMG sensors are used in scientific research to study muscle activity during various tasks and under different conditions. This allows scientists to better understand the mechanisms of muscle and nervous system function. EMG technology is also applied in the field of biometrics and device control using muscle signals. For example, it can be used for unlocking smartphones or controlling prosthetics.

Areas of EMG sensor usage include stress regulation, monitoring abnormal health conditions, biofeedback training, and studying human-computer interaction. Electroencephalography (EEG), electrocardiography (ECG), glucose, and electromyography (EMG) sensors gives doctor a lot of useful information about a person’s mental health and how their body reacts to different stimuli. They can track changes in heart conductivity, which lets doctors make personalized interventions and find ways to reduce stress. Figure 6 illustrates the design of the proposed device.

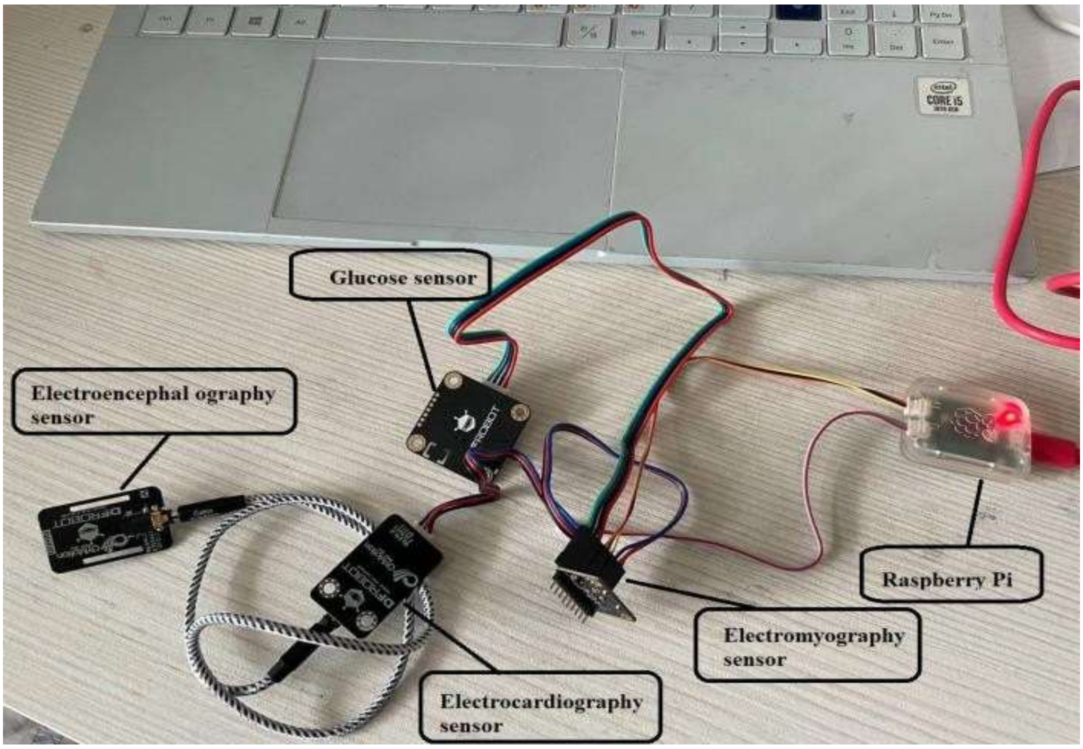


**Figure 6.**
Design of the proposed device.

## 3. Results

Python is a programming language that is widely used in Internet applications, software development, data science, and machine learning (ML). Developers use Python because it is efficient, easy to learn, and works on different platforms. Python programs can be downloaded for free; they are compatible with all types of systems and increase the speed of development.

Using the Python programming language, algorithms have been developed for 4 sensors electroencephalography sensors, electrocardiogram sensors, glucose sensors, and electromyography for the monitoring of patients.

```python
from flask import Flask, request, jsonify
from gpiozero import MCP3008
import time

app = Flask(__name__)

glucose_port = MCP3008(channel=2)

def get_ecg_data():
    glucose_value = glucose_port.value

    return jsonify({'glucose_value': glucose_value})

if __name__ == '__main__':
    app.run(debug=True)

```

**Figure 7.**
The glucometer algorithm.

As we can see from Figure 7, the MCP3008 object was taken from the Pizero library to work with analogue data. Analogue data is sent to the recording port for the analogue sensor. An analogue signal is read from the glucose sensor. Next, the data is sent in JSON format to the client side.

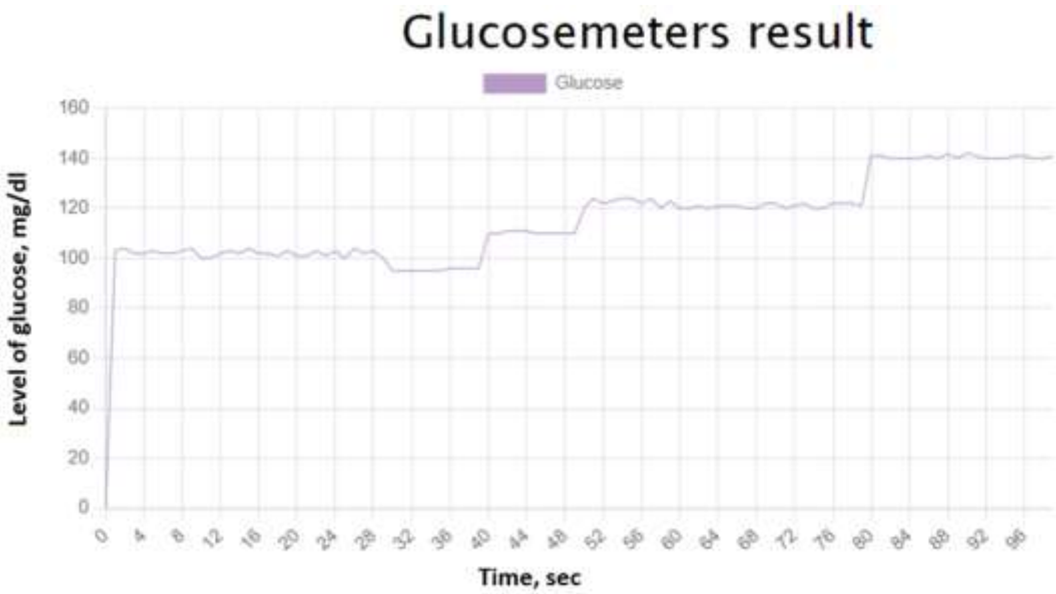


**Figure 8.**
Glucose levels predicted for average under normal conditions.

Figure 8 shows glucose levels predicted using a double-moving average under normal conditions. Glycaemic observation in the elderly responds to a plasma glucose degree the day before a meal of 90 to 130 mg/dl and a decrease in plasma glucose degree after a meal of 180 mg/dl. We considered two groups of dependence: self-dependent and function-dependent, according to the International Diabetes Federation. No intervention is required for withdrawal. One notified, a specialist must access the caregivers' efforts. By looking at the graph, we can see that there are no peaks or variations in the prediction that the system generated, there is no stressed state, and there should be no warning. According to the analyzed readings, the early moment was brought to the pre-holiday stage. Then happened a meal that activated an increase in glucose degree, but without exceeding 180 mg/dl, starting the prognosis. With no values exceeding 180 mg/dl, there was no need to send an orange alert. When the monitoring exceeds 200 mg/dl, it means that an upward pattern is observed, and the system sends a red alert sign identifying a dangerous condition. It is worth noting that the algorithm envisages a state in which the patient perceives food and does not issue an erroneous.

```
from flask import Flask, request, jsonify
from gpiozero import MCP3008
import time

app = Flask(__name__)

ecg_port = MCP3008(channel=1)

def get_ecg_data():
    ecg_value = ecg_port.value

    return jsonify({'ecg_value': ecg_value})

if __name__ == '__main__':
    app.run(debug=True)

```

**Figure 9.**
EEG algorithm.

Figure 9 shows the EEG algorithm. To develop this algorithm, we import the MCP3008 object from the Pizero library to work with analog data. We transfer the data to the recording port for the analogue sensor. The analogue signal is read from the ECG sensor. Next, the data is sent in JavaScript Object Notation (JSON) format to the client side.

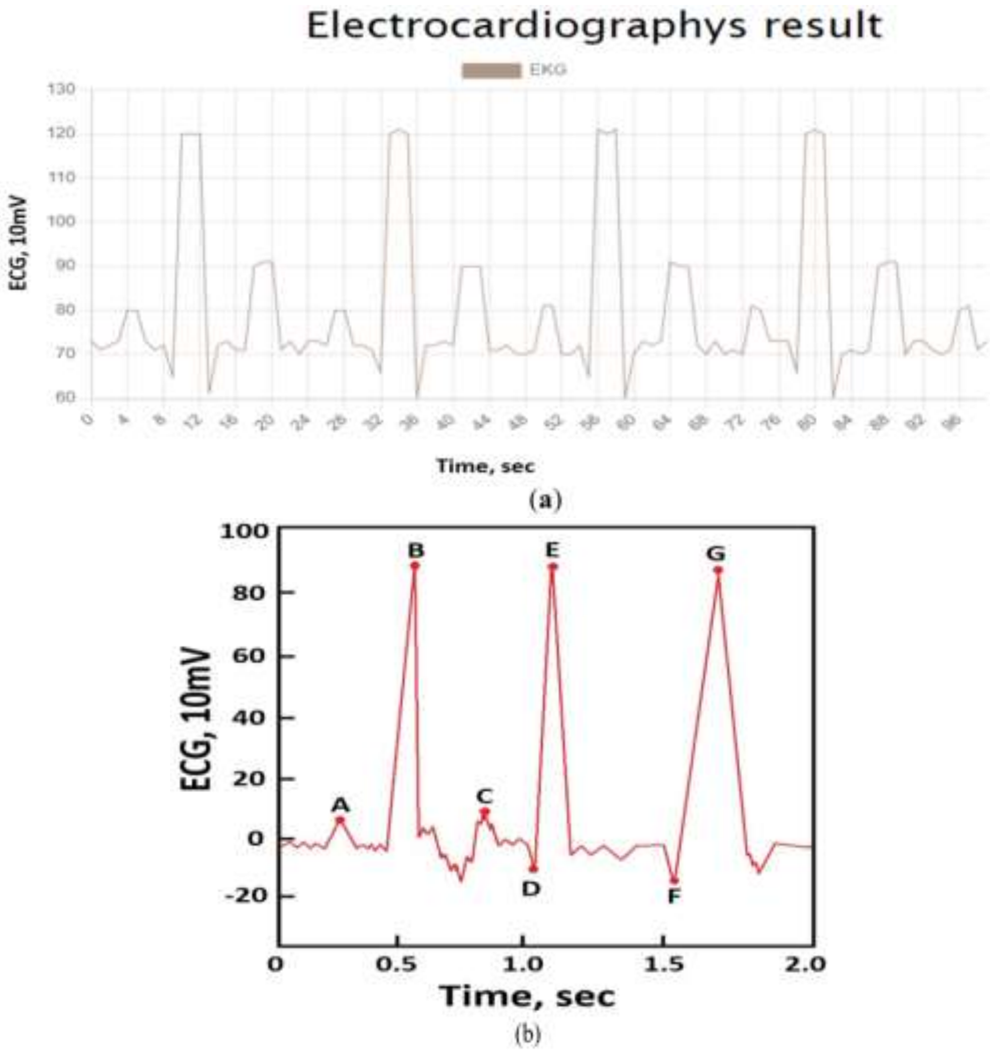


**Figure 10.**
ECG signal analysis: (a) plot of raw ECG data; (b) ECG plot for quality remote service (QRS) detection.

To define the ensemble, the starting data, the marginal significance, and the minimum value were taken as data "A," "B," and "C" Wave peak points B, E, and G and possible interference peaks were marked in order to extract the difference in the basic order for the ECG information sequence and subsequently detect the highest point. These marks B, E, and G were represented by analyzing the section (Figure 10 a, b) that was extracted from the plot of the undisturbed ECG information. The middle of the largest amplitude value of the shown largest point was applied as the liminal value because the amplitude of the wave limit value was large, and the largest value dissimilar to the wave limit value was excluded.

```
from flask import Flask, request, jsonify
from gpiozero import MCP3008
import time

app = Flask(__name__)

emg_port = MCP3008(channel=0)

def get_ecg_data():
    emg_value = emg_port.value

    return jsonify({'emg_value': emg_value})

if __name__ == '__main__':
    app.run(debug=True)
```

**Figure 11.**
EMG algorithm.

Figure 11 shows the EMG algorithm. To develop this algorithm, we import the MicroPythonMCP3008 object from the Pizero library to work with analogue data. We transfer the data to the recording port for the analogue sensor. The analogue signal is read from the ECG sensor. Next, the data is sent in JSON format to the client side.

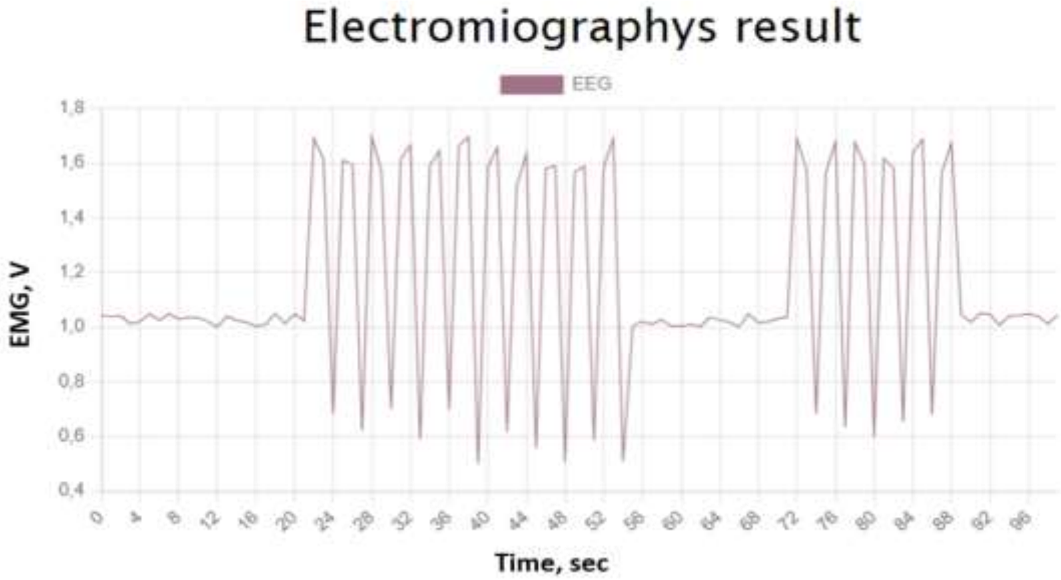


**Figure 12.**
EMG signal processing raw EMG signal.

RMS baselines were extracted from the raw EMG signal (Figure 12) to test the algorithm. Using the calculated Remote Monitoring System (RMS) values, you can find out what the raw EMG signal looks like and how active the muscles are. RMS value can possibly reflect the level of physiological enterprise of the motor apparatus during contraction. For weak muscular enterprise, the interdependence between the intensity of enterprise and EMG signal had the same tendency. For strong muscular enterprise, the same interdependence did not fit the fluctuations of activity tension, which required a different way of calculation because the amplitude of the muscular vigor signal was saturated.

```

sfreq = 1000
times = np.arange(0, 10, 1/sfreq)

n_channels = 16
info = mne.create_info(chs=ch_names, sfreq=sfreq, ch_types='eeg')
data = np.random.randn(n_channels, len(times)) * 10
raw = mne.io.RawArray(data, info)

def get_eeg_data():
    eeg_data, _ = raw[:, :]

    eeg_data_json = eeg_data.tolist()

    return jsonify({'eeg_data': eeg_data_json})

if __name__ == '__main__':
    app.run(debug=True)
```

**Figure 13.**
EEG algorithm.

Figure 13 shows the EEG algorithm. To develop this algorithm, the sampling frequency in Hz is selected. Data is read from 16 "mne" channels and stored. Then the data is written from raw, and the data is converted to JSON format. Next, the data is sent in JSON format to the client side.

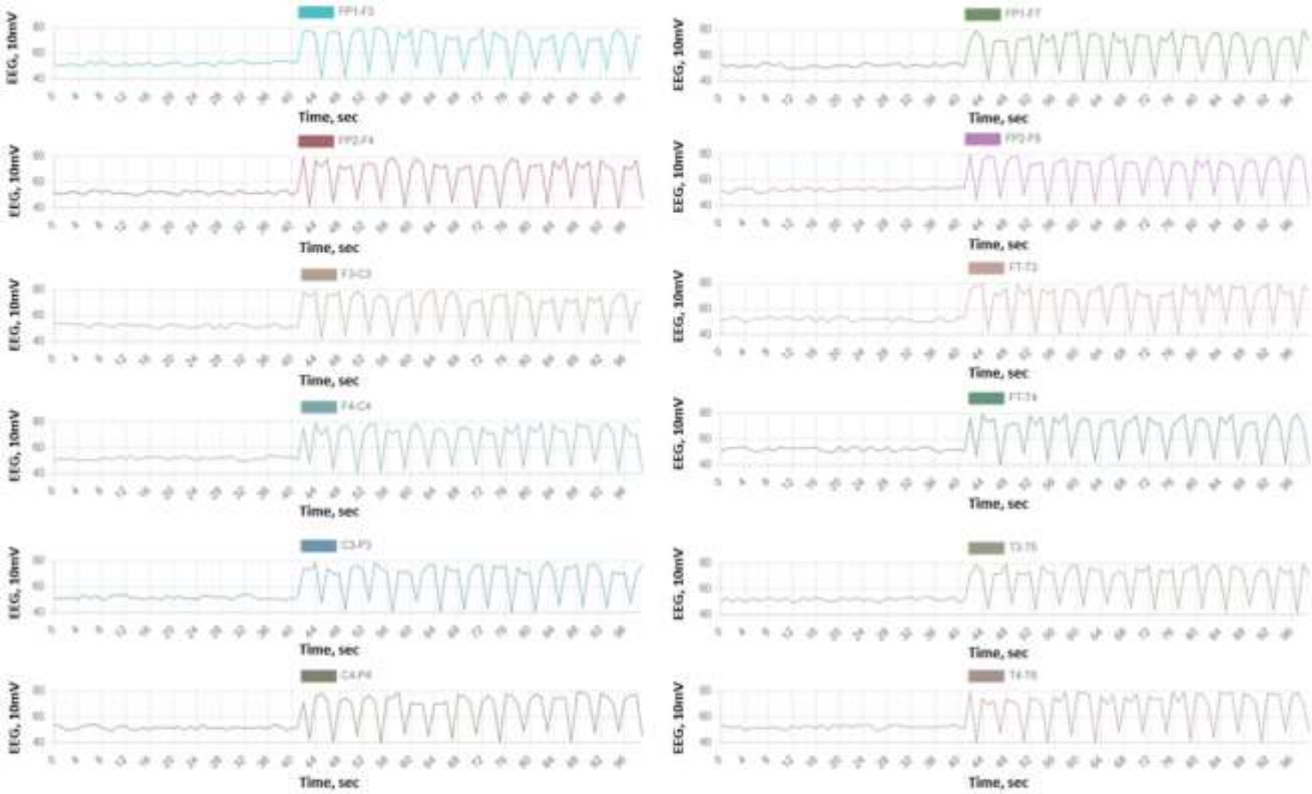


**Figure 14.**
a,b shows the actual input EEG communication during the active phase of patency.

Figures 14a, b illustrates the actual EEG input coupling during the active patency phase.

Tests were performed on the desired EEG signal to determine the suitability of the proposed structure, and the signal was recovered by long-term 4000 Hz frequency control. The results of this approach are presented in this section.

Tests were performed on the desired EEG signal to determine the suitability of the proposed structure, and the signal was recovered by long-term 4000 Hz frequency control. The results of this approach are presented in this section.

The initial distance in the experiment is applied as a learning phase for any individual. Generally, the reversion from a typical value to a state of exhaustion was associated with a steady decrease in heart rate and an increase in HRV. When stable SVM HRV values are observed, it is possible to determine whether an individual is feeling fatigued, and the software design can decide on urgent actions such as alerting. Thus, long-lasting, non-threatening, and small rehabilitation training can be promised based on such augmentations. In this experiment, one subject (male, 45 years old and 80 kg, 180 cm, healthy) was employed as a demonstration sample for secondary measurements and analyses. According to his individual sensations, the agitated pattern naturally occurred in the morning and the fatigue state in the evening; thus, the information on agitated stay and fatigue state were supposed to be taken at 9:00 a.m. and 12:00 p.m. respectively. Baseline ECGs acquired in the agitated state and fatigue state can be used to validate the System Variability Monitoring (SVM) estimation. Figures 15 a, b show the HRV values for the excited state and fatigue state, respectively, and show that the height of Heart Rate Variability (HRV) changes was irregular when the subject was in the excited state and became regular when the subject was in the drowsy state.

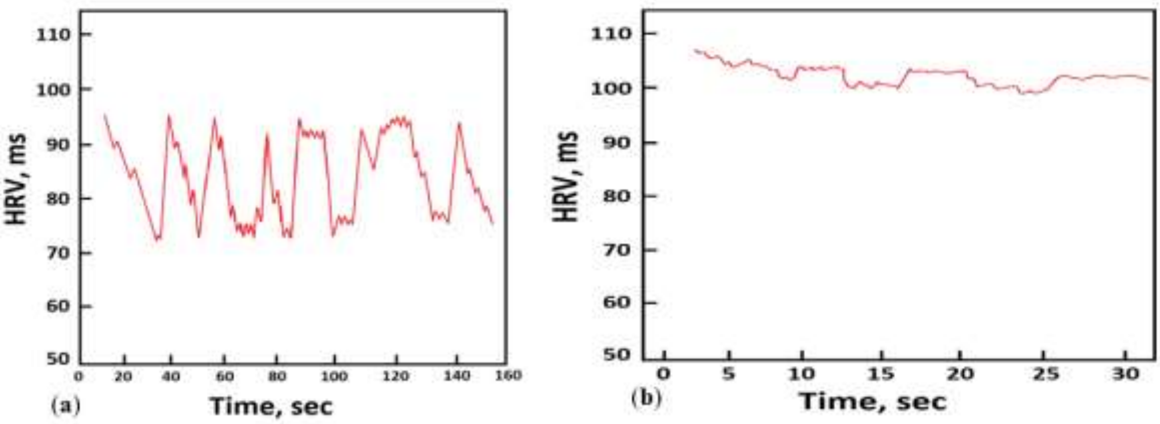


**Figure 15.**
Heart rate variability values for activity analysis: (a) excited state; (b) fatigue state.

## 4. Conclusions

RPMS are essential to our daily lives. Technological advancements in the field of RPMS have demonstrated this. In conclusion, the development of an Internet of Things (IoT)-enabled stress sensing device has formidable potential to transform the way we understand and manage stress. Explored the various nuances of this technology and its implications for personal wellbeing and public health. Integrating the abilities of Internet of Things devices has uncovered fresh-faced potential for monitoring stress in the system of the moment, providing invaluable information about users' physiological and behavioural responses. Using the IoT, these devices can pick up and review a limitless range of biometric data, ranging from heart rate variability to human brain activity, a way to monitor blood glucose levels in diabetic patients, and measurements of muscle electrical activity, allowing for the suspension of stress. With this data at their disposal, users can acquire a concept of their stress, action modifications, and reactions, allowing them to utilize more common-sense coping mechanisms and make positive lifestyle changes. In the present study, a device was created to detect and quantify the degree of stress using topical indicators. The electroencephalography sensor showed a decrease in frequency values ranging from 50 to 79 beats per minute. Electrocardiogram sensor depicted values ranging from 65% to 80%. Glucose sensor showed values from 40 to 65%, and the electromyography sensor showed values from 45 to 67%. For stress levels, an abnormality of 7% on average was observed. Future studies will allow the impact of stress on a specific lingering disorder to be investigated and more sensors to be used to clearly measure stress levels.

## References


[1] B. Talbot *et al.*, "Patient and clinician perspectives on the use of remote patient monitoring in peritoneal dialysis," *Canadian Journal of Kidney Health and Disease,* vol. 9, p. 20543581221084499, 2022. https://doi.org/10.1177/20543581221084499

[2] T. Malche *et al.*, "Artificial intelligence of things-(aiot-) based patient activity tracking system for remote patient monitoring," *Journal of Healthcare Engineering,* vol. 2022, 2022. https://doi.org/10.1155/2022/8732213

[3] H. Fouad, A. S. Hassanein, A. M. Soliman, and H. Al-Feel, "Analyzing patient health information based on IoT sensor with AI for improving patient assistance in the future direction," *Measurement,* vol. 159, p. 107757, 2020. https://doi.org/10.1016/j.measurement.2020.107757

[4] A. C. Van Graan, B. Scrooby, and Y. Bruin, "Recording and interpretation of vital signs in a selected private hospital in the KwaZulu-Natal province of South Africa," *International Journal of Africa Nursing Sciences,* vol. 12, p. 100199, 2020. https://doi.org/10.1016/j.ijans.2020.100199

[5] J. Mohammed, C. H. Lung, A. Ocneanu, A. Thakral, C. Jones, and A. Adler, "Internet of things: Remote patient monitoring using web services and cloud computing," in *In: Proceedings of the 2014 IEEE International Conference on Internet of Things (iThings), 2014, pp. 256-263. 2014 IEEE Int. Conf. Green Comput. Commun. GreenCom 2014 IEEE International Conference Cyber-Physical-Social Comput. CPS 20*, 2014.

[6] M. A. Panhwar, D. Zhong Liang, K. A. Memon, S. A. Khuhro, M. A. K. Abbasi, and Z. Ali, "Energy-efficient routing optimization algorithm in WBANs for patient monitoring," *Journal of Ambient Intelligence and Humanized Computing,* vol. 12, pp. 8069-8081, 2021. https://doi.org/10.1007/s12652-020-02541-7

[7] F. A. C. d. Farias, C. M. Dagostini, Y. d. A. Bicca, V. F. Falavigna, and A. Falavigna, "Remote patient monitoring: A systematic review," *Telemedicine and e-Health,* vol. 26, no. 5, pp. 576-583, 2020.

[8] M. U. Ahmed, M. Björkman, A. Čaušević, H. Fotouhi, and M. Lindén, *An overview on the internet of things for health monitoring systems*. Rome, Italy: Internet of Things. IoT Infrastructures: Second International Summit, IoT 360° 2015, October 27–29, 2015, Revised Selected Papers, Part I, 2016.

[9] A. H. Azizulkarim, M. M. A. Jamil, and R. Ambar, "Design and development of patient monitoring system," presented at the In IOP Conference Series: Materials Science and Engineering, IOP Publishing, 2017.

[10] M. Dhinakaran, K. Phasinam, J. Alanya-Beltran, K. Srivastava, D. V. Babu, and S. K. Singh, "A system of remote patients' monitoring and alerting using the machine learning technique," *Journal of Food Quality,* vol. 2022, 2022. https://doi.org/10.1155/2022/6274092

[11] S. Majumder *et al.*, "Smart homes for elderly healthcare—Recent advances and research challenges," *Sensors*, vol. 17, no. 11, pp. E2496-E2496, 2017.

[12] H. M. Reeve, A. M. Mescher, and A. F. Emery, "Experimental and numerical investigation of polymer preform heating, Am. Emery, Experimental and numerical investigation of polymer preform heating," *HTD - American Society of Mechanical Engineers Heat Transf Div*, vol. 369, no. 6, pp. 321-332, 2001. https://doi.org/10.1016/j.sciaf.2023.e01638

[13] F. H. El-Fouly and R. A. Ramadan, "E3AF: Energy efficient environment-aware fusion based reliable routing in wireless sensor networks," *IEEE Access*, vol. 8, pp. 112145-112159, 2020. https://doi.org/10.1109/access.2020.3003155

[14] L. P. Malasinghe, N. Ramzan, and K. Dahal, "Remote patient monitoring: A comprehensive study," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 1, pp. 57-76, 2019. https://doi.org/10.1007/s12652-017-0598-x

[15] P. Gope, "Body area sensor networks challenges and opportunies," *Univeristy of Virginia IEEE Sensors Journal*, vol. 13, no. 5, pp. 415-418, 2016.

[16] S. Majumder, T. Mondal, and M. J. Deen, "Wearable sensors for remote health monitoring," *Sensors*, vol. 17, no. 1, p. 130, 2017. https://doi.org/10.3390/s17010130

[17] C. Chakraborty, A. Banerjee, M. H. Kolekar, L. Garg, and B. Chakraborty, *Internet of things for healthcare technologies*. Springer, 2021.

[18] B.-S. Kim, K. H. Kim, and K.-I. Kim, "A survey on mobility support in wireless body area networks," *Sensors*, vol. 17, no. 4, p. 797, 2017. https://doi.org/10.3390/s17040797

[19] K. Wei, L. Zhang, Y. Guo, and X. Jiang, "Health monitoring based on internet of medical things: Architecture, enabling technologies, and applications," *IEEE Access*, vol. 8, pp. 27468-27478, 2020. https://doi.org/10.1109/ACCESS.2020.2971654

[20] A. L. Minn, K. P. Seng, G. K. Ijemaru, and A. M. Zungeru, "Deployment of IoV for smart cities: Applications, architecture, and challenges," *IEEE Access*, vol. 7, pp. 6473-6492, 2018. https://doi.org/10.1109/access.2018.2887076

[21] T. Thirugnanam and M. R. Ghalib, "A new healthcare architecture using IoV technology for continuous health monitoring system," *Health and Technology*, vol. 10, no. 3, pp. 289-302, 2020. https://doi.org/10.1007/s12553-019-00306-7

[22] Bizvibe, "Top 10 remote patient monitoring companies in the world, remote patient monitoring market," Retrieved: https://blog.bizvibe.com/blog/top-remote-patient-monitoring-companies. [Accessed 2020.

[23] S. Dolanl, "Top remote patient monitoring companies & startups in 2022," Retrieved: https://www.insiderintelligence.com/insights/remote-patient-monitoring-companies-startups/. [Accessed 21- Jul-2022], 2022.

[24] R. K. Pathinarupothi, M. V. Ramesh, and E. Rangan, "Multi-layer architectures for remote health monitoring," in *In: Proceedings of the " IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom),*, 2016.

[25] K. Li and S. Warren, "A wireless reflectance pulse oximeter with digital baseline control for unfiltered photoplethysmograms," *IEEE Transactions on Biomedical Circuits and Systems,* vol. 6, no. 3, pp. 269-278, 2011. https://doi.org/10.1109/tbcas.2011.2167717

[26] P. Oğuz and G. Ertaş, "Wireless dual channel human body temperature measurement device," presented at the In 2013 International Conference on Electronics, Computer and Computation, IEEE, 2013.

[27] C. Dong *et al.*, "Non-contact screening system based for COVID-19 on XGBoost and logistic regression," *Computers in biology and medicine,* vol. 141, p. 105003, 2022. https://doi.org/10.2196/preprints.27151

[28] N. Kumar, S. Panda, P. Pradhan, and R. Kaushal, "IoT based hybrid system for patient monitoring and medication," *EAI Endorsed Transactions on Pervasive Health and Technology,* vol. 5, no. 19, 2019. https://doi.org/10.4108/eai.13-7-2018.162805

[29] S. Kumar *et al.*, "A wristwatch-based wireless sensor platform for IoT health monitoring applications," *Sensors,* vol. 20, no. 6, p. 1675, 2020. https://doi.org/10.3390/s20061675