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**ORIGINAL RESEARCH ARTICLE**

# A non-invasive smart healthcare monitoring system based on the Internet of things

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## ABSTRACT

A worldwide increase in healthcare problems and disorders underscored the significance of across the globe healthcare monitoring (HCM). Several countries have increased lifespans due to technological medical developments, government health initiatives, and personal cleanliness. Globalization has led to a gradually rising elderly population and a decrease in fertility, which might result in problems with socioeconomic status. In order to assist older adults, HCM technologies must be cost-effective and simple to implement. Autonomous HCM could be feasible, incorporating wearable devices with sensors, actuators, and communication. The above approach enables practical and efficient personal medical care for older people, minimizing their requirement for costly hospital treatment. The entire study emphasizes the non-invasive blood glucose monitoring (NIBGM). The idea for the project includes developing a non-invasive medical device with RFID tags login, data storage, and smart sensors that allow the monitoring of several organs. The small in size, interconnected sensor monitors body temperature (BT), blood glucose level (BGL), blood pressure (BP), heart rate (HR), and oxygen saturation (OS). The internet-based monitoring device permits healthcare providers to keep track of patient's health metrics in real-time and send data to remote places. The new method allows healthcare professionals to present rapid assistance and reinforcement, enhancing the results for patients.

***Keywords:*** WSN; IoT; RFID; healthcare; non-invasive blood glucose monitoring

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## 1. Introduction

The global market for healthcare monitoring (HCM) has increased significantly as a result of growing health problems and disorders[1–5]. The lifespan has increased primarily because of health care and public safety Improvements, which have caused a growing elderly population and social and economic problems. Cost-effective and easy-to-use wireless HCM using mobile sensors and advanced technology for communication may attain the objectives mentioned above[6–10]. This approach makes personal medical monitoring of older adults simple and successful, reducing the demand for more expensive hospital treatment. Investigators everywhere are examining non-invasive blood glucose monitoring (NIBGM) innovation, which has benefited many patients[11–15]. Monitoring several healthcare records and not obtaining an electronic device (e-Device) capable of measuring every sign of health is challenging. Standard blood glucose level (BGL) tests require finger tapping, resulting in the risk of infection and aches[16–20].

The main objective of the study recommended is to develop and manufacture a device for medical use capable of measuring physiological parameters like body temperature (BT), blood glucose level (BGL), blood pressure (BP), heart rate (HR), and oxygen saturation (OS). Patients at their residences or hospitalized have no trouble employing this integrated device[21–25]. This device utilizes RFID tags to securely log and transmit data collected in the public cloud for virtual medical professional monitoring and preliminary health diagnosis. Patient access and ease of use will be enhanced by the device's minimized pulmonary function test referrals to healthcare centers. Sensors are devices that are readers for RFID tags stored in the cloud storage system and have been designed to be integrated[26–30]. The e-Device will be thoroughly assessed for precision, dependability, and accessibility. A less expensive, easy-to-use, trustworthy healthcare device capable of measuring critical physiological conditions in a single location and allowing monitoring of HCM for enhanced quality of healthcare is desired[31–35].

The idea for a medical e-Device is new and promises significant medical improvements. This integrated sensor detects the Temperature of the BT, BGL, BP, HR, and OS[36–40]. By reducing the demand for different devices to monitor every essential warning, this medical e-Device provides patients with an inexpensive and easy-to-use choice. The small e-Device privately stores and maintains data collected in a public cloud using RFID tags, permitting professionals to monitor HCM and identify medical conditions early, boosting medical results.

Patients can utilize the medical device at their residence without lengthy processes, thus rendering it approachable to everyone. The recommended medical device is a novel, cutting-edge approach to patient life assessment problems that is cost-effective, easy, and readily available, allowing virtual monitoring and enhancing healthcare results.

The research paper has been organized in an orderly approach: Following the overview of the existing literature study in section 2, the approach used will be addressed in section 3, the results of the analysis are presented in section 4, and the study is concluded in section 5.

## 2. Related works

Recent advances in information and communication technology (ICT) have led to the development of telehealth monitoring services and the submission of related proposals. An algorithm using electrocardiogram (ECG) data to monitor blood glucose levels that use the CNN method to extract the features of ECG has been developed. The importance of the P wave and PR segment in participants with low BGL, indicating atrial impact, and the significance of the QT interval at low BGL ranges are also highlighted[41]. A rapid measurement system for numerous health factors is created utilizing multiple sensors and an Arduino Uno Microcontroller (AUM). Through a single application, customers may check their measurement data and promptly communicate their health metrics with the doctor support to the microcontroller's connection to a mobile app and LCD through Bluetooth[42]. Recent advancements in healthcare informatics explicitly focusing on non-invasive data acquisition using the Internet of things (IoT), such as real-time HR extraction using computer vision (CV) algorithms, non-invasive body temperature sensing targeting the forehead, and the impact of software design on enhancing data acquisition algorithms and reducing processing power usage are discussed in works of literature[43]. In order to promote dependable, affordable, and quick intelligent HCM systems, a review of such literature aids in the creation of intelligent non-invasive sensing techniques.

In order to predict unrecognized and treatable health conditions in older adults, a wearable HCM system that integrates temperature, respiration, and HR sensors incorporated in a wearable belt is designed. This system offers end-to-end encrypted data transmission for security and the ability to send location information and processed data to family members or health centers, making it a valuable tool for monitoring elderly patients[44]. The challenge of implementing novel remote patient monitoring (RPM) interventions in healthcare practice despite their potential is highlighted in the review article. Limited evidence supports non-invasive RPM interventions' improved health outcomes and cost benefits. The systematic review emphasizes the prevalent use of multi-component interventions for chronic disease monitoring in the elderly population. The effectiveness and utility of RPM technology for different patients must be evaluated through more research with robust study designs[45].

Recent progress in NIBGM technology that offers continuous real-time HCM, overcoming the limitations of traditional invasive blood glucose meters, is discussed in survey papers. Non-invasive methods can be classified into optical, microwave, and electrochemical categories. While visual and microwave methods provide continuous monitoring without discomfort, they may require algorithm correction and face challenges related to individual differences and complex detection means[46]. A NIBGM system utilizing IoT devices has the potential to aid in diabetes management. The system captures images from the finger or ear instead of blood samples and employs an artificial neural network (ANN) model to estimate and classify BGL attention[47]. The use of a deep neural network (DNN) model based on photoplethysmography (PPG) signals in a novel system for non-invasive assessment of hemoglobin, glucose, and creatinine levels is presented[48]. The technology uses a smartphone fitted with an 850 nm near-infrared LED to illuminate the fingertip and analyze PPG signals to provide real-time HCM from the comfort of one's home. Estimating blood component levels using feature selection and DNN models is incredibly successful.

Physiological models use machine learning (ML) approaches like multivariate linear regression (MLR) and support vector regression (SVR) to fit arterial volume-pressure models and increase the accuracy of BP estimates. Wearable technology and deep learning (DL) algorithms are also promising for estimating blood pressure[49]. A VIS-NIR optical device for non-invasive glucose prediction is proposed where multi-wavelength measurements improve the accuracy of BGL awareness approximation. Regression and classification models demonstrate good performance, with the FFNN regression model outperforming the MLR model and classification algorithms, achieving successful classification into normal, hypo, and hyperglycemic ranges[50].

Numerous studies have significantly advanced invasive and non-invasive HCM by incorporating IoT and ML techniques. In this context, 'invasive' refers to monitoring systems that involve penetrating the body, while 'non-invasive' pertains to methods that do not require penetration. Understanding these terms is essential in comprehending the nuances of HCM technologies[51]. The literature highlights the potential of IoT and ML techniques to improve healthcare outcomes, reduce costs, and enhance patients' quality of life despite facing inherent introducing notable improvements[52]. By emphasizing the advancements achieved in the work, the work focuses on a meaningful contribution to the ongoing evolution of intelligent HCM systems, thereby addressing the current challenges and opening promising avenues for future research and development in this domain[53].

A brief overview of the contemporary IoT-based HCM systems is provided in **Table 1**.

**Table 1.** Summary of IoT-based HCM system.

| Ref | Problem statement | Methodology | Benefits | Performance metrics |
| --- | --- | --- | --- | --- |
| [54] | An IoT-based patient HCM system connected to the cloud-based Talk network depends on these technologies. | Patient care is performed with the lowest possible input level from individual patients. | Prevention of diseases | HR |
| [55] | Researchers invented a small sensor connection that can be maintained and has the potential to measure an enormous number of biological signals. | The device used as the mobile gateway is a smartphone, the fixed gateway is a Raspberry Pi 3, and the data transfer metrics are selected by a Bluetooth Wireless Low Power device. | Designed in a rigid-flex setup, the framework is developed. The electrocardiogram, HR, and BT are monitored, and the PAT is applied to estimate the blood pressure. Data is protected. | HR, BGL, BP. |
| [56] | A real-time IoT system has been suggested in order to track the health metrics of patients in addition to the climate of the location. | An ESP32 works to collect data from sensors that perform research on the results and then upload it to the IoT. | It is helpful to have a framework functioning correctly when viral illnesses are evident. | BGL, HR |
| | A mobile phone is used as a tool in the IoT HCM system that was developed. | The sensor data is collected and analyzed by the system using the AUM, which sends it to the cloud via Wi-Fi. | It was created as a mobile application. This function secures data by transmitting it to a selected mobile. | HR, OS, BGL |
| [57] | The IoT-based remote HCM system model has been created. | The AUM provides the network to collect and analyze sensor data, and the third generation of the Raspberry Pi is responsible for sending the data to the IoT. | A smartphone application was designed to obtain information from the Google Firebase database. Security is on the information's transmission; only authorized users can retrieve information. | HR, BT, BGL |
| [58] | It provides for the transmission of aggregated data between three distinct modes—BGL, the Global System for Mobile, and Wi-Fi—which enhances the accessibility of medical services. | Pay attention to the following variables and send information using all three methods. | The data can be retrieved in many methods. Automatically alerts carers of possible hazards. It minimizes the probability of missing the location of a patient in a scenario where one of the ways ceases to function or malfunctions. | HR, BT, and BP. |

## 3. Proposed work

The proposed work aims to develop an integrated medical e-Device that integrates RFID login, sensor technology, and database storage to measure critical body vital organs. By combining these features, the device eliminates the need for separate devices, resulting in cost reduction and simplified monitoring for patients. Patients and healthcare professionals may examine data stored using RFID tags for secure login and reliable cloud-based storage. The device detects BT, BGL, BP, GR, and OS in the blood non-invasively utilizing wireless sensors[59].

Patients have no trouble employing the suggested device due to its simplicity. The smartphone application enables physicians to remotely monitor patients' health metrics, improving patient tracking quicker. Mobile application notifications for important principles boost functionality and allow rapid responses[60].

The recommended integrated healthcare e-Device addresses the challenge of assessing health information in a low-cost and easy-to-use method. RFID, the existing sensor, and an easy-to-use application for mobile devices enhance device performance and connectivity. The medical device enhances patient safety and ease of use with NIBGM[61–62]. This novel device might boost the health of patients and their well-being by remotely tracking and automating access to data.

## 4. Design of proposed work

As illustrated in **Figure 1**, the data evaluating unit monitors all critical parameters employing sensors that are the AMU chip evaluates the results, and the resultant unit accepts the information collected. At the output end, an LCD is the measured parameters, which are also stored in the cloud for future use. An LED connected to the output indicates the abnormality in the estimated readings.

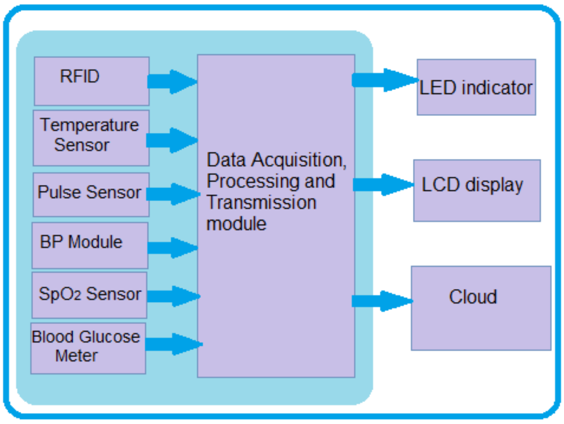



**Figure 1.** Block diagram of the proposed system.

The multiple hardware devices and software tools used to develop the proposed model are described in this section.

## Hardware components used

The RC522 RFID tags and card reader module are used to collect the patients' database. This database helps authenticate a patient during HCM and keeps a record of the patients for future use. Node MCU ESP8266 module integrated with Wi-Fi technology is used as a firmware and development board that targets the proposed work for IoT applications. The AMU boards are based on the ATmega328P microprocessor, where various sensors, display units, LEDs, and buzzers are interfaced. It is programmed using the wiring-based AMU programming language[63].


**Figure 2.** MLX90614 contactless infrared (IR) temperature sensor.

The MLX90614 shown in **Figure 2** is a contactless IR temperature sensor interfaced via the I2C interface with the AMU board. It utilizes IR radiation detection and conversion into electrical signals for accurate temperature measurements. Its dual thermopile, integrated amplifier, and ADC convert the IR radiation into a digital output that microcontrollers like Arduino can easily read. **Figure 3** is a MAX30100 pulse oximeter and HR monitor sensor that uses infrared and red light to detect blood OS levels and heart rate. A tightly coupled sensor that is being tested uses LEDs and photodetectors to monitor BP through radiation.

**Figure 3.** Pulse sensor.

The MAX30100 sensor that is being tested interacts with the AMU processor with the aid of I2C at 1.8 V to 5.5 V. SpO2 levels and the HR is precisely determined by the MAX30100 unit by sending radiation onto the surface of the skin and examining the light that is reflected. The background light canceling algorithm minimizes background light interruptions. The MAX30100 sensor that is being tested unit is precise and dependable for use in healthcare and fitness apps.


**Figure 4.** BP sensor module.

Medical e-Devices, including **Figure 4**'s BP sensor that is being tested in the unit, detect BP levels. The collar over the top of the arm is deflated to stop blood circulation in the pressure sensor unit temporarily. After sensing cuff pressure, the module's algorithm determines BP[64]. BP sensor that is being tested unit connected with Raspberry shows both diastolic and systolic BP-NIBGM employs the AMU-interfaced 940 nm NIR LED and monitors in real-time. This 16 × 2 LCD and 0.96-inch OLED panels integrate protocol I2C to connect with AMU and report sensor-measured necessary data.

## 5. Implementation and results

### 5.1. Temperature and pulse measurement

For the aim of measuring the BT and the HR, the hardware setup is shown in **Figure 5**. The setup incorporates a reader for RFID tags, sensors that are a board powered by an AMU, and an LCD.

Patinets users can connect the MLX90640 sensor that is being tested to the Raspberry AMU by connecting its VCC and GND pins to the board's Arduino connectors. The sensor's SDA and SCL pins are linked to the Arduino's A4 and A5 pins, with the pull-up resistors specified. Attaching the pulse measurement sensor's VCC and GND pins to the Arduino's pins and attaching the output of the signal pin to any of the digital pins connects them instantly. Then, BT and HR measurement APIs like the Adafruit MLX90640 and Pulse Sensor Laboratory are retrieved and deployed. Read data on temperatures and read values from each 32 × 24 pixel employing the Adafruit MLX90640 microcontroller.

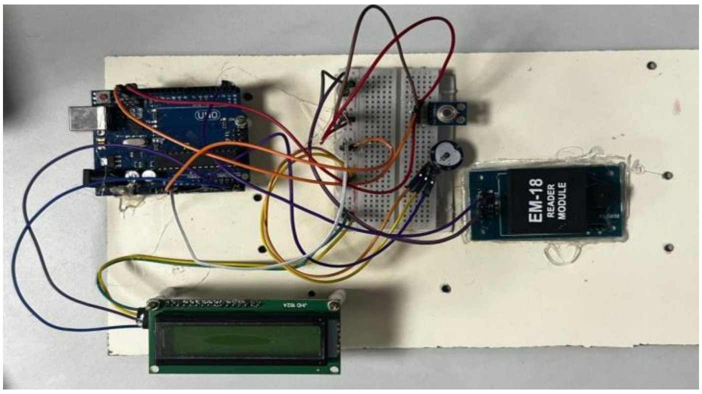



**Figure 5.** Temperature and pulse sensor setup.

Likewise, the PulseSensor library is implemented to read HR data and calculate the heart rate based on detected pulses. Subsequently, the acquired data is transmitted to the cloud through a connection to an MQTT-compatible service. To establish this connection, an MQTT library is installed on the AMU, and BT and HR data are published to a designated topic. Real-time data visualization is achieved through a web-based dashboard or mobile application.

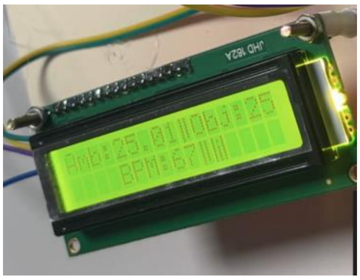


**Figure 6.** Output of temperature and pulse sensor in serial monitor.

The data acquired by the Temperature and the pulse sensor is displayed in the serial monitor shown in **Figure 6**. This data is further moved to the cloud, as discussed earlier.

### 5.2. BP measurement and RFID

The BP sensor Module is connected to the AMU using the SCL and SDA pins in the Arduino, as shown in **Figure 7**.

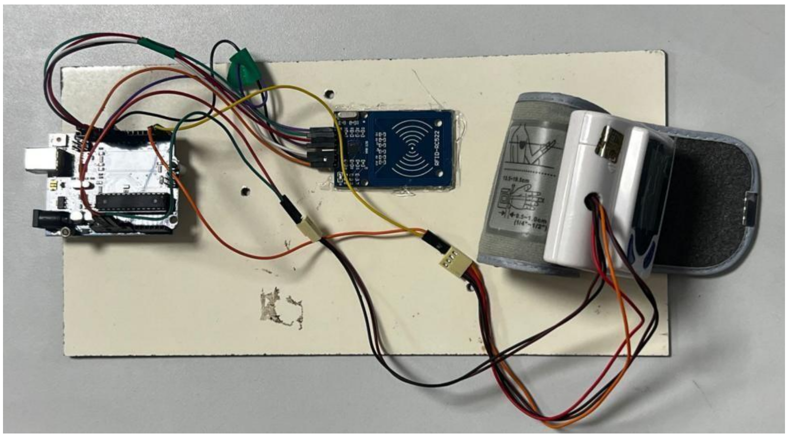


**Figure 7.** BP sensor module and RFID setup.

The RFID Reader module is also connected to the AMU in order to make an entry of the data in the cloud.

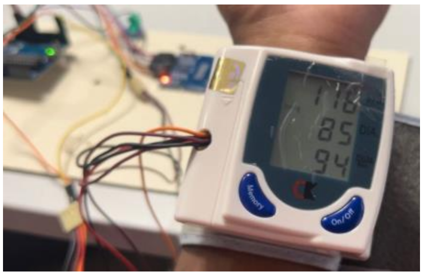


**Figure 8.** Output of BP sensor module.

The output of the BP sensor module, along with the personal information obtained from the RFID, is displayed in the serial port shown in **Figure 8**.

### 5.3. BGL measurement

#### 5.3.1. Principle of BGL measurement

The principle of BGL measurement using NIR sensors involves a non-invasive approach to measuring BGL. NIR sensors emit light in the NIR wavelength range, typically around 940 nm, which the BP under the skin absorbs. This absorption varies depending on the BGL. When the NIR light is emitted onto the skin, it penetrates the tissue and interacts with the BP. The light is partially absorbed by the blood, and the remaining light is reflected to the sensor. The sensor detects the intensity of the reflected light, which is then used to estimate the BGL. The absorption of NIR light by blood is influenced by glucose molecules. As the BGL increases, more light is absorbed by the blood, decreasing the intensity of the reflected light. Conversely, lower BGL leads to less absorption and a higher intensity of reflected light, as shown in **Figure 9**.

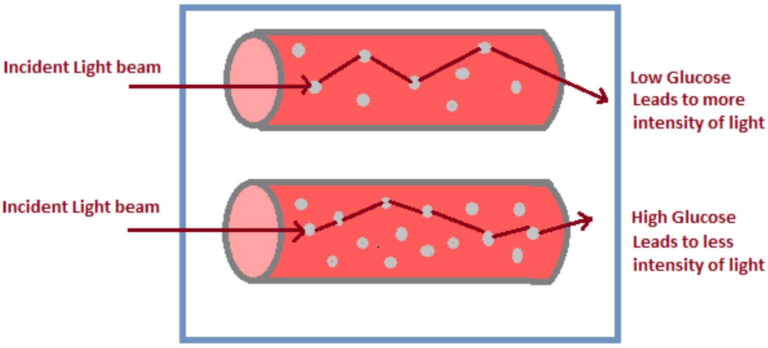



**Figure 9.** Scattering of light with BGL.

Non-invasive BGL measurement using NIR sensors offers several advantages over invasive methods, such as finger pricking. It eliminates the need for painful procedures, reduces the risk of infection, and allows for more frequent BGL monitoring.

#### 5.3.2. Hardware setup of BGL measurement

To measure the BGL, the hardware setup is connected based on the connection, as shown in **Figure 10**.

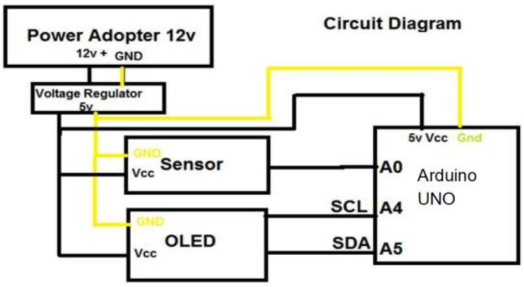



**Figure 10.** Circuit connection for NIBGM.

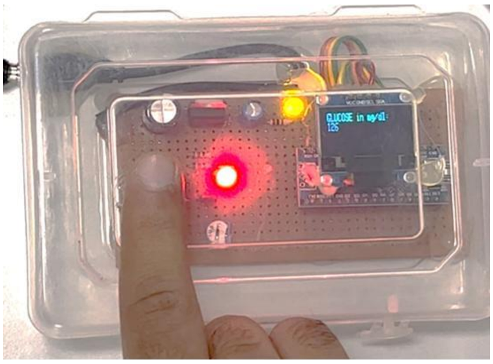


**Figure 11.** Prototype model of NIBGM.

The optimal NIR light source for monitoring BGL is one with a wavelength of 940 nm. The setup on either side of the measurement site, often the fingertip, consists of an NIR transmitter and an NIR receiver (photodetector). The prototype model of the BGL meter is depicted in **Figure 11**.

NIR light travels through the skin and is absorbed by interacting with the BGL. Depending on the BGL, some NIR light is absorbed while the remainder passes through the fingertip. The amount of BGL affects how much NIR light can pass through the fingertip. The OLED and the web server both display the obtained BGL value.

### 5.3.3. Validation of results

The proposed method is validated by measuring the BGL readings of 20 individuals using invasive and non-invasive techniques, and the readings are tabulated in **Table 2**.

**Table 2.** Comparison of results based on invasive method and non invasive methods.

| Test | BGL obtained by invasive method (mg/dL) | BGL obtained by non-invasive method (mg/dL) | Difference | Accuracy (%) |
|---|---|---|---|---|
| 1 | 117 | 118 | +1 | 99.1 |
| 2 | 143 | 143 | 0 | 100 |
| 3 | 112 | 115 | +3 | 97.3 |
| 4 | 106 | 103 | −3 | 97.1 |
| 5 | 166 | 169 | +3 | 98 |
| 6 | 193 | 192 | −1 | 99.4 |
| 7 | 88 | 88 | 0 | 100 |
| 8 | 108 | 110 | +2 | 98.1 |
| 9 | 110 | 117 | −7 | 93.6 |
| 10 | 134 | 151 | −17 | 87.3 |
| 11 | 145 | 156 | −11 | 92.4 |
| 12 | 170 | 161 | 9 | 94.7 |
| 13 | 113 | 108 | 5 | 95.5 |
| 14 | 110 | 132 | −22 | 80 |
| 15 | 165 | 152 | 13 | 92.1 |
| 16 | 227 | 258 | −31 | 86.3 |
| 17 | 149 | 160 | −11 | 92.6 |
| 18 | 130 | 104 | 26 | 80 |
| 19 | 220 | 198 | 22 | 90 |
| 20 | 129 | 136 | −7 | 94.5 |

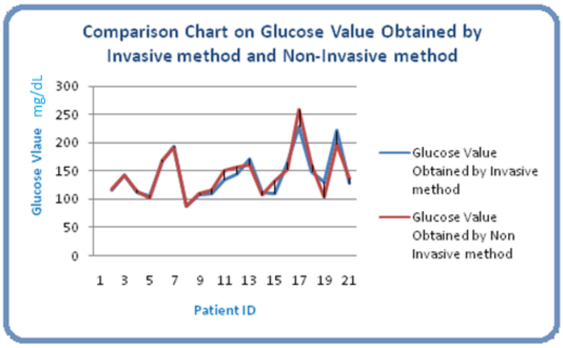



**Figure 12.** Comparison chart on BGL obtained by invasive and non-invasive methods.

**Figure 12** represents the comparison chart on the BGL values obtained by invasive and non-invasive methods. This chart depicts the closeness of both the values and the accuracy of the proposed BGL measurement device, which is calculated using the following formula:

$$\text{Accuracy} = 100\% - \text{Error rate}$$

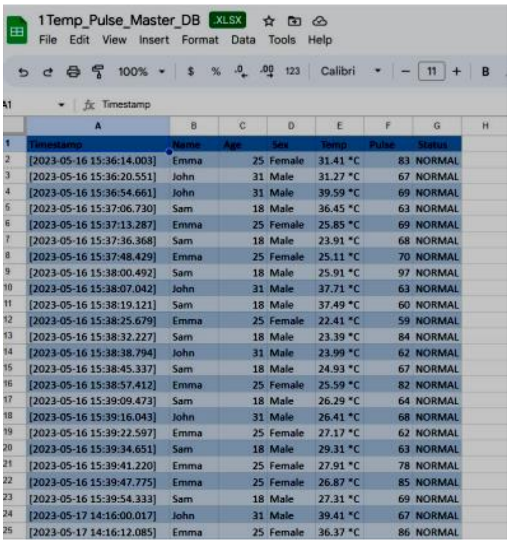
$$\text{Error rate} = (\text{Observed value} - \text{Actual value})/\text{Actual value} \times 100$$

Total accuracy obtained: 93%.

It is important to note that NIR sensors may be affected by external factors, such as ambient light and variations in skin properties, which need to be carefully addressed in the calibration and measurement process.

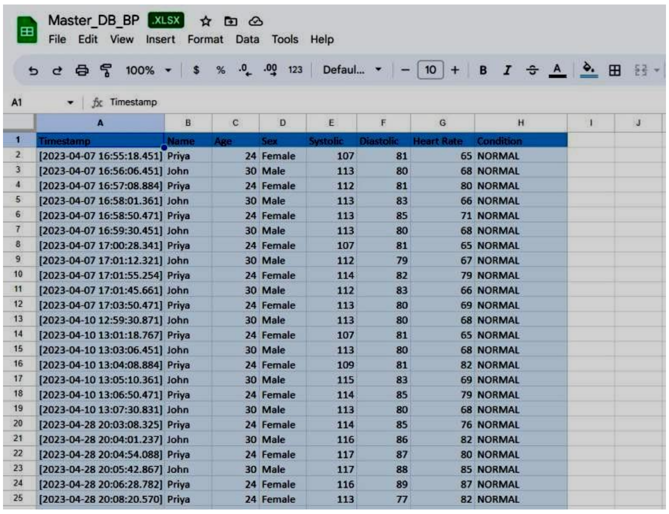
### 5.4. Cloud database

The measured body vitals from the sensors are gathered and stored in the database along with the patient details and the time of the logged data, as shown in **Figure 13a**,**b**.




| Timestamp | Name | Age | Sex | Temp | Pulse | Status |
|---|---|---|---|---|---|---|
| [2023-05-16 15:36:14.003] | Emma | 25 | Female | 31.41 °C | 83 | NORMAL |
| [2023-05-16 15:36:20.551] | John | 31 | Male | 31.27 °C | 67 | NORMAL |
| [2023-05-16 15:36:54.661] | John | 31 | Male | 39.59 °C | 69 | NORMAL |
| [2023-05-16 15:37:06.730] | Sam | 18 | Male | 36.45 °C | 63 | NORMAL |
| [2023-05-16 15:37:13.287] | Emma | 25 | Female | 25.85 °C | 69 | NORMAL |
| [2023-05-16 15:37:36.368] | Sam | 18 | Male | 23.91 °C | 68 | NORMAL |
| [2023-05-16 15:37:48.429] | Emma | 25 | Female | 25.11 °C | 70 | NORMAL |
| [2023-05-16 15:38:00.492] | Sam | 18 | Male | 25.91 °C | 97 | NORMAL |
| [2023-05-16 15:38:07.042] | John | 31 | Male | 37.71 °C | 63 | NORMAL |
| [2023-05-16 15:38:19.121] | Sam | 18 | Male | 37.49 °C | 60 | NORMAL |
| [2023-05-16 15:38:25.679] | Emma | 25 | Female | 22.41 °C | 59 | NORMAL |
| [2023-05-16 15:38:32.227] | Sam | 18 | Male | 23.39 °C | 84 | NORMAL |
| [2023-05-16 15:38:38.794] | John | 31 | Male | 23.99 °C | 62 | NORMAL |
| [2023-05-16 15:38:45.337] | Sam | 18 | Male | 24.93 °C | 67 | NORMAL |
| [2023-05-16 15:38:57.412] | Emma | 25 | Female | 25.59 °C | 82 | NORMAL |
| [2023-05-16 15:39:09.473] | Sam | 18 | Male | 26.29 °C | 64 | NORMAL |
| [2023-05-16 15:39:16.043] | John | 31 | Male | 26.41 °C | 68 | NORMAL |
| [2023-05-16 15:39:22.597] | Emma | 25 | Female | 27.17 °C | 62 | NORMAL |
| [2023-05-16 15:39:34.651] | Sam | 18 | Male | 29.31 °C | 63 | NORMAL |
| [2023-05-16 15:39:41.220] | Emma | 25 | Female | 27.91 °C | 78 | NORMAL |
| [2023-05-16 15:39:47.775] | Emma | 25 | Female | 26.87 °C | 85 | NORMAL |
| [2023-05-16 15:39:54.333] | Sam | 18 | Male | 27.31 °C | 69 | NORMAL |
| [2023-05-17 14:16:00.017] | John | 31 | Male | 39.41 °C | 67 | NORMAL |
| [2023-05-17 14:16:12.085] | Emma | 25 | Female | 36.37 °C | 86 | NORMAL |

**(a)**




| Timestamp | Name | Age | Sex | Systolic | Diastolic | Heart Rate | Condition |
|---|---|---|---|---|---|---|---|
| [2023-04-07 16:55:18.451] | Priya | 24 | Female | 107 | 81 | 65 | NORMAL |
| [2023-04-07 16:56:06.451] | John | 30 | Male | 113 | 80 | 68 | NORMAL |
| [2023-04-07 16:57:08.884] | Priya | 24 | Female | 112 | 81 | 80 | NORMAL |
| [2023-04-07 16:58:01.361] | John | 30 | Male | 113 | 83 | 66 | NORMAL |
| [2023-04-07 16:58:50.471] | Priya | 24 | Female | 113 | 85 | 71 | NORMAL |
| [2023-04-07 16:59:30.451] | John | 30 | Male | 113 | 80 | 68 | NORMAL |
| [2023-04-07 17:00:28.341] | Priya | 24 | Female | 107 | 81 | 65 | NORMAL |
| [2023-04-07 17:01:12.321] | John | 30 | Male | 112 | 79 | 67 | NORMAL |
| [2023-04-07 17:01:55.254] | Priya | 24 | Female | 114 | 82 | 79 | NORMAL |
| [2023-04-07 17:01:45.661] | John | 30 | Male | 112 | 83 | 66 | NORMAL |
| [2023-04-07 17:03:50.471] | Priya | 24 | Female | 113 | 80 | 69 | NORMAL |
| [2023-04-10 12:59:30.871] | John | 30 | Male | 113 | 80 | 68 | NORMAL |
| [2023-04-10 13:01:18.767] | Priya | 24 | Female | 107 | 81 | 65 | NORMAL |
| [2023-04-10 13:03:06.451] | John | 30 | Male | 113 | 80 | 68 | NORMAL |
| [2023-04-10 13:04:08.884] | Priya | 24 | Female | 109 | 81 | 82 | NORMAL |
| [2023-04-10 13:05:10.361] | John | 30 | Male | 115 | 83 | 69 | NORMAL |
| [2023-04-10 13:06:50.471] | Priya | 24 | Female | 114 | 85 | 79 | NORMAL |
| [2023-04-10 13:07:30.831] | John | 30 | Male | 113 | 80 | 68 | NORMAL |
| [2023-04-28 20:03:08.325] | Priya | 24 | Female | 114 | 85 | 76 | NORMAL |
| [2023-04-28 20:04:01.237] | John | 30 | Male | 116 | 86 | 82 | NORMAL |
| [2023-04-28 20:04:54.088] | Priya | 24 | Female | 117 | 87 | 80 | NORMAL |
| [2023-04-28 20:05:42.867] | John | 30 | Male | 117 | 88 | 85 | NORMAL |
| [2023-04-28 20:06:28.782] | Priya | 24 | Female | 116 | 89 | 87 | NORMAL |
| [2023-04-28 20:08:20.570] | Priya | 24 | Female | 113 | 77 | 82 | NORMAL |

**(b)**

**Figure 13.** **(a)** Measured body vitals—Temperature and pulse rate stored in the database; **(b)** measured body vitals—BP and heart rate stored in the database.

A Google Drive database is used here, and this database can be accessed by doctors and patients for further analysis.

## 6. Conclusion and future work

A comprehensive method to monitor body temperature (BT), blood glucose level (BGL), blood pressure (BP), heart rate (HR), and oxygen saturation (OS) is presented. RFID logging into the system, the storage of databases, and the use of sensors ease and reduce monitoring costs. The medical device additionally permits the use of remote access for immediate health monitoring, enhancing the quality of life for patients. The work of art monitors BT, BGL, HR, BP, and OS with Arduino Microprocessor Uno chips and sensors. Using OLEDs and LCDs, it presents distinct visual feedback.

The BGL measurements of the NIR sensor that is being tested are 93% accurate, making it a cost-effective healthcare approach. The non-invasive approach, easy-to-use interface, and accessibility via the Internet make it approachable for numerous patients. Early healthcare diagnosis and treatment are essential. Several crucial components should be tackled in order to maximize this. First, enhancing data analysis can help identify and resolve medical problems immediately. Second, adding an application for smartphones for monitoring in real-time, particular medical recommendations, and remote healthcare assistance may provide additional results. Third, energy optimization, wireless charging for devices, and batteries with long lifespans might allow uninterrupted monitoring of health indicators. Data privacy and security require robust encryption, strong patient authentication, and secure storage. Accuracy and effectiveness require clinical investigations and testing with medical specialists and research centers—easy accessibility and affordability require cost-effectiveness.

## Author contributions

Conceptualization, KS and VB; methodology, VB; software, HMAG; validation, SS; formal analysis, K S, VB, SS; investigation, SS; resources, SV; data curation, SL; writing—original draft preparation, KS; writing—review and editing, HMAG and SS; visualization, VB; supervision, VB and KS; project administration, SS; funding acquisition, KS, VB, HMAG. All authors have read and agreed to the published version of the manuscript.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## Conflict of interest

The authors declare no conflict of interest.

## References


1. Li J, Tobore I, Liu Y, et al. Non-invasive Monitoring of Three Glucose Ranges Based on ECG By Using DBSCAN-CNN. IEEE Journal of Biomedical and Health Informatics. 2021; 25(9): 3340-3350. doi: 10.1109/jbhi.2021.3072628
2. Khan MM, Alanazi TM, Albraikan AA, et al. IoT-Based Health Monitoring System Development and Analysis. Arif M, ed. Security and Communication Networks. 2022; 2022: 1-11. doi: 10.1155/2022/9639195
3. Salem M, Elkaseer A, El-Maddah IAM, et al. Non-Invasive Data Acquisition and IoT Solution for Human Vital Signs Monitoring: Applications, Limitations and Future Prospects. Sensors. 2022; 22(17): 6625. doi: 10.3390/s22176625
4. Sumathy B, Kavimullai S, Shushmithaa S, Anusha S. Wearable Non-Invasive Health Monitoring Device for Elderly using IOT. IOP Conference Series: Materials Science and Engineering. 2021.
5. Vegesna A, Tran M, Angelaccio M, et al. Remote Patient Monitoring via Non-Invasive Digital Technologies: A Systematic Review. Telemedicine and e-Health. 2017; 23(1): 3-17. doi: 10.1089/tmj.2016.0051
6. Tang L, Chang SJ, Chen CJ, et al. Non-Invasive Blood Glucose Monitoring Technology: A Review. Sensors. 2020; 20(23): 6925. doi: 10.3390/s20236925
7. Valero M, Pola P, Falaiye O, et al. Development of a Noninvasive Blood Glucose Monitoring System Prototype: Pilot Study. JMIR Formative Research. 2022; 6(8): e38664. doi: 10.2196/38664
8. Haque MdR, Raju SMTU, Golap MdAU, et al. A Novel Technique for Non-Invasive Measurement of Human Blood Component Levels from Fingertip Video Using DNN Based Models. IEEE Access. 2021; 9: 19025-19042. doi: 10.1109/access.2021.3054236
9. Panula T, Sirkia JP, Wong D, et al. Advances in Non-Invasive Blood Pressure Measurement Techniques. IEEE

Reviews in Biomedical Engineering. 2023; 16: 424-438. doi: 10.1109/rbme.2022.3141877
10. Shokrekhodaei M, Cistola DP, Roberts RC, et al. Non-Invasive Glucose Monitoring Using Optical Sensor and Machine Learning Techniques for Diabetes Applications. IEEE Access. 2021; 9: 73029-73045. doi: 10.1109/access.2021.3079182
11. Daarani P, Kavithamani A. Blood glucose level monitoring by noninvasive method using near infra-red sensor. International Journal of Latest Trends in Engineering and Technology. 2017; doi: 10.21172/1.ires.19
12. Hina A, Saadeh W. Noninvasive Blood Glucose Monitoring Systems Using Near-Infrared Technology—A Review. Sensors. 2022; 22(13): 4855. doi: 10.3390/s22134855
13. Bhattacharjya A. A Holistic Study on the Use of Blockchain Technology in Cps and Iot Architectures Maintaining the Cia Triad in Data Communication. International Journal of Applied Mathematics and Computer Science. 2022; 32(3): 403–413.
14. Sahu AK, Swain G. Reversible Image Steganography Using Dual-Layer LSB Matching. Sensing and Imaging. 2019; 21(1). doi: 10.1007/s11220-019-0262-y
15. Mubarakali A, Ashwin M, Mavaluru D, et al. Design an attribute based health record protection algorithm for healthcare services in cloud environment. Multimedia Tools and Applications. 2019; 79(5-6): 3943-3956. doi: 10.1007/s11042-019-7494-7
16. Vanaja A, Yella VR. Evolution of machine learning in biosciences: A bibliometric network analysis. Journal of Applied Biology & Biotechnology. Published online July 20, 2022: 45-51. doi: 10.7324/jabb.2022.100505
17. Krsihna BV, Ahmadsaidulu S, Teja SST, et al. Design and Development of Graphene FET Biosensor for the Detection of SARS-CoV-2. Silicon. 2021; 14(11): 5913-5921. doi: 10.1007/s12633-021-01372-1
18. Banchhor C, Srinivasu N. Integrating Cuckoo search-grey wolf optimization and Correlative Naive Bayes classifier with Map Reduce model for big data classification. Data & Knowledge Engineering. 2020; 127: 101788. doi: 10.1016/j.datak.2019.101788
19. Sridhar C, Pareek PK, Kalidoss R, et al. Optimal Medical Image Size Reduction Model Creation Using Recurrent Neural Network and GenPSOWVQ. Abdulhay E, ed. Journal of Healthcare Engineering. 2022; 2022: 1-8. doi: 10.1155/2022/2354866
20. Neal Joshua ES, Bhattacharyya D, Chakkravarthy M, et al. 3D CNN with Visual Insights for Early Detection of Lung Cancer Using Gradient-Weighted Class Activation. Gritli H, ed. Journal of Healthcare Engineering. 2021; 2021: 1-11. doi: 10.1155/2021/6695518
21. Mohammad GB, Shitharth S, Syed SA, et al. Mechanism of Internet of Things (IoT) Integrated with Radio Frequency Identification (RFID) Technology for Healthcare System. Mustapha A, ed. Mathematical Problems in Engineering. 2022; 2022: 1-8. doi: 10.1155/2022/4167700
22. Priyatharsini GS, Babu AJ, Kiran MG, et al. Self secured model for cloud based IOT systems. Measurement: Sensors. 2022; 24: 100490. doi: 10.1016/j.measen.2022.100490
23. Goyal A, kanyal HS, Kaushik S, et al. IoT based cloud network for smart health care using optimization algorithm. Informatics in Medicine Unlocked. 2021; 27: 100792. doi: 10.1016/j.imu.2021.100792
24. Khan J, Khan GA, Li JP, et al. Secure Smart Healthcare Monitoring in Industrial Internet of Things (IIoT) Ecosystem with Cosine Function Hybrid Chaotic Map Encryption. Khan HU, ed. Scientific Programming. 2022; 2022: 1-22. doi: 10.1155/2022/8853448
25. Paul J, Bhukya R. Forty-five years of International Journal of Consumer Studies: A bibliometric review and directions for future research. International Journal of Consumer Studies. 2021; 45(5): 937-963. doi: 10.1111/ijcs.12727
26. Budati AK, Katta RB. An automated brain tumor detection and classification from MRI images using machine learning techniques with IoT. Environment, Development and Sustainability. 2021; 24(9): 10570-10584. doi: 10.1007/s10668-021-01861-8
27. Ramesh KKD, Kiran Kumar G, Swapna K, et al. A review of medical image segmentation algorithms. EAI Endorsed Transactions on Pervasive Health and Technology. 2021; 7(27).
28. Rajendra Prasad K, Mohammed M, Noorullah RM. Visual topic models for healthcare data clustering. Evolutionary Intelligence. 2019; 14(2): 545-562. doi: 10.1007/s12065-019-00300-y
29. Rao KS, Samyuktha W, Vardhan DV, et al. Design and sensitivity analysis of capacitive MEMS pressure sensor for blood pressure measurement. Microsystem Technologies. 2020; 26(8): 2371-2379. doi: 10.1007/s00542-020-04777-x
30. Saikumar K, Rajesh V, Babu BS. Heart Disease Detection Based on Feature Fusion Technique with Augmented Classification Using Deep Learning Technology. Traitement du Signal. 2022; 39(1): 31-42. doi: 10.18280/ts.390104
31. Deepthi BK, Kolluru VR, Varghese GT, et al. IoT based Smart Environment Using Node-Red and MQTT. Journal of Advanced Research in Dynamical and Control Systems. 2020; 12(5): 21-26. doi: 10.5373/jardcs/v12i5/20201684
32. Nagadasari MP, Bojja P. Industrial IoT Enabled Fuzzy Logic Based Flame Image Processing for Rotary Kiln Control. Wireless Personal Communications. 2022; 125(3): 2647-2665. doi: 10.1007/s11277-022-09677-z
33. Singh NP, Kanakamalla A, Shahzad SA, et al. Remote Monitoring System of Heart Conditions for Elderly Persons with ECG Machine Using IOT Platform. Journal of Information Systems and Telecommunication (JIST). 2022;

10(37): 11-19. doi: 10.52547/jist.15692.10.37.11
34. Rajendran N, Singh R, Moudgil MR, et al. Secured control systems through integrated IoT devices and control systems. Measurement: Sensors. 2022; 24: 100487. doi: 10.1016/j.measen.2022.100487
35. Chithaluru P, Al-Turjman F, Stephan T, et al. Energy-efficient blockchain implementation for Cognitive Wireless Communication Networks (CWCNs). Energy Reports. 2021; 7: 8277-8286. doi: 10.1016/j.egyr.2021.07.136
36. Pareek PK, Sridhar C, Kalidoss R, et al. IntOPMICM: Intelligent Medical Image Size Reduction Model. Gloria A, ed. Journal of Healthcare Engineering. 2022; 2022: 1-11. doi: 10.1155/2022/5171016
37. Nagesh P, Srinivasu N. Modeling an efficient authentic provable data possession model using legacy filter model for IOT and cloud environment. Information Security Journal: A Global Perspective. 2022; 32(6): 430-443. doi: 10.1080/19393555.2022.2107584
38. Sailaja P. IoT and ML based Periodic Table for Visually Impaired. Journal of Advanced Research in Dynamical and Control Systems. 2020; 12(SP7): 2673-2682. doi: 10.5373/jardcs/v12sp7/20202404
39. Sharma P, Moparthi NR, Namasudra S, et al. Blockchain-based IoT architecture to secure healthcare system using identity-based encryption. Expert Systems. 2021; 39(10). doi: 10.1111/exsy.12915
40. Gowthamani R, Kala Rani KS, Swarna SA, et al. Efficient churn prediction system with ML-IOT. International Journal of Advanced Science and Technology. 2020; 29(3): 8251–8258.
41. Karnati R, Rao HJ, P. G. OP, Maram B. Deep computation model to the estimation of sulphur dioxide for plant health monitoring in IoT. International Journal of Intelligent Systems. 2021; 37(1): 944-971. doi: 10.1002/int.22653
42. Dharmadhikari SC, Gampala V, Rao ChM, et al. A smart grid incorporated with ML and IoT for a secure management system. Microprocessors and Microsystems. 2021; 83: 103954. doi: 10.1016/j.micpro.2021.103954
43. Achanta SDM, Karthikeyan T, Kanna RV. Wearable sensor based acoustic gait analysis using phase transition-based optimization algorithm on IoT. International Journal of Speech Technology. Published online September 9, 2021. doi: 10.1007/s10772-021-09893-1
44. Kumar S, Jain A, Kumar Agarwal A, et al. Object-Based Image Retrieval Using the U-Net-Based Neural Network. Gupta SK, ed. Computational Intelligence and Neuroscience. 2021; 2021: 1-14. doi: 10.1155/2021/4395646
45. Maloji S, Lokesh SMS, Sai KN, et al. An innovative approach for infant monitoring system using model s.Odi based IOT system. International Journal of Advanced Science and Technology. 2020; 29(6): 3623–3630.
46. Namasudra S, Chakraborty R, Majumder A, et al. Securing Multimedia by Using DNA-Based Encryption in the Cloud Computing Environment. ACM Transactions on Multimedia Computing, Communications, and Applications. 2020; 16(3s): 1-19. doi: 10.1145/3392665
47. Ch SS, Krishna BC, Madhav B. Analytical Study of an IOT-based Accident Detection and Information Management System. International Journal on Recent and Innovation Trends in Computing and Communication. 2022; 10(2s): 174-181. doi: 10.17762/ijritcc.v10i2s.5925
48. Chintalapati SS, Krishna BC, Madhav BTP. Analysis on IoT environment for detection and prevention of road accidents with communication modules. Journal of Green Engineering. 2020; 10(11): 12006–12036.
49. Saba SS, Sreelakshmi D, Kumar PS, et al. Logistic regression machine learning algorithm on MRI brain image for fast and accurate diagnosis. International Journal of Scientific and Technology Research. 2020; 9(3): 7076–7081.
50. Sengan S, Rao GRK, Khalaf OI, Babu MR. Markov mathematical analysis for comprehensive real-time data-driven in healthcare. Mathematics in Engineering, Science, and Aerospace. 2021; 12(1): 77–94.
51. Sengan S, Khalaf OI, Vidya Sagar P., et al. Secured and Privacy-Based IDS for Healthcare Systems on E-Medical Data Using Machine Learning Approach. International Journal of Reliable and Quality E-Healthcare. 2021; 11(3): 1-11. doi: 10.4018/ijrqeh.289175
52. Sravanthi S, Ganesan GV. Internet of Things (IoT) based predictive analytics for Medical services and telemedicine applications. Materials Today: Proceedings, 2021.
53. Stalin S, Roy V, Shukla PK, et al. A Machine Learning-Based Big EEG Data Artifact Detection and Wavelet-Based Removal: An Empirical Approach. Pereira AMB, ed. Mathematical Problems in Engineering. 2021; 2021: 1-11. doi: 10.1155/2021/2942808
54. Velliangiri S, Joseph IT, Pandiaraj S, et al. An enhanced security framework for IoT environment using Jaya optimisation-based genetic algorithm. International Journal of Internet Technology and Secured Transactions. 2023; 13(1): 11. doi: 10.1504/ijitst.2023.127388
55. Kavitha T, Mathai PP, Karthikeyan C, et al. Deep Learning Based Capsule Neural Network Model for Breast Cancer Diagnosis Using Mammogram Images. Interdisciplinary Sciences: Computational Life Sciences. 2021; 14(1): 113-129. doi: 10.1007/s12539-021-00467-y
56. Gorla US, Rao K, Kulandaivelu US, et al. Lead Finding from Selected Flavonoids with Antiviral (SARS-CoV-2) Potentials Against COVID-19: An In-silico Evaluation. Combinatorial Chemistry & High Throughput Screening. 2021; 24(6): 879-890. doi: 10.2174/1386207323999200818162706
57. Bandi V, Bhattacharyya D, Midhunchakkravarthy D. Prediction of Brain Stroke Severity Using Machine Learning. Revue d'Intelligence Artificielle. 2020; 34(6): 753-761. doi: 10.18280/ria.340609
58. Chapala V, Bojja P. IoT based lung cancer detection using machine learning and cuckoo search optimization. International Journal of Pervasive Computing and Communications. 2021; 17(5): 549-562. doi: 10.1108/ijpcc-10-2020-0160

59. Kumar V, Lalotra GS, Sasikala P, et al. Addressing Binary Classification over Class Imbalanced Clinical Datasets Using Computationally Intelligent Techniques. Healthcare. 2022; 10(7): 1293. doi: 10.3390/healthcare10071293
60. Talasila V, Madhubabu K, et al. The Prediction of Diseases using Rough Set Theory with Recurrent Neural Network in Big Data Analytics. International Journal of Intelligent Engineering and Systems. 2020; 13(5): 10-18. doi: 10.22266/ijies2020.1031.02
61. Aroulanandam VV, Satyam, Sherubha P, et al. Sensor data fusion for optimal robotic navigation using regression based on an IOT system. Measurement: Sensors. 2022; 24: 100598. doi: 10.1016/j.measen.2022.100598
62. Venkatesh C, Bojja P. Lung Cancer Detection using Bio-Inspired Algorithm in CT Scans and Secure Data Transmission through IoT Cloud. International Journal of Advanced Computer Science and Applications. 2020; 11(11). doi: 10.14569/ijacsa.2020.0111148
63. Available online: https://www.arduino.cc/ (accessed on 14 March 2023).
64. Available online: https://www.sunrom.com/p/blood-pressure-sensor-serial-output (accessed on 14 March 2023).