An internet of things-based healthcare system performing on a prediction approach based on random forest regression

Fahad Ahmed Shaban, Sajjad Golshannavaz
Faculty of Electrical and Computer Engineering, Urmia University, Urmia, Iran

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ABSTRACT

To predict physiological indicators, such as heart rate, blood pressure, and body heat sensors, this study develops an internet of things (IoT)-based healthcare approach performing on random forest regression models and mean square error (MSE). Machine learning approaches such as random forest design is trained to predict factors like age, heart rate, and recorded physiological measures using a dataset generated by sensors with Raspberry Pi. The precision and dependability of the models are assessed by contrasting the predictions with the physiological degrees produced by sensors. IoT-enabled models and sensors are useful for a variety of healthcare monitoring tasks, such as early anomaly detection and quick assistance for medical interventions. It is seen that the proposed model could provide appropriate predictions that are in line with common datasets demonstrated by the results. Moreover, there is strong agreement between the sensor readings and the predicted values for the considered parameters showcasing the outperformance of the proposed healthcare system.

Corresponding Author:

Sajjad Golshannavaz
Faculty of Electrical and Computer Engineering, Urmia University
Nazlo Campus, 11th km, Sero Road, Urmia, West Azerbaijan, Iran
Email: s.golshannavaz@urmia.ac.ir

1. INTRODUCTION

This section deals with the concept of internet of things (IoT) and plans a well-being checking framework utilizing Raspberry Pi and infield sensors. The need to get to therapeutic assets, the increment within the number of more seasoned people with inveterate conditions and their requirement for further observing, rising restorative consumptions, and the want for telemedicine all contribute to the IoT being a captivating theme in healthcare frameworks. The IoT has impressively moved forward in the healthcare division by permitting persistent observation and real-time information collection.

IoT approval systems maintain a strategic distance from visits to pros and social occasions between patients and specialists. The analysts made a shrewd system for observing well-being utilizing IoT advancement that's competent for observing a person's blood pressure, heart rate, oxygen level, and temperature. It was summarized that if any changes occur in the patient's health based on standard values, the IoT system will give statistics appropriately to the specialist and independently, as well as a validation and error rate system. This consideration was propelled by the truth that IoT innovation contrasts with experts in collecting real-time data, effortlessly. High-speed web permits the system to check parameters at normal intervals [1].

Zhu *et al*. [2] come to the conclusion that while smartphone-based implementations have limitations such as short battery life and require clients to hold the device in order to measure confidential patient information, algorithms are difficult to implement in real clinical settings because of the high computational resource demand. With regard to real-time blood sugar prediction and explicit deficiency detection, they suggest the deep learning approach which incorporates a low-cost, low-power framework-on-a-chip that can conduct Bluetooth mesh and edge computing. It is implemented using evidence-based recurrent neural organization and mapping of an IoT-enabled wearable tool. The implant demonstration was evaluated using three clinical datasets with 47 type 1 diabetes (T1D) patients. Furthermore, the comprehensive IoT framework with low-glucose management was tested with 10 virtual adults with T1D through device-in-the-loop experiment. This totally reduced hypoglycemia and advanced glycemic control. The results of this study inspired the authors to propose a new method for measuring hypoglycemia in real-time, based on computing and through devices connected to the internet [2].

Scientists have been working to develop an implantable frame that runs on a Raspberry Pi which would allow for quicker and more effective electrocardiogram (ECG) scanning. When combined with a Raspberry Pi, wired and remote connectivity is made possible, which promotes the development of an implantable ECG demonstration framework for quick reaction to any cardiac benefit aberrations and real-time identification of them. This investigation provides a framework for measuring and displaying an ECG marker that consists of an extensive electrical circuit with both analog and sophisticated components. An analog-to-digital converter, required to transform the received analog tag. The advanced section includes converting the files to a digital format that is suitable with the Raspberry Pi. By detecting ECG signals at varying heart rates, the device accurately records all axial peaks that may be used as health indicators. The authors were motivated by this study to use special techniques to measure heart rate and ECG simultaneously to reduce the cost [3]. Maleh *et al.* [4] designed the implemented system to measure key health parameters including heart rate (HR), blood oxygen sink (SpO2), and body temperature, at the same time. They recently uploaded the physiological signals to the cloud after processing and encrypting them using advanced encryption standard (AES) computing. The network is managed, encrypted, and made Wi-Fi accessible to the cloud via the ESP8266 coordinate module. The estimates of the proposed framework are compared with a few commercial therapeutic tools. They determined that the estimations of the suggested system fell within the 95% confidence interval, demonstrating the proposed system's excellent accuracy and stability. From this study, the possibility of checking body temperature simultaneously with measuring other sensors, such as heart rate was noticed [4]. Researchers discussed advances in communications and data innovation in regard to the IoT. They discovered that in numerous industries, including healthcare, smart cities, design, and others, the IoT is essential for tracking, archiving, storing, displaying, and transmitting data. They communicated information through the system and adhered to fundamental well-being guidelines using an IoT-based verification method. The microcontroller used to gather data from sensors for positioning and well-being is a Raspberry Pi 4B.

The patient care system is useful for simultaneous monitoring of the patient's state of well-being, which allows decisive treatment choices by specialists promptly, as well as knowing the patient's location if has any brain problems that include memory loss and not knowing his location [5]. High accuracy is essential in predictive healthcare data analytics since low accuracy can result in misdiagnosis. Low accuracy might result to major health implications or death. Fast prediction is also seen as a key need, especially for machines and mobile devices with limited memory and processing capacity. Such characteristics (high accuracy and rapid prediction) are especially desirable in real-time healthcare analytics systems, particularly those that operate on mobile devices. In [6], the authors proposed to employ an ensemble regression approach based on CLUB-DRF, a pruned random forest using these characteristics. An experimental investigation using three medical data sets from three distinct disorders confirmed the method's speed and accuracy. Although, reviewed literatures have performed initial and well steps to this issues, these items could be listed as the research gap which should be pursued: i) current applications lack seamless integration and immediate response to data analysis, especially in critical situations; ii) in the aforementioned studies, smartphones suffer from limited battery life, in addition to the need for low-cost devices to perform complex operations with high efficiency; iii) devices that improve ECG monitoring are difficult to integrate seamlessly with vital monitoring tools and still remains as a challenge; iv) one of the obstacles is the need to enhance processing and encryption techniques to protect patient data as well as improve high accuracy and prediction during real-time analysis; and v) accuracy must also be ensured in high and rapid predictions of device performance and data analysis, which represents a major challenge.

Taking the aforementioned notions in mind, the authors in this study are developing a framework which incorporates two portable applications, one for patients and one for specialists, in conjunction with cloud capacity for information. The developed framework empowers real-time checking of crucial physiological indicators or say as signs, such as heart rate, blood pressure, and body heat. Moreover, machine learning prediction techniques, such as random forest regressor and mean squared error (MSE), are included in the developed system and the patient data are involved in the training process. Predictions are made using artificial intelligence to develop and obtain the samples that are compared with the original data to determine the extent of its accuracy and validity, as well as analyzing the error rate to ensure the effectiveness of the devices and the proposed model dependability. In brief, the main contributions of this study are as follows: i) development of an integrated system for monitoring of healthcare using the IoT by monitoring multiple standards, different devices, and systems in real time; ii) the proposed system is featured by advanced processing power and defect detection as well as a low-cost framework and high efficiency; iii) rapid prediction of performance and analysis to measure the efficiency of devices and results; iv) strong encryption ensures high data security as well as the ability to expand in the future; and v) the proposed model, verified by clinical tests, provides a reliable and comprehensive solution for real-time patient health management and results in the development of applications in the healthcare field for the IoT on a large scale.

The remainder of this manuscript is organized as follows. Section 2 addresses the methodology developed in this paper. More specifically, it clarifies the strategy, calculations, guidelines, as well as the work approach endeavored. Section 3 explores the simulation and experimental results by taking look into the conducted tests. Section 4 gathers the discussions and main aspects to be discussed. Eventually, concluding remarks are given in section 5.

2. METHOD

As mentioned earlier, an application would be designed here utilizing an electronic framework associated with a Raspberry Pi and containing restorative sensors joined to the patient's body. The framework incorporates two versatile applications, one for patients and one for specialists, together with cloud capacity of information. The framework empowers real-time observation of imperative signs, such as heart rate, body temperature, blood weight, and oxygen immersion. Through IoT innovations, the framework would give persistent case observation, empowering detect variations from the norm and convenient therapeutic mediation [6]. Where heart rate, blood pressure, as well as body temperature, are measured by putting extraordinary sensors that degree the well-being rates specified over for each persistent. When the task is done, machine learning techniques like MSE and random forest regressor are initiated. These approaches use output samples that are input by sensors to contain all of the patient data that are analyzed. Artificial intelligence is used to develop predictions based on this data. Then, these predictions are analyzed to produce real samples that are compared to the original data to assess the degree of validity and accuracy. The error rate in the data is also examined to guarantee the dependability and efficiency of the devices [7]. The sensors application contains the code it uses to support the Raspberry Pi by routing these sensors. The sensitive sensors used in the scope are programmed using C++ and the Raspberry Pi is modified with Python. In addition, the Java language is used to create a mobile application within the testing software plan, which can be placed near the specialist to monitor patient samples and test results [8]. The observing program is put close to the administering specialist utilizing Android Studio. Two portable applications are required, one to be put to the administering specialist and one for the persistent. A persistent database takes the comes about from the application which is put away within the cloud and after that exchanges to the application which is following to the watching specialist. Figure 1 illustrates these aspects.

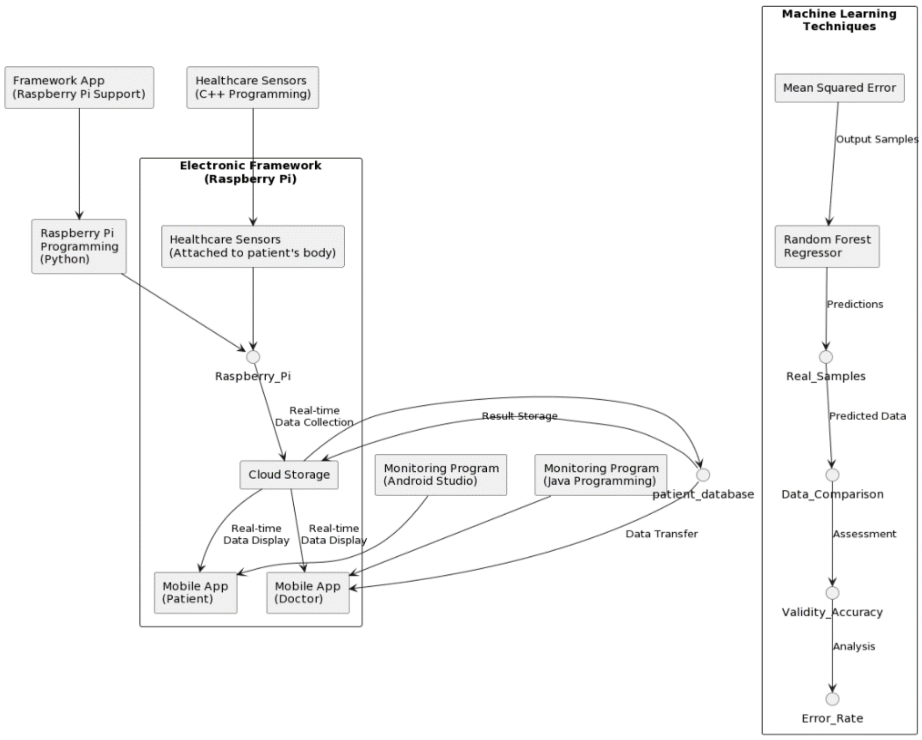

Figure 1. IoT-based remote health monitoring system software

2.1. Heart pulse rate sensor

It is a finger-interfacing optical sensor that uses the light flag it receives from the finger to guide the pulse. When the heart pumps blood, a blood vessel’s volume changes. This phenomenon is known as a beat wave and a beat sensor is a device that detects and records this volume alteration [9]. Transmission and reflection are the two types of photoelectric pulse wave sensors depending on how they are measured. By emitting red or infrared light from the body’s surface and analyzing variations in blood flow as a change in the amount of light transmitted through the body during heartbeats, transmission types can monitor pulse waves [10]. Figure 2 represents a picture of the sensor connected to the Raspberry Pi with the connection method.

The specifications of the heartbeat are mentioned in Table 1. A significant DC signal that indicates leftover venous and arterial blood as well as bloodless tissues is detected by the photodetector. The arterial pulse (1% of the observed signal) is represented by the AC signal. Through the use of a communication protocol, the system gathers data from sensors and send it to the doctor’s monitoring system [11].

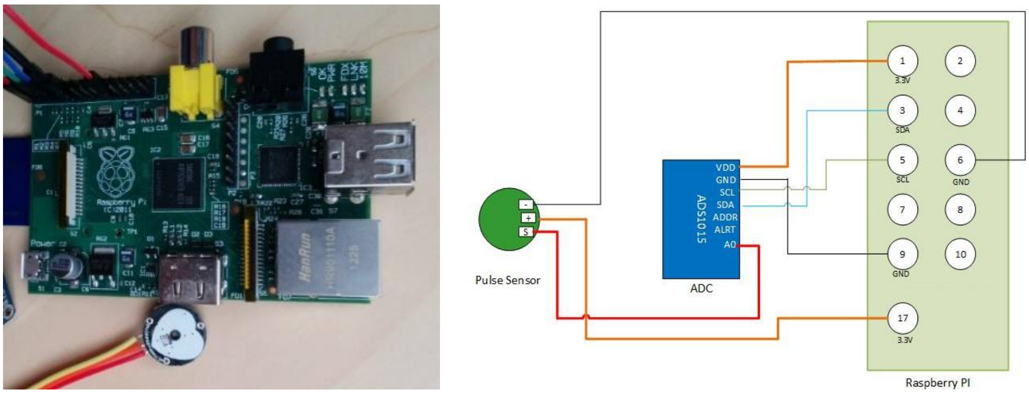

Figure 2. Heart pulse rate sensor with Raspberry Pi connection diagram

Table 1. Specifications of the heartbeat

Parameters		Values
V_{cc}		(3 – 5.5) V
Maximum ratings	I_{max} (Maximum current draw)	< 4 mA
	V_{out} (Output voltage range)	0.3 V to V_{cc}
Wavelength	LED output	565 nm
	Sensor input	525 nm
Dimensions	L×W (PCB)	15.8 mm (0.625″)
	Lead length	20 cm (7.8″)

2.2. Blood pressure measurement

Human blood pressure can be measured non-invasively with the use of a blood pressure sensor. It uses the Oscillo metric method to calculate the mean arterial pressure, diastolic pressure, and systolic pressure [12]. Here, the blood pressure value is displayed online via a Raspberry Pi gateway. The findings demonstrated that the design can use a USB TTL serial cable directly connected to the Raspberry Pi to transfer data from the blood pressure detector to the monitoring system in the treating physician’s computer over the network [13]. Figure 3 displays the embedded system.

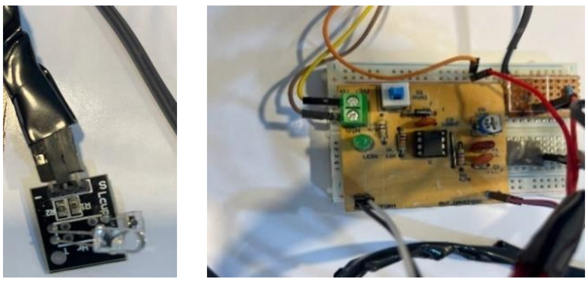

Figure 3. Blood pressure measurement

2.3. Heat body sensor

Advanced external temperature measurement has also seen the light of day with the development of sensing technologies, improved monitoring tools, and improved accuracy. Its information might be crucial for patients suffering from various conditions, such as infections and hypothermia. It is possible to determine the body's surface temperature using skin or body temperature sensors [14]. Various temperature-measuring applications employ thermocouples, negative thermal coefficient (NTC), digital temperature sensors, and thermistor to accommodate wide thermistors circumstances, accuracy, and packaging. As seen in Figure 4, sensors are affixed to the patient's body, connected to the Internet and cloud via a transmission media and powered by the voltage across the diode ends. The temperature rises in response to an increase in voltage. A voltage drop in the diode between the transistor's base and emitter terminals occurs next [15].

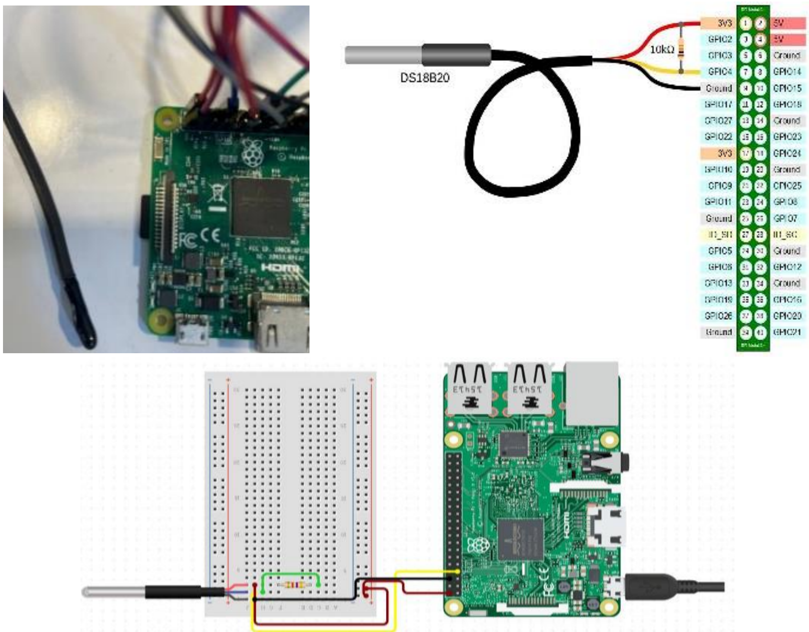

Figure 4. Heat body sensor with connection method

2.4. Random forest prediction

Random forest prediction uses a cluster learning approach in which multiple decision trees are generated and combined for prediction. Each tree in the forest is predicted independently; however, the final prediction is determined by the combination of predictions for all trees [16]. This procedure helps reduce overfitting and increases model accuracy and robustness. This approach is versatile and effective for classification and post-processing as shown in Figure 5 and is widely used in a variety of industries including healthcare, finance, and commerce [17]. Below is the mathematical representation of this method.

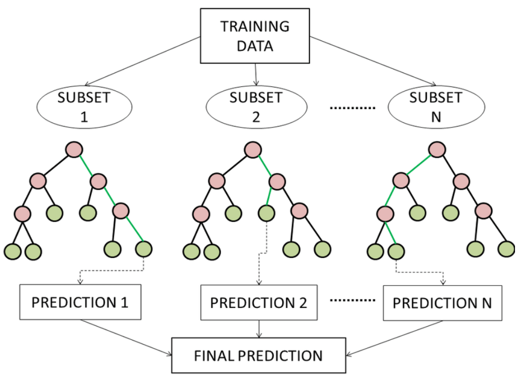

Figure 5. Random forest prediction approach architecture [18]

$$y^{\wedge} = (x) = argmax_k \left(\sum_{i=1}^{N} 1(f_i(x)=k)\right) \quad (1)$$

Here N is the total number of decision trees in the random forest, $f_i(x)$ is the prediction made by the i-th decision tree, $y^{\wedge}(x)$ can be determined by a majority vote among the predictions of individual decision trees, $1(\cdot)$ is the indicator function, and k is the total number of classes.

2.5. Mean squared error

Mean squared error (MSE) is a measure used to determine the mean squared discrimination between predicted values and actual values in a data set. The mean squared differences between each expected parameter and its corresponding actual value are calculated. A lower MSE indicates that the model predictions are trending toward the actual values, reflecting better accuracy [19]. MSE is a widely employed approach in regression practices to evaluate the overall performance of predictive models. It provides a quantitative score of a release's ability to maintain the integrity of records, helping to evaluate different models, and guiding release selection [20]. The mathematical representation of MSE is mentioned as (2).

$$MSE = \frac{1}{n}\left(\sum_{i=1}^{N}(yi - y^{\wedge}i\right)^2 \quad (2)$$

where n is the total number of samples in the dataset, y_i represents the actual (observed) value for the i-th sample, and $y^{\wedge}i$ represents the predicted value for the i-th sample. The squared difference between each actual and forecasted value is determined by the summing term. The average squared difference, or MSE, is calculated by dividing the sum of these squared differences by the total number of samples.

3. EXPERIMENTAL RESULT AND DISCUSSION

In this section, the values of the sensors connected to the patient's body are compared with the regular devices and the prediction values based on random forest algorithm, mean square error, as well as the percentage of the error are scrutinized. Figure 6 displays the hardware block diagram implemented for system operations. Here, three input signals are obtained for each patient (temperature, pulse rate, and blood pressure sensors) and then controlled and gathered by the system. To choose the patient, the Raspberry Pi microcontroller sends six output control signals to the database. Wi-Fi is used to transfer control signals (patient and lead selection) and acquired data (temperature, pulse heart rate, and blood pressure sensors) between the database module and the base station computer. Through a Wi-Fi network, the obtained data and control signals are sent from the base station (close to the patient) to the distant mobile device or from the mobile device to the caller data. Based on the reported data and verifications, the correct performance of the proposed approach is discussed and certified.

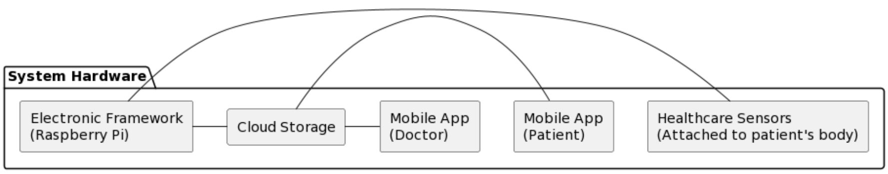

Figure 6. The proposed system hardware diagram

3.1. Pulse rate measurement

Five patients make up the case study that is being put under investigation. Each patient's heart-beat rate results are reported in Table 2. A common (standard) heart-beat rate measuring tool is also used to measure the patient's heart-beat rate. Between the sensor and the natural device, the data output values are closed.

Table 2. Result of heart-beat for sensor and original device

Name of patient	Age (years)	Heart-beat rate (Sensor)	Heart-beat rate (Device)
Mohmmed Ali	13	78 BP	77 BP
Ahmed Younis	23	81 BP	78 BP
Laith Ahmed	28	76 BP	74 BP
Omar Ali	26	85 BP	81 BP
Othman Saad	32	77 BP	75 BP

3.2. Blood pressure analysis

The results as seen on the device screen for the doctor's desktop program in the monitoring room, two patients in the case study are now in use. Each patient's blood pressure readings are added together in the table. In order to compare the results, the patient's blood pressure rate is also monitored using a typical blood pressure monitor, as shown in Table 3. As seen, between the sensor and the natural device, the output data values are so close, demonstrating the outperformance of the proposed system [21].

Table 3. Results of blood pressure for sensor and original device

Name of patient	Age (years)	Blood pressure (sensor)	Blood pressure (device)
Mohmmed Ali	13	116/77	117/78
Ahmed Younis	23	120/79	122/80
Laith Ahmed	28	121/78	120/78
Fahad Ahmed	26	123/81	129/85
Othman Saad	32	122/81	125/80

3.3. Body heat analysis

The patients' body heat results as they are shown on the doctor's application in the monitoring room device screen comprise the case study that is put into practice. Each patient's body heat results are tabulated in Table 4. In the patient "Fahad Ahmed", the test result is shown in red since the patient's temperature is higher than usual. This table also displays the results comparison with a medical thermometer.

Table 4. Results of body temperature for sensor and original device

Name of patient	Age (years)	Body heat temperature (sensor)	Body heat temperature (device)
Mohmmed Ali	13	38.1	37.4
Ahmed Younis	23	36.5	36
Laith Ahmed	28	37.2	37
Fahad Ahmed	26	39.1	38.7
Othman Saad	32	36.3	37.2

3.4. Error percentage

Table 5 contains the test values for temperature, blood pressure, and heart rate. The values generated through the traditional device are compared with the samples generated by the sensors in the proposed method to reach the error rates and determine the accuracy of the results [22]. The error calculation of data is done through (3). From this table, it can be inferred that there are slight differences in pulse rate and temperature between the reading of the sensor and the device due to the generally low and non-variable error percentage rate. It is noted that there is a greater variation in the error rates for blood pressure, which indicates the presence of potential discrepancies in blood pressure measurements between the sensors and devices.

$$Error\ Percentage = \frac{\text{Sensor Reading} - \text{Device Reading}}{\text{Device Reading}} \times 100 \quad (3)$$

Table 5. Error percentage in different parameters

Name of patient	Error percentages (pulse rate)	Error percentages (blood pressure)	Error percentages (temperature)
Mohmmed Ali	1.30%	1.03%	1.87%
Ahmed Younis	3.85%	1.49%	1.38%
Laith Ahmed	2.70%	0.51%	0.54%
Omar ali	4.94%	4.67%	1.03%
Othman Saad	2.67%	0.98%	2.41%

3.5. Random forest prediction

Table 6 uses random forest regression models. These models are trained based on supplied data to estimate heart-rate, body-heat, systolic blood pressure (SBP), and diastolic blood pressure (DBP) for each individual to obtain clearer measurements compared to the results of the sensor and traditional device. The projected values for SBP and DBP are displayed in the output. As can be seen, appropriate performance of the developed models could be verified certifying the outperformance of them [23].

Table 6. Random forest prediction values

Name of Patient	Age (years)	Heart rate	Body heat	Blood pressure (Systolic BP/Diastolic BP)
Mohmmed Ali	13	78	38.36	116.67/ 77.43
Ahmed Younis	23	80.87	36.61	120.08/ 79.15
Laith Ahmed	28	76.83	37.07	121/ 77.89
Fahad Ahmed	26	85.06	39.01	122.92/ 81.09
Othman Saad	32	77.09	36.26	121.83/ 80.45

3.6. MSE analysis

The MSE in Table 7 displays the average squared error difference between the sensor values and the predicted body temperature, blood pressure, and coronary heart rates. A lower MSE score indicates a better settlement between the actual and the expected values [24]. The computer MSE, which is based on the capabilities offered, shows that the random forest prediction approach performs rather well in terms of prediction when it comes to determining body heat and coronary heart rates.

Table 7. Patient's error percentages

	MSE value for	
Heart rate	Body heat	Blood pressure
0.12	0.05	0.98

As for body temperature, the MSE value is low equal to 0.05 as well as for the heart rate value of 0.12 which indicates good agreement between the sensor measurements and the expected values. This means that the proposed model estimates body temperature and heart rate so effectively. For blood pressure say as systolic and diastolic, the individual MSE values indicate 0.19 and 1.51, respectively. This record leads to some discrepancies between the sensor readings and the expected values. For total blood pressure, the MSE value of 0.98 indicates reasonable agreement in general and that the overall estimate of blood pressure remains relatively accurate [25].

3.7. Comparison

The investigated literatures are compared with the method proposed in this study. It is inferred that the proposed approach provides greater improvements in multiple areas such as battery life and integration as well as a low-power framework. Through the proposed approach, prediction accuracy and speed in performance is improved with the ability to verify the validity of results and metrics. Data security through encryption methods can provide an advantage over previous methods, which makes the study a comprehensive solution to modern health care needs.

3.8. Discussions

It is essential to assess the predictions using regular levels or typical values for these physiological indicators to judge the inferences from the expected statistics for heart rate, blood pressure, and the body heat and the exact values. The following notices are seen.

- Heart rate: An adult's resting heart rate typically ranges from 60 to 100 beats per minute (BPM). The individuals' predicted coronary heart rates fall within this normal range, indicating that the random forest prediction models accurately represented the correlations between age, heart rate, and other factors. Since the estimated heart rates are consistent with regular values, the random forest prediction models may be used to estimate heart rates only from physiological and demographic factors.
- Blood pressure (both systolic and diastolic): An adult's normal blood pressure is typically established at 120/80 mmHg. With a few minor variations, the anticipated systolic and diastolic blood pressure values for the people fall within this typical range. Some projections show little differences from the average number, while some are quite accurate. Although the random forest prediction models provide reasonable blood pressure estimates, further refining is necessary to increase accuracy, particularly for those whose blood stress is outside of the typical range.
- Body heat: A typical body temperature ranges from 36.5 to 37.5 degrees Celsius (°C). For the majority of people, the expected body heat readings fall within this typical range. According to the predictions, body heat may be accurately estimated using random forest prediction fashions depending on age and other variables. However, its capacity to reliably assess body temperature is demonstrated by the anticipated body heat values, which closely match normal levels.

- Final notice: In summary, based on age and other pertinent factors, the random forest regression models show outperformance in forecasting body heat, blood pressure, and heart rate. Even while the forecasts are generally in line with average physiological levels, there can be small differences that call for more research and optimization. Overall, these approaches have the potential for applications in early abnormality identification and healthcare tracking; however, further improvement and validation are essential to guarantee their dependability and efficiency.

4. CONCLUSION

To sum up, the random forest prediction regression models that were used to predict body heat, heart rate, and blood pressure showed an acceptable performance in predicting physiological parameters, mostly based on age and other relevant factors. The expected values generally fit in well with normal physiological ranges showing that the models are good at describing the connections between the input variables and health metrics. Nonetheless, a few forecast errors with slight differences were seen, indicating potential areas for the models to be improved. Both the body temperature and heart rate with low MSE values of 0.05 and 0.12 were recorded, indicating high agreement between the sensor results and the anticipated values for these parameters. This indicates that the suggested model accurately calculates heart rate and body temperature. The separate MSE values for blood pressure (systolic and diastolic) reveal 0.19 and 1.51, respectively, which causes some disparities between the measurements from the sensor and the predicted values. The MSE score of 0.98 for total blood pressure showed that there is a reasonable agreement and that the estimate of blood pressure is still generally correct. Despite these differences, IoT-enabled models and sensors continue to have a wide range of applications in healthcare monitoring, including early abnormality identification, and rapid medical intervention support. Continuous validation, refinement, and validation of those models are essential to make sure about their reliability, accuracy, and effectiveness in real-world healthcare settings.

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BIOGRAPHIES OF AUTHORS

Fahad Ahmed Shaban was born in Mosul-Iraq, in 1993. He holds a bachelor's degree in computer technology engineering from the Northern Technical University/College of Engineering Technology. He ranked first in his class for the year 2015-2016 and holds a master's degree in computer technology engineering from the Northern Technical University College of Engineering Technology, Mosul-Iraq 2018-2019. Currently, has been working as a computer engineer at the Ministry of Water Resources since 2023. He is currently a PhD student in computer engineering, Urmia University, Urmia, Iran, in the Faculty of Electrical and Computer Engineering. His research interests are related to internet of things, computer network design, project management system design, database design in all journals, and neural networks. He can be contacted at email: f.ahmedshaban@urmia.ac.ir

Sajjad Golshannavaz was born in Urmia, Iran, in 1986. He received the B.Sc. (Honors) and M.Sc. (Honors) degrees in electrical engineering from Urmia University, Urmia, Iran, in 2009 and 2011, respectively. He received his Ph.D. degree in electrical power engineering from School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran, in 2015. Currently, he is an associate professor in Electrical Engineering Department, Urmia University, Urmia, Iran. Since 2014 he has been collaborating with the smart electric grid research laboratory, Department of Industrial Engineering, University of Salerno, Salerno, Italy. His research interests are in smart distribution grid operation and planning studies, design of distribution management system (DMS), demand side management (DSM) concepts and applications, microgrid design and operation studies, design of energy management system (EMS), application of FACTS controllers in power systems, application of intelligent controllers in power systems. He can be contacted at email: s.golshannavaz@urmia.ac.ir.