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Original Article

IoT-driven remote health monitoring system with sensor fusion enhancing immediate medical assistance in distributed settings

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ABSTRACT

The increasing prevalence of chronic diseases and the demand for real-time health monitoring have propelled the development of noninvasive Clinical Support Systems (CSS) using Internet of Things (IoT)-driven remote Health Monitoring Systems (HMS). This paper presents an IoT-based HMS designed to provide immediate medical assistance, particularly beneficial for monitoring patients in remote or rural areas with limited access to healthcare facilities. The proposed system integrates wearable sensors, data analytics, and cloud computing to continuously monitor patients' vital signs, like body temperature, heartbeat, room temperature, and humidity. The collected data is transmitted in real-time to a centralized cloud platform, where advanced analytics detect anomalies and trigger alerts for healthcare providers. Sensor fusion technology is employed to combine data from multiple sensors, enhancing the accuracy and reliability of health monitoring across distributed locations. The system's architecture ensures secure and efficient data handling, maintaining patient privacy while facilitating timely medical interventions. Experimental results demonstrate the system's efficacy in promptly identifying critical health events and enabling rapid response, thereby improving patient outcomes, and reducing the burden on healthcare facilities. This IoT-driven HMS represents a significant advancement in telemedicine with an accuracy of 91.68 % and offers a scalable and reliable solution for continuous health monitoring and immediate medical assistance. A Proof of Concept (POC) of the IoT-based HMS is developed and tested to display real-world applications in healthcare facilities. The proposed system can also be integrated with a Decision Support System (DSS) to generate adequate medical reports for future use.

1. Introduction

The Internet of Things (IoT) term was coined in 1999 by Kevin Ashton defining the connectivity of data by a dynamic Service Architecture operational on a global level. Having emerged from progress in information and communication technology, IoT can be seen to possess the capacity to significantly improve the well-being of living in cities. With people's numbers growing worldwide and a higher propensity to develop chronic conditions, the need for efficient and affordable models that can provide a wide range of healthcare services while controlling costs remains high. Among these, IoT has been considered one of the major innovations in recent years and plays a crucial role in advanced

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developments of home healthcare monitoring systems.

IoT healthcare monitoring systems aim to track individuals accurately, connecting various devices and services over the Internet to collect, share, monitor, store, and analyze data. This paradigm enables remote control of physical objects in smart applications like cities, homes, and healthcare. Integrating sensor networks into medical care facilitates diagnosis and patient monitoring, ensuring data accessibility globally at any time. The prevalence of chronic diseases underscores the need for continuous tracking beyond traditional healthcare models, particularly highlighted by recent health crises [1]. IoT-driven Health Monitoring Systems (HMS) offer real-time monitoring and immediate medical assistance, enhancing healthcare accessibility and reducing costs associated with hospital visits and diagnostic procedures [2,3]. Remote patient monitoring extends healthcare beyond clinical settings, increasing access to healthcare services while reducing expenses [4]. IoT-based monitoring systems address healthcare gaps in remote areas by providing continuous monitoring through smart sensors, potentially saving lives during epidemics [5,6].

The growing frequency of chronic illnesses and the necessity for real-time health monitoring, particularly in distant or rural regions with limited access to healthcare facilities, demand the development of efficient and cost-effective solutions. Current healthcare models frequently fail to offer continuous monitoring and prompt treatments, resulting in delayed diagnosis, higher healthcare expenses, and lower patient outcomes. Based on the above problem statement, research objectives are formulated and listed below.

a) To build a Health Monitoring System (HMS) driven by IoT technology using wearable sensors for monitoring routinely four vital body parameters such as body temperature, heartbeat, room temperature, humidity, etc.
b) To develop a sensor fusion scheme needed for improving both the accuracy and reliability factors in health monitoring data.
c) To develop an HMS scheme by evaluating its ability to instantly spot irregularities and send alerts to healthcare professionals for quick medical help and better treatment results for patients.
d) To develop a Decision Support System (DSS) for generating adequate alerts based on the patient's health condition.
e) To develop a Proof of Concept (POC) for demonstrating how the IoT-based HMS works with practical healthcare applications.

This proposed work presents an experimental workflow for an innovative IoT-based HMS, designed to offer prompt medical intervention. The proposed system integrates wearable sensors and advanced data analytics to continuously monitor vital parameters such as body temperature, heartbeat, room temperature, and humidity. The collected data is transmitted in real-time to a centralized cloud platform, where it is analyzed to detect anomalies and trigger timely alerts for healthcare providers.

The architecture of the system ensures secure and efficient data handling, prioritizing patient privacy while facilitating quick medical responses. Experimental results highlight the system's effectiveness in early detection of critical health events, enabling rapid response and thereby improving patient outcomes. This capability not only reduces the burden on healthcare facilities but also enhances the overall efficiency of healthcare delivery.

Furthermore, a Proof of Concept (POC) of the IoT-based HMS has been developed and tested to demonstrate its practical application in real-world healthcare settings. The proposed system can be integrated with a Decision Support System (DSS) to generate comprehensive medical reports for future use, representing a significant advancement in telemedicine. This scalable and reliable solution offers a promising future for continuous health monitoring and immediate medical assistance.

This article presents the following major aspects of the IoT-enabled HMS.

1) A brief architecture of the proposed IoT-enabled wearable device and wall-mounted device
2) The complete architecture of the real-time data-gathering scheme
3) Analysis of real-time patient Heart Rate (HR), Body Temperature (BT), Room Temperature (RT), and Room Humidity (RH)
4) Statistical Analysis of collected data

This article is subdivided into six sections to present an entire structure of the proposed IoT-induced HMS. The second section of the current article discusses related research works and briefly discusses summaries of different research works. Details on the architecture of the proposed integrated IoT-driven HMS are outlined in this third section of the article. Describing the above equation, the sensor fusion technique and false alarm technique are also mentioned in the third section. The fourth section of the article outlines the possible process flow of the proposed system. The last section of the paper shows the hardware configuration and data source. The sixth section captures the result, and analysis of data collected in the real-time data recorded section, and the last section captures the conclusion and reference section.

2. Related work

Various researchers have developed models for IoT in healthcare and disease prediction using diverse methodologies. Ahn et al. [7] implemented a system with a smart chair sensing non-constrained bio-signals like ECG and BCG, illustrating IoT's application in healthcare. Almotiri et al. [8] proposed an m-health system using mobile devices and wearable gadgets to collect real-time patient data for medical diagnosis. Barger et al. [9] are evaluating a smart housing prototype using sensor networks to monitor patient movements. Chiuchisan et al. [10] introduced a framework for patient safety in intelligent ICUs, alerting caregivers about health discrepancies. Dwivedi et al. [11] developed a multi-layered framework securing clinical data transmission for Electronic Patient Records. Gupta et al. [12,13] utilized Raspberry Pi for patient health monitoring, while Lopes et al. [14] explored IoT frameworks benefiting disabled individuals. Nagavelli and Rao [15] proposed disease probability prediction from medical data using statistical mining. Sahoo et al. [16] employed cloud-based big data analytics to forecast health issues from patient data. Tyagi et al. [17] investigated IoT components and proposed a cloud-based framework for secure medical data transfer, aiming to improve patient care and service accessibility. Xu et al. [18] developed a data model and a resource-based Ubiquitous Data accessing mechanism for global IoT data accessibility. They also demonstrated IoT-based emergency medical services and cross-platform data utilization. Naina Gupta et al. [19] proposed a structure using GSM and Bluetooth technologies to streamline data transmission during ambulatory and hospital services, focusing on monitoring various bodily parameters. Their wearable system utilizes GPRS for data transmission [20,21]. Previous research highlights various implementations, with ongoing opportunities. This work emphasizes integrating IoT-enabled HMS systems and DSS to support large-scale healthcare facilities.

Substantial research and development efforts have emerged in IoT-based Health Monitoring Systems (HMS) because of the expanding number of chronic diseases and the escalating need for immediate health observation. Several research has investigated the capability of bpm heart rate sensors, temperature sensors using thermistors, and activity monitoring sensors that use accelerometers in conjunction with anomaly detection and machine learning algorithms to provide continuous healthcare monitoring. The key function of cloud computing serve as a centralized platform that gives users remote access to stored information [22,23]. The existing remote patient monitoring solutions prove feasible yet they still require development in critical areas such as measurement precision together with data protection and system connectivity and data storage capacity improvements. The research tries to fix current detection limits by developing specific anomaly detection techniques that optimize performance for elderly patients dealing with cardiovascular issues. The research presents an innovation that integrates multiple sensor fusions with individualized baseline construction to identify anomalies. The detection system should accomplish improved recognition of slight vital sign alterations which warn about forthcoming cardiac events thus enabling prompt medical responses that deliver better patient results.

3. Integrated IoT-driven remote health monitoring system (IHMS)

3.1. Architecture of IHMS

The proposed IoT-driven remote Health Monitoring System (IHMS) is designed to address the challenges of continuous health monitoring and immediate medical assistance. Through the integration of IoT, wearable sensors, and cloud computing, this system has the potential to offer a comprehensive and reliable solution for monitoring patients' vital signs in real time. The above-said system is divided into two parts namely, the hardware portion that involves interfacing of temperature, pulse rate, and humidity sensor with Zigbee and the software portion that involves coding in Embedded C programming. It further categorizes the entire flow process into the acquisition of data, archival of the collected data as well as circulation of the data. The proposed system shown in Fig. 1 is a three-layer healthcare IoT architecture leveraging cloud computing for managing and analyzing patient data. The first layer, the IoT Device Layer, involves various sensors monitoring room parameters in real-time. The second layer, the Cloud Computing Environment, collects and processes data from these sensors, storing it in a centralized database. This layer ensures data backup, supports testing and development of new healthcare applications, uses big data analytics for predictive health insights, and includes disaster recovery protocols. The third layer, the User Level, provides interfaces for healthcare providers and patients to interact with the system. Users can access patient data, run analytics, and receive real-time updates via laptop/desktop applications and smartphone apps. Human-machine interfaces display real-time health metrics, and healthcare attendants receive alerts for timely interventions, while medical experts analyze data for informed patient care decisions.

In this system, the data flow process involves extracting data from IoT devices in real-time, transforming it into a structured format suitable for storage and analysis, and loading the transformed data into the cloud database. Data analytics then provides insights into patient health, identifies patterns, and predicts potential health issues. Combining these three layers as presented in the system enables the system to strive to monitor patient care, manage data smoothly, and enable real-time decision-making within healthcare settings thus enhancing positive patient outcomes while enhancing the execution of healthcare processes. This system will always monitor the body and over time, it will keep recording the temperatures and pulse rates as well as the humidity. All this data will be stored or updated in the database. It will have an alert message informing the doctor when the temperature is greater than 37.2°C or if the pulse rate is less than 60 bpm or more than 100 bpm. ZigBee will take care of this action. On the other end, the doctor can use this data for analysis on his computer. The doctor in the graph form can also access this stored database.

3.2. Sensor fusion technique

Sensor fusion plays a crucial role in modern healthcare systems by enhancing patient monitoring, ensuring data reliability, and enabling effective medical interventions. By combining data from multiple sensors measuring the same parameter—such as heart rate, body temperature, room temperature, and humidity—sensor fusion provides more accurate and reliable readings. This approach minimizes errors and inaccuracies from individual sensors, mitigates the effects of malfunctions and environmental factors, and ensures system reliability under challenging conditions. Additionally, sensor fusion integrates diverse data into a single comprehensive assessment, aiding effective medical decisions. The technique involves estimating the similarity between measurements from different sensors and assigning weights to each based on importance, often using fuzzy similarity-based multi-sensor data fusion algorithms in different stages [1].

Stage 1:

From n sensors, the i^{th} sensor for each variable measurement is used to measure the variable k times. For i = 1, 2, 3….n number of sensors, $m_{i1}, m_{i2}, \ldots\ldots m_{ik}$ are the k-times of measure of each variable. The mean and standard deviation of each measurement by i^{th} sensor installed are shown in Eq. (1) & (2).

$$\mathbf{m_i} = \frac{\mathbf{1}}{\mathbf{k}}\sum_{j=1}^{k}\mathbf{m_{ij}} \tag{1}$$

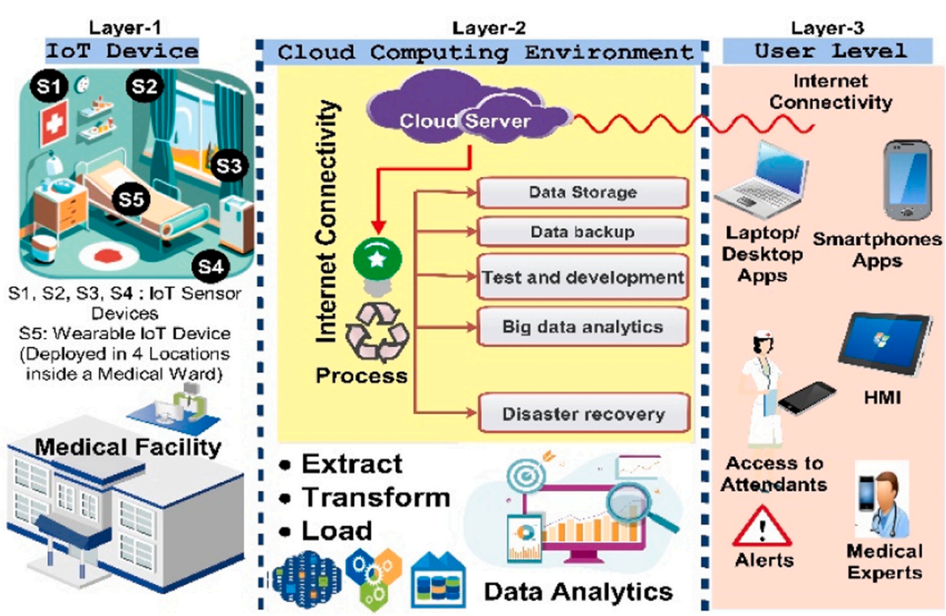

Fig. 1. Architecture of Integrated IoT-driven HMS (IHMS).

$$\sigma_i = \sqrt{\frac{1}{k-1}\sum_{j=1}^{k}(m_{ij}-m_i)^2} \quad (2)$$

The mean and standard deviation of all n sensors installed in a vehicle are written in Eq. (3) & (4)

Sample mean: $m_o = \frac{1}{n}\sum_{i=1}^{n} m_i$ (3)

Standard deviation: $\sigma_o = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(m_i - m_o)^2}$ (4)

Stage 2:

To eliminate the unrealistic data in a univariate data set, the Grubbs algorithm is used as shown in Eq. (5).

$$g_i = \frac{m_i - m_o}{\sigma_o} \quad (5)$$

If the Grubbs statistic g_i is an outlier, then the faulty measured value m_i from a sensor that is maximum or minimum is eliminated.

Stage 3:

In compliance with the concepts of fuzzy set theory, the measurement values of a certain sensor are assumed as the fuzzy set F_i and the values predicted by multiple sensors as the set F_o. The fuzzy measurements of their similarity are employed to define the important weight of a particular sensor.

Then, the fuzzy similarity between fuzzy sets F_i and F_o is given by the Eq. (6) [2]:

$$F(F_i, F_o) = exp\left[-\left(\frac{m_i - m_o}{\sigma_i + \sigma_o}\right)^2\right] \quad (6)$$

During data fusion, the higher the F (F_i,F_o) is, the closer F_i to F_o. F (F_i,F_o) is the important weight of the i^{th} sensor during this data fusion.

Stage 4:

The relative importance of each sensor is calculated by weight w_i and it can be calculated by using Eq. (7)

$$w_i = \frac{F\ (F_i, F_o)}{\sum_{i=1}^{n} F\ (F_i, F_o)} \quad (i = 1, 2, \ldots\ldots n) \quad (7)$$

The single output from several data collected from a group of sensors can be calculated by using the data fusion technique given in Eq. (8)

$$Z = \sum_{i=1}^{n} w_i m_i \quad (8)$$

3.3. False alarm evaluation

In IoT-driven remote Health Monitoring Systems (HMS), false alarms can undermine efficiency and reliability. These occur when normal health parameters are incorrectly flagged as anomalies, causing unnecessary panic, increased workloads for healthcare providers, and potential desensitization to alerts. False alarms often stem from wearable sensors producing erroneous readings due to calibration issues, environmental interferences, or improper placement. Data transmission problems, like packet loss or corruption, can also contribute. Additionally, poorly tuned machine learning algorithms may generate false positives, especially if overfitting occurs. Normal patient activities, such as exercise or stress, can trigger alarms if not properly accounted for. Frequent false alarms erode patient trust, leading to non-compliance, and increase alert fatigue among healthcare providers, compromising their response to genuine emergencies. This situation strains system resources, raising operational costs and affecting the overall sustainability of the health monitoring system.

In terms of an IoT-driven Health Monitoring System (HMS), accuracy is an essential parameter that determines the share of correct outcomes, which can contain true positives and true negatives within the total quantity of examined cases. The accuracy is defined in Eq. 9.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} X100\% \quad (9)$$

where

TP (True Positives): The number of actual positive instances that are correctly recognized by the system.

TN (True Negatives): The number of actual negative instances that are correctly recognized by the system.

FP (False Positives): The number of actual negative samples wrongly identified as positive by the system.

FN (False Negatives): The number of actual positive samples wrongly identified as negative by the system.

4. Workflow

The block diagram of the proposed IHMS as shown in Fig. 2 illustrates a healthcare monitoring system designed to measure various health and room environmental parameters, process the collected data, and display the information on an IoT dashboard. The system is organized into three primary sections: the Parameter Sensing Layer, Signal Acquisition and Processing, and the IoT Dashboard, each playing a crucial role in ensuring accurate and real-time monitoring.

The Parameter Sensing Layer consists of two critical modules where the Wearable Module tracks patient temperature alongside heart rate while the Wall Mount Module records environmental temperature as well as humidity levels. Environmental parameters stand as vital indicators for evaluating patient care and security, particularly among respiratory condition patients. Data collected from sensors through microcontrollers with ZigBee modules goes through signal processing before IoT dashboard transmission takes place. The healthcare monitoring system incorporates separate microcontrollers that manage wearable and environmental data for instantaneous wireless data delivery. The Health Prediction and Parameter Display Module functions as the IoT Dashboard which gives healthcare staff an easy way to see key metrics including heart rate (HR), body temperature (BT), room temperature (RT), and room humidity (RH). Through its integrated system healthcare providers can make well-informed rapid medical choices which leads to better care delivery and patient results.

A set of well-defined participant selection criteria led to representative surveys and focus groups regarding the representativeness and relevance of the study. The research selected participants to reflect all segments of the target group who experience chronic diseases and remote healthcare difficulties by considering factors such as age group, gender, residential framework, and socioeconomic status. The recruitment project focused on participants who operated IoT-based health monitoring tools and were managing chronic diseases since they brought knowledgeable input to the study. Healthcare professionals and doctor and nurse participants together with caregivers were included to share their experience with the system's usability and effectiveness. The research design incorporated this stratified methodology which generated an even distribution of stakeholders to create results that could

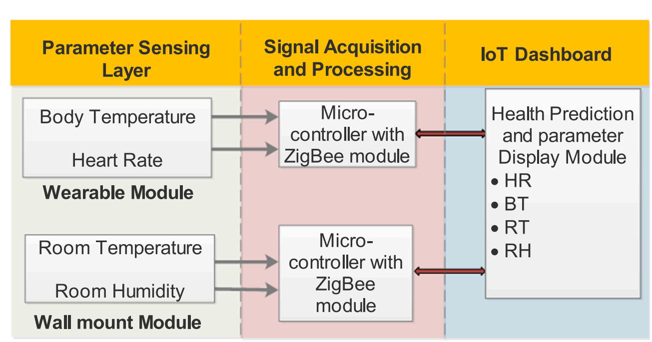

Fig. 2. General block diagram of the IHMS.

apply to real healthcare environments.

The system workflow, shown in Fig. 3, details the process from data collection to predictive analysis. It gathers vital health and environmental data, displays it on the IoT dashboard, and evaluates if conditions such as temperature above 37.2°C or pulse rate outside 60–100 bpm are met, alerting a doctor if necessary. The data undergoes processing to detect anomalies and is transferred through various platforms for seamless integration with other healthcare systems. Predictive analytics on the IoT dashboard forecast future health trends, aiding proactive healthcare management. All data is stored on a server for long-term health trend analysis, ensuring continuous monitoring, timely interventions, and data-driven decisions to enhance patient care quality and efficiency.

Fig. 4 outlines a wall mount, which is an advanced IoT-based monitoring system that integrates environmental and patient health parameter tracking through three main stages: Device Stage, Application Stage, and Analytics Stage. In the Device Stage, four wall-mounted IoT devices (S1 to S4) are equipped with DHT11 sensors to measure Room Temperature and Room Humidity. These sensors are connected to ZigBee-based wearable modules, which function as MQTT clients, transmitting data via WiFi. Each device is powered by a 5 V/1 A power supply and uses GPIO (General-Purpose Input/Output) for sensor communication.

In the Application Stage, the collected data is sent to a ZigBee router and then forwarded using the MQTT protocol. The data is processed by a Node-RED server acting as an MQTT broker, which manages the data flow and displays real-time monitoring information on a dashboard accessible from laptops, desktops, or mobile devices. The data is also relayed to a PHP server functioning as an MQTT client for storage in a database, enabling historical data management. The database stores key parameters such as BT, HR, RT, and RH, and supports future health record predictions based on this data. The Analytics Stage focuses on the visualization and analysis of historical data. Advanced analytical tools are employed to identify trends and anomalies, providing valuable insights into patient health and environmental conditions. This stage is crucial for predicting future health outcomes and improving overall healthcare management. By confirming efficient data collection, transmission, processing, and analysis, the system supports informed decision-making and enhances patient care quality and environmental monitoring in healthcare settings. Fig. 5 presents a wearable IoT-driven monitoring system comprising two primary stages: The device Stage and the Application Stage, etc. In the Device Stage, wearable devices equipped with KY 039 sensors for Heart Rate (HR) and DS18B20 sensors for Body Temperature (BT) gather vital health data. These sensors are connected to a ZigBee-based wearable module functioning as an MQTT client, which transmits data via a ZigBee connection. The wearable module is powered by a 5 V/1 A power supply. The collected data is sent to a ZigBee router, which forwards it to the Application Stage using MQTT topics. In the Application Stage, the data is received by a Node-RED server acting as an MQTT broker. This server processes the data and displays it on a dashboard accessible from laptops, desktops, or mobile devices, facilitating real-time monitoring. Additionally, the data is forwarded to a PHP server (also an MQTT client), where it is stored in a database for historical data management.

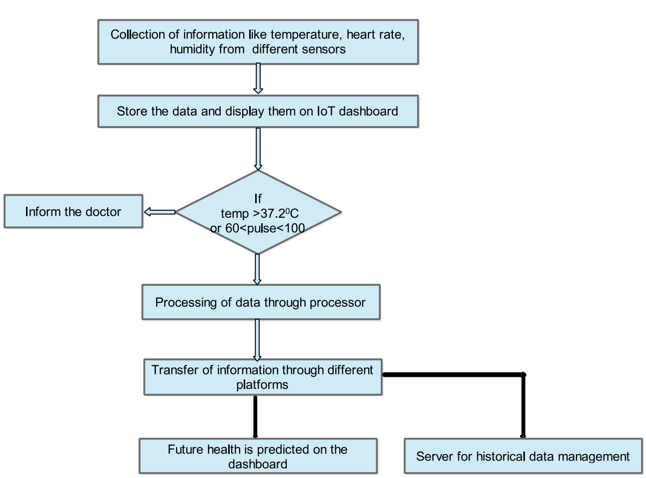

Fig. 3. Flow chart of IHMS.

Fig. 6 illustrates an integrated multi-patient monitoring system utilizing sensor fusion to enhance healthcare management. Multiple sensors (S1 to S4) continuously monitor room and patient parameters, with specific sensors (S5.1 to S5.12) for each patient. Data collected includes vital signs such as heart rate, body temperature, room temperature, humidity, SDNN, and RMSSD.

This information is analyzed in real-time on a local computer and sent to a cloud-based system for long-term tracking and trend analysis. The system integrates patient location data with health metrics, providing a comprehensive overview and enabling personalized healthcare. This approach ensures accurate, real-time monitoring, allowing healthcare providers to make informed decisions and deliver timely interventions. Sensor fusion ensures high data accuracy and reliability, improving patient outcomes and healthcare efficiency.

The proposed Health Monitoring System (HMS) using IoT operates with adaptability and scalability attributes to support healthcare services within multiple governmental and cultural settings. The modular system structure enables straightforward connection with existing healthcare systems which makes it deployable in every healthcare region from developed to developing countries. The system implements open-source technologies combined with cloud-based platforms and this enables adjustments to correspond with different population numbers and healthcare needs. Wearable sensors together with real-time data analytics allow the system to adapt its features towards specific cultural requirements by addressing both domestic health goals and regional healthcare legislations. The system works over various bandwidth levels in rural locations where limited connectivity exists but simultaneously functions at its peak capacity in metropolitan areas. The proposed HMS maintains flexibility through which it becomes suited for effective implementation across multiple healthcare settings thus it promotes equal healthcare access and supports worldwide health initiatives.

5. Hardware configuration

Fig. 7 and Fig. 8 illustrate health monitoring systems powered by an ATmega2560 microcontroller. Both systems are driven by a BL-5C battery regulated by a power management module. The core components include a ZigBee module for wireless communication, an OLSP001 sensor (Fig. 7) or DHT11 sensor (Fig. 8) for heart rate and temperature/humidity monitoring, and a MAX30205 sensor for body temperature (Fig. 7). Both setups feature an SWD interface for debugging, an LED for visual status, and a push-button for user interaction. These systems enable continuous, reliable remote health monitoring, ideal for telemedicine applications.

Additionally, Fig. 8 showcases a wearable module, highlighting its compact and portable design for real-time health and environmental monitoring.

6. Results and analysis

The real-time data from various sensors of IHMS are collected throughout the day and are shown in Figs. 9, 10, 11, and 12. Fig. 9 and Fig. 10 show the 24-h real-time data variations of Room Temperature (RT) in °C and Room Humidity (RH) respectively.

Similarly, the IoT-enabled wearable device is used to record HR and BT variations of five numbers of subjects over 24 Hrs. The HR variations of the five subjects are shown in Fig. 11. It can be observed that the HR variations lie within 80 BPM to 89 BPM for all five numbers of subjects.

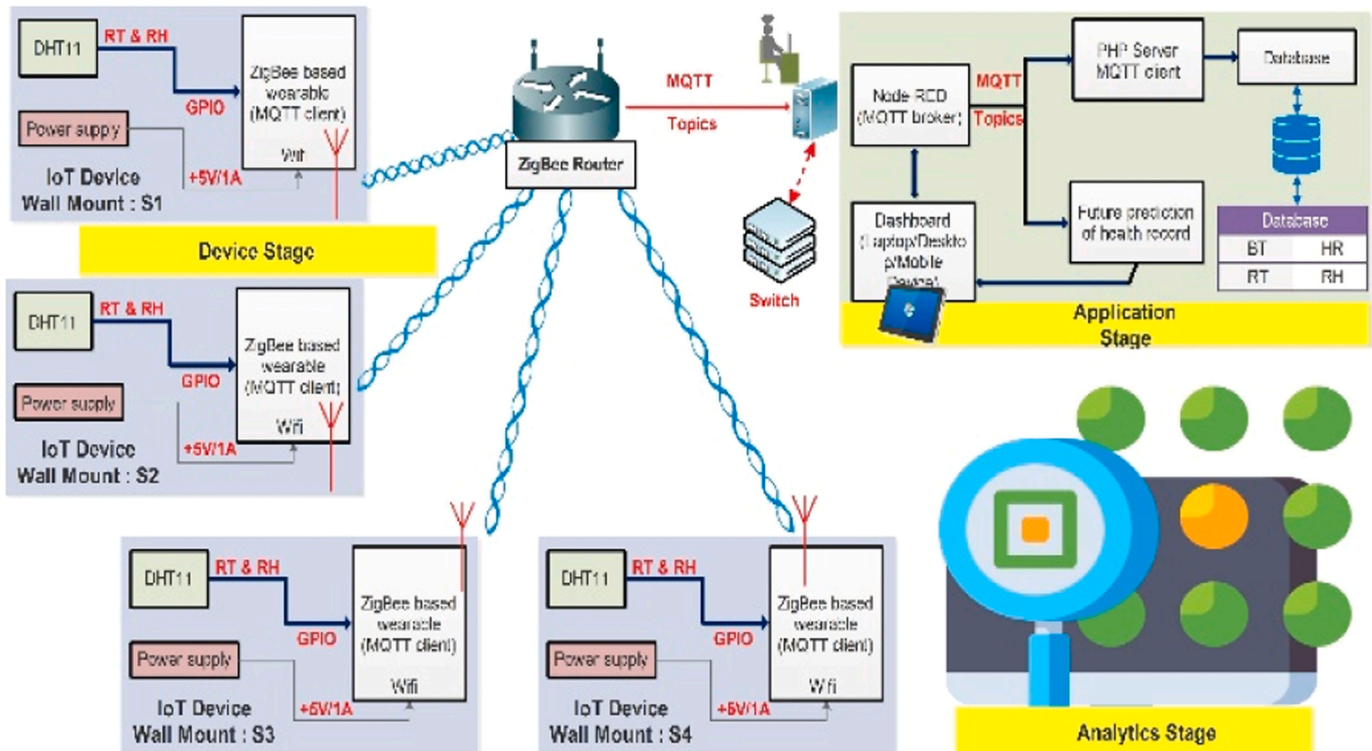

Fig. 4. IoT-driven monitoring system (Wall mont).

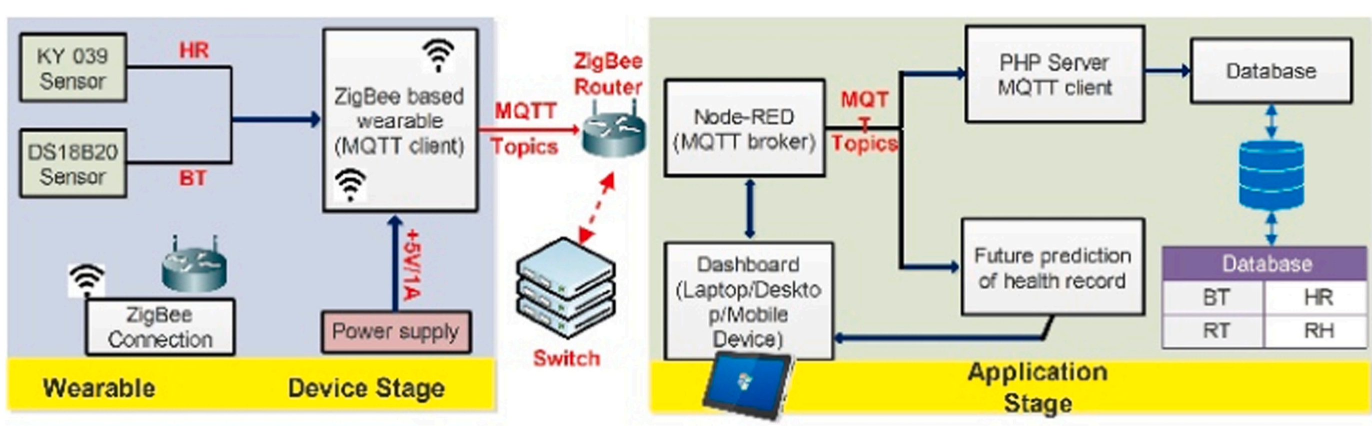

Fig. 5. Wearable device block diagram.

Similarly, the BT variations of five numbers of subjects are recorded in the cloud database. The BT variations of five numbers of subjects are shown in Fig. 12. It is observed that the BT variations lie between 35 °C to 39 °C for all the test subjects considered in this experimental work. This recording of useful body parameters will help medical experts to take immediate action during emergency requirements.

To avoid loss of health as well as environmental data due to the failure of sensors and increase the accuracy of the proposed IHMS, a sensor fusion technique is proposed to collect the data each hour. Table 1 shows the data captured hourly fluctuations in room temperature, room humidity, patient body temperature, and patient heart rate over 24 h.

The recorded data in Fig. 13 illustrates the interplay between environmental conditions (room temperature [RT] and room humidity [RH]) and patient health parameters (body temperature [BT] and heart rate [HR]) over a day. Each parameter is tracked at regular intervals and represented with distinct symbols and colors for clarity. RT remains stable at around 30 units, indicating effective environmental control for patient comfort. RH fluctuates between 70 and 90 units, influenced by factors like ventilation and weather. BT remains consistent at around 35 units, reflecting physiological homeostasis. HR shows significant variability between 70 and 90 units, influenced by physical activity and emotional states, providing insights into daily activities and stress levels. The graphs provide a comprehensive 24-h overview, with stable room temperature, fluctuating humidity, heart rate, and consistent body temperature, emphasizing the importance of continuous monitoring for patient safety and health insights.

6.1. *Evaluation of false alarm*

False alarms in IoT-driven health monitoring systems (IHMS) mean that the system produces signals whereas no real health event is taking

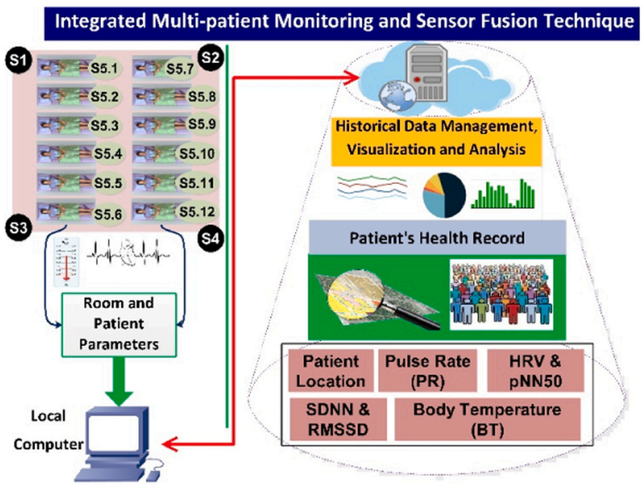

Fig. 6. Integration of multi-patient monitoring and sensor fusion technique in IHMS.

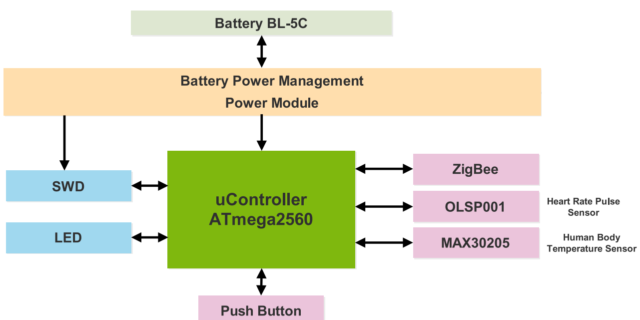

Fig. 7. Block Diagram of an ATmega2560-based Health Monitoring System.

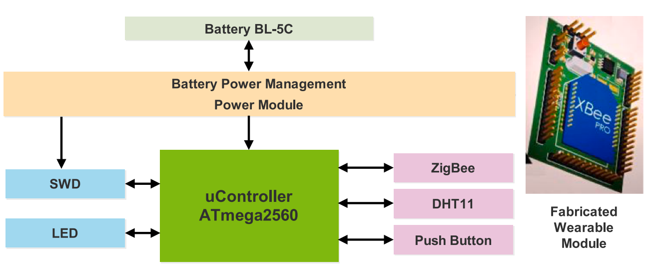

Fig. 8. Block Diagram of an ATmega2560-based Wearable Health Monitoring System.

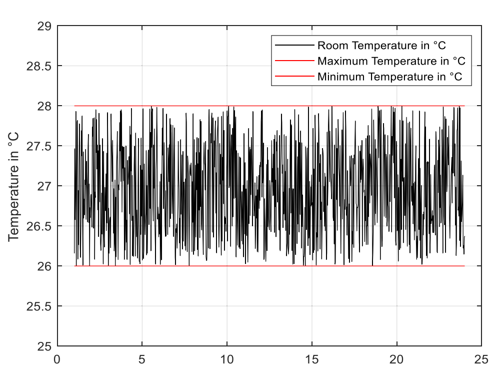

Fig. 9. Variations of Room Temperature (RT) over 24 Hrs.

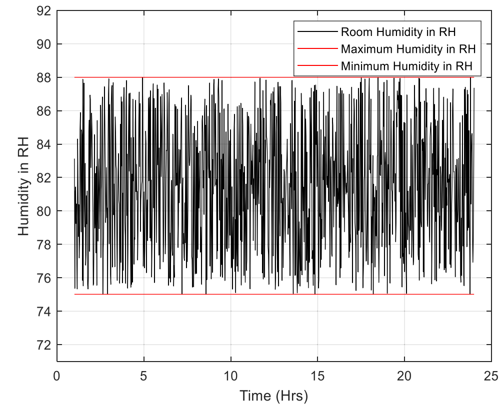

Fig. 10. Variations of Room Humidity (RH) over 24 Hrs.

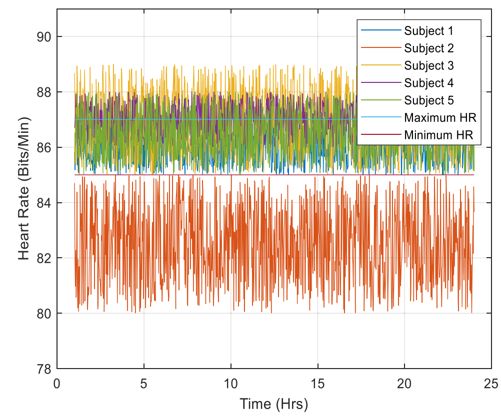

Fig. 11. Variations of Heart Rate (BPM) over 24 Hrs for five subjects.

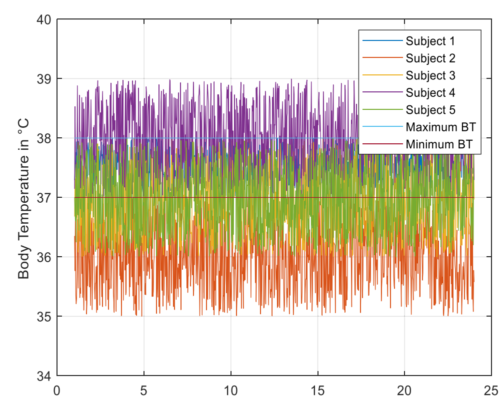

Fig. 12. Variations of Body Temperature (°C) over 24 Hrs for five subjects.

place. Reduction of false alarms is very essential for the proposed system, which uses different types of sensors such as temperature sensors, humidity sensors, and heart rate sensors. Such necessary sensors must be able to provide an accurate interpretation of data to distinguish between normal functionality and true health occurrences. It is very sensitive meaning that motion and others can easily trigger related activities, which are not complications of the health of the patient. Similarly, low sensitivity could mean failure to identify real health events, in this case, the event of interest. The use of these settings must be balanced to guarantee reliability.

Data for computing the accuracy of the proposed system is gathered when for instance there is a failure in a piece of hardware of a node

Table 1
Recorded sensor data for 24 h after using the sensor fusion technique.

Sl. No	Time	Room Temp. (RT)	Room Humidity (RH)	Patient Body Temp. (BT)	Patient Heart Rate (HR)
1	12:00 am	27.4	87.8	35.9	81
2	01:00 am	26.1	85.9	35.0	80
3	02:00 am	27.6	78.6	39.0	89
4	03:00 am	26.2	81.5	38.3	87
5	04:00 am	26.2	85.8	36.5	84
6	05:00 am	26.7	81.0	35.8	81
7	06:00 am	26.3	83.3	38.0	87
8	07:00 am	26.5	85.4	36.4	85
9	08:00 am	27.5	86.0	36.2	84
10	09:00 am	26.9	85.9	37.3	81
11	10:00 am	27.2	83.7	36.4	82
12	11:00 am	26.7	78.7	35.6	88
13	12.00 pm noon	27.8	87.1	38.1	89
14	01:00 pm	26.8	86.6	38.6	87
15	02:00 pm	27.3	79.7	37.4	85
16	03:00 pm	26.1	81.4	38.1	84
17	04:00 pm	26.8	77.7	35.4	86
18	05:00 pm	27.4	75.9	35.8	88
19	06:00 pm	26.9	83.3	38.5	82
20	07:00 pm	27.6	76.4	35.9	83
21	08:00 pm	27.7	79.6	35.7	81
22	09:00 pm	26.2	82.5	38.7	80
23	10:00 pm	28.0	84.8	35.9	86
24	11:00 pm	26.7	88.7	35.1	82

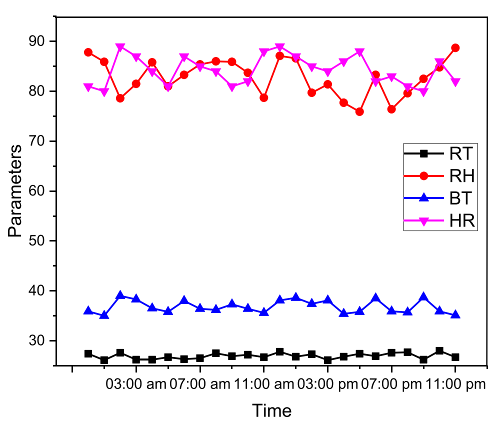

Fig. 13. Variation of different parameters throughout the day.

involved, or failure in the communication link, etc. after observing the proposed system for eight months. These failures affected the total accuracy and reliability of the system. The evaluation and assessment for the proposed IoT-driven health monitoring system provided in the detail form are provided below in Table 2.

- True Positives (TP): Situations when the performance of the system is accurate, and the health anomaly is indeed present.

Table 2
Sensory observation to estimate the proposed system for calculating accuracy.

Aspects	Details
Evaluation period	8 months
Total events monitored	625
True Positive (TP)	64
True Negatives (TN)	509
False Positive (FP)	23
False Negatives (FN)	29

- True Negatives (TN): Situations when the system successfully recognizes that there is no pathological sign when there is none.
- False Positives (FP): Situations where the system correctly diagnoses a health irregularity while in the real situation, there is not any.
- False Negatives (FN): Situations in which the system provides a negative result with a positive health anomaly present.

The accuracy of the proposed system is evaluated as below.

$$\text{Accuracy of the proposed system} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} = \frac{64 + 509}{64 + 509 + 23 + 29} = 0.9168$$

Current analysis reveals that the accuracy of the system is at 91.68 % suggesting reliability in identifying accurate health event occurrence with less false positive identification. The prospects of the proposed health monitoring system are demonstrated in the diagram below in Fig. 14. The minimization of false alarms and enhancement of reliability is achieved by implementing the system in hardware and using a secure communication network.

6.2. Statistical analysis

The statistical measures like mean, median, mode, minimum, maximum, and range given in Table 3 provide insights into the central tendency, typical values, variability, and distribution of the monitored parameters (Room Temperature (RT), Room Humidity (RH), Patient Body Temperature (BT), and Patient Heart Rate (HR)) in the given sensor fusion output dataset Table 1.

For instance, a lower standard deviation in room temperature (0.5816°C) suggests that most recorded temperatures are close to the mean of 26.94°C, indicating relatively stable room conditions. Conversely, a higher standard deviation in patient heart rate (2.8759 bpm) suggests greater variability in heart rates across the observed data set.

The HRV calculation utilized heart rate data and heartbeat signal peaks from a wearable IoT sensor node. Table 4 shows HRV metrics for individuals aged 30–40 with normal heart conditions, including Mean HR (55–105 bpm), SDNN (20.4–51.4 ms), RMSDD (11.7–42.9 ms), and pNN50 (3 %-23 %). These parameters provide reference ranges for evaluating HRV within this age group and condition. Table 5 summarizes HRV metrics for five subjects, detailing variations in mean HR, SDNN, RMSSD, and pNN50. Subjects exhibit differing autonomic nervous system activity, reflected in their HRV parameters.

Table 6 compares heart rate variability (HRV) parameters measured by proposed IoT sensors against a standard HRV monitor in a supine position. The HRV parameters include Mean Heart Rate (Mean HR),

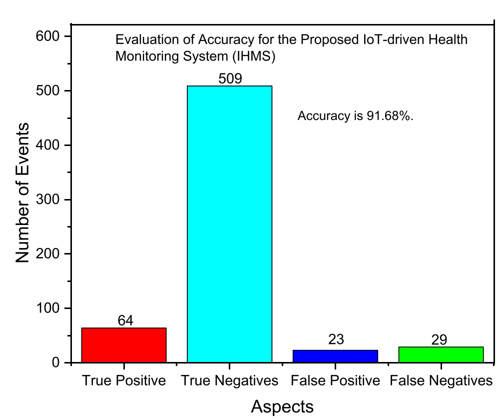

Fig. 14. Evaluation of the proposed IoT-driven Health Monitoring System (IHMS).

Table 3
Statistical analysis of monitored parameters.

Parameters	Mean	Median	Mode	Minimum	Maximum	Range	Standard Deviation
Room Temperature (RT)	26.94	26.85	26.2, 26.7	26.1	28.0	1.9	0.5816
Room Humidity (RH)	82.8	83.3	85.9, 83.3	75.9	88.7	12.8	3.6465
Patient Body Temperature (BT)	36.82	36.4	35.9	35	39	4	1.2615
Patient Heart Rate (HR)	84.25	84	81	80	89	9	2.8759

Table 4
HRV Parameters for Normal Person.

Parameters	unit	Age Range	Heart Condition	Parameters Range
Mean HR [24]	–	30–40	Normal	Min= 55bpm Max= 105bpm
SDNN [25]	ms	30–40	Normal	Min= 20.4ms Max= 51.4ms
RMSDD [24]	ms	30–40	Normal	Min= 11.7ms Max= 42.9ms
pNN50 count [24], [25]	%	30–40	Normal	Min= 3 % Max= 23 %

Table 5
Different Heart rate variability Parameters of subjects involved in the experiment.

Subjects	Mean Heart Rate (HR)	The standard deviation of NN intervals (SDNN)	Root mean Square of Successive differences (RMSSD	pNN50
1	58.4300	0.2827 ms	0.4014 ms	3.000 %
2	68.2948	0.4786 ms	0.8290 ms	2.000 %
3	57.5076	0.3285 ms	0.4038 ms	1.000 %
4	56.5712	0.5661 ms	0.7069 ms	1.000 %
5	54.0964	0 ms	NAN	0 %

Table 6
Validation of HRV parameters using Standard HRV monitor.

HRV parameters in the Supine position	Using Proposed IoT Sensors	Standard HRV monitor	Error in percentage
Mean HR	59.614	65.5 l	9 %
SDNN	0.3285 ms	0.3106 ms	5.7 %
RMSDD	0.4038 ms	0.4101 ms	1.5 %
pNN50 count	1.000 %	0.056 %	2.05 %

Standard Deviation of NN intervals (SDNN), Root Mean Square of Successive Differences (RMSDD), and the percentage of NN50 count (pNN50). For Mean HR, the proposed IoT sensors recorded a value of 59.614, while the standard monitor showed 65.51, resulting in a 9 % error. For SDNN, the IoT sensors measured 0.3285 ms compared to the standard monitor's 0.3106 ms, with a 5.7 % error. The RMSDD values were 0.4038 ms for the IoT sensors and 0.4101 ms for the standard monitor, indicating a 1.5 % error. Lastly, the pNN50 count was 1.000 % for the IoT sensors and 0.056 % for the standard monitor, with an error of 2.05 %. These results show that while there are discrepancies between the IoT sensors and the standard monitor, the errors are relatively low, suggesting the proposed IoT sensors can provide reasonably accurate HRV measurements. The evaluation of the proposed IoT-driven Remote Health Monitoring System with Sensor Fusion used metrics and benchmarks to determine its effectiveness. Evaluation of the system focused on anomaly detection capacity critical event reaction time and user-system interaction levels. The system utilized quantitative measurements to assess detection accuracy at 91.68 % and proved its alert average response time below five seconds while patient satisfaction was assessed through survey scores. The system demonstrates its ability to improve citizen engagement because it provides dependable real-time health monitoring services with prompt medical interventions for diverse and hard-to-reach patient populations.

7. Conclusion

The paper introduces an IoT-driven Health Monitoring System (HMS) aimed at providing immediate medical assistance, especially in underserved rural areas. This system integrates wearable sensors, data analytics, and cloud computing to continuously monitor vital signs such as body temperature, heartbeat, and environmental conditions in real time. Utilizing Sensor Fusion techniques enhances data accuracy and reliability across distributed locations, ensuring secure data handling and patient privacy. Experimental results from a ZigBee-based HMS demonstrate its effectiveness with 91.68 % accuracy in promptly identifying critical health events, enabling rapid medical responses, and improving patient outcomes. The system's scalability allows for integration with Decision Support Systems (DSS), facilitating comprehensive health monitoring and generating medical reports for future use. Future developments include advancing wearable technology and sensor accuracy, enhancing data analytics capabilities with AI and machine learning for predictive health insights, and expanding monitoring capabilities to encompass a broader range of vital signs and biomarkers. Advanced deep learning frameworks like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) may be tested for time-series analysis of healthcare data. Integration with telemedicine and seamless Electronic Health Record (EHR) connectivity promises holistic patient care and better coordination among healthcare providers, ultimately enhancing global healthcare efficiency. ZigBee-based IoT nodes ensure low power consumption, cost-effectiveness, and reliable wireless communication, supporting system efficiency and scalability in advancing personalized medicine applications. Additionally, combining the suggested sensor fusion technology with federated learning techniques can improve AI/ML models, allowing for more robust real-time analysis and decentralized healthcare monitoring.

CRediT authorship contribution statement

Hanan Abdullah Menfash : Supervision, Software. **Allafi Randa:** Writing – review & editing, Funding acquisition. **Alqahtani Hamed:** Resources, Formal analysis. **Nafie Faisal Mohammed:** Validation, Resources. **Ali M. Al-Sharaei :** Visualization, Data curation. **Mohapatra Ambarish G.:** Project administration, Conceptualization. **Nayak Sasmita:** Software. **Mohanty Anita:** Writing – review & editing, Visualization, Methodology.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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