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Original Article

VitalCare-IoT: An Integrated Wearable–Gateway–Cloud Architecture with Learning-Based Analytics for Continuous Patient Observation and Health Condition Detection

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Abstract *- Remote Patient Monitoring (RPM) involves using technology outside traditional healthcare facilities, such as in patients' homes. This technology allows healthcare providers to gather patient data remotely and track their health immediately. These systems are important for improving patient outcomes, increasing access to care, managing chronic diseases, and providing personalised care cost-effectively. Monitoring patients remotely must be affordable and accessible to everyone. Innovations in technology, including Artificial Intelligence (AI) and the Internet of Things (IoT), are making remote patient monitoring systems a reality. To this end, it has developed a simple yet effective system for monitoring remote patients. This system serves a dual purpose: collecting patient data and using data analytics tools to detect potential diseases. Cloud-based IoT middleware stores the data, which is then analysed using machine learning algorithms to identify possible illnesses. Several algorithms have been proposed for monitoring patients' vital signs and notifying patients, caregivers, or healthcare professionals. The system features user-friendly mobile and web interfaces for patients, doctors, relatives or caregivers. It can also be integrated with healthcare applications to achieve a cost-effective distant patient observation system.*

Keywords - *Remote Patient Monitoring, Internet of Things, Artificial Intelligence, Machine Learning, Health sensors.*

1. Introduction

Smart IoT applications have been made possible in the modern world by ICT innovations, including Cyber-Physical Systems (CPS), 5G cellular technology, and the Internet of Things (IoT). Ambient Assisted Living (AAL), Mobile Health (mHealth), and Electronic Health (eHealth) are three particularly significant IoT use cases in the healthcare industry. People allocate a substantial portion of their income to healthcare, and traditional healthcare services are often plagued by delays and wasted time and money. Nevertheless, for those who need it, IoT's intelligence and predictive powers may be used for Remote Patient Monitoring (RPM) in a variety of contexts (home, office, or hospital). IoT-based RPM can serve as an early warning system for possible crises by utilising wearable technology, sensor networks, and other digital infrastructure. This can help prevent severe health complications and even patient fatalities due to poor and/or untimely care. Wearable technology (biosensors) may instantly provide patients' vital signs to physicians through Internet of Things integration. This allows for the start of therapy quickly. The RPM method can improve patients' quality of life and the quality of healthcare services while also saving time and reducing expenses. Overall, the goal of the work is to develop an AI- and IoT-based framework for realising a data analytics-based Remote Patient Monitoring System (RPMS). This could improve the quality of patient care and healthcare services by saving time and money.

This offers a low-tech, high-impact remote patient monitoring device. This system has two functions: patient data collection and the application of data analytics tools to identify possible diseases. Patient data is stored in the cloud-based IoT middle tier, and machine intelligence is used to analyse the data and determine who could be diagnosed with a disease. Several algorithms for monitoring patients' vital signs and alerting patients, caregivers, or healthcare professionals are proposed. Patients, doctors and patient relatives/caregivers have easy-to-use mobile and web access options to the system. Additionally, it may be used with already-in-use healthcare apps to provide an affordable remote patient monitoring system.

Although Internet of Things (IoT), Wearable Sensing Technologies, Cloud Computing, and Artificial Intelligence (AI) for Remote Patient Monitoring (RPM) are all significant achievements, there are still several drawbacks. Many current RPM solutions monitor a single physiological parameter, require extensive hardware systems, lack real-time intelligent analysis, or offer little interaction among patients, care providers, and healthcare professionals. Moreover, many existing systems focus on data collection, leaving out continuous health monitoring, abnormality detection, disease prediction, and emergency notification in an integrated and cost-effective manner.

As chronic diseases become more common and the need for home healthcare services grows, the demand for a scalable, affordable, and intelligent remote patient monitoring solution that can continuously monitor and intervene is increasing. Especially, those living in rural and resource-poor areas are likely to experience problems accessing health care services and prompt medical care in emergencies.

This work aimed to present a merged wearable–gateway–cloud architecture, named VitalCare-IoT, to overcome these challenges and provide continuous observation of patient health and condition detection via a wearable health sensor, IoT communication, and cloud-assisted data management, coupled with machine learning. The proposed system will allow vital signs to be monitored in real time, abnormalities to be detected automatically, falls to be detected automatically, automatic emergency alert generation, and intelligent health assessment, all on a single platform accessible to the patient, doctor, and caregiver. The proposed system combines these features in a cost-effective design to enhance the accessibility, early diagnosis, and safety of healthcare.

The key contributions of this work are: (i) design of an integrated remote patient monitoring architecture using wearable sensors, edge gateways, cloud services, and Android Wear OS device; (ii) design of real-time monitoring mechanisms for heart rate, blood pressure and fall detection; (iii) design of machine learning-based analytics for health condition assessment and disease prediction; and (iv) provision of a unified platform to facilitate communication between patients, healthcare professionals, and caregivers for timely medical intervention.

The rest of the paper discusses existing technologies for using artificial intelligence and IoT to support remote patient monitoring. A compelling scenario is presented in Section 3 to aid in the understanding of the suggested approach. Section 4 outlines the proposed methodology and underlying algorithms for a cost-effective remote patient monitoring system. Section 6 wraps up the effort, while Section 5 presents the experimental outcomes and provides possible avenues for future research.

2. Related Work

There are several approaches to realising a remote patient monitoring system. Anand et al. [1] discuss how IoT integrates the physical world with computer systems, reducing human intervention. They propose introducing a remote health monitoring system to assist in the effective care of patients. The authors of Gupta et al. [2] highlight the significance of the collaboration between the Internet of Things (IoT) and edge computing in facilitating the secure and efficient retrieval of health data, moving beyond IP-based constraints and bolstering privacy safeguards. In [3], Nduka et al. discuss the modelling of large networks, including convergence and practical solutions to simulation issues. Saha et al. [4] highlight the importance of the IoT-based health monitoring paradigm, as the need to track and communicate with patients has increased. To monitor the patient, cloud computing and IoT technology are used by Iranpak et al. [5] with high accuracy by using the LSTM neural network. Here, Sundarasekar et al. [6] have introduced the MODWT for analysing ECG signals, with a focus on R-wave detection. The results obtained from the evaluation of performance against HWT and DWT are more sensitive and specific.

Akkaş et al. ([7]) discuss how IoT is affecting healthcare, particularly in the use of WBANs. They come up with a Prototype of the system using ZigBee nodes effectively. Unlike existing designs, Mohammed et al. [8] prove that CDRA is efficient for CD generation of OAM waves at frequencies beyond their limitations. Abawajy et al. [9] emphasise the rising healthcare costs and call for intelligent patient surveillance solutions. The built-in PPHM system provides flexibility, scalability, and efficiency. Saha et al. [10] discuss the advantages of IoT for remote health monitoring, enabling data collection, alarm triggering, and alerts while ensuring patient convenience and safety. One study by Rais et al. [11] demonstrates the role of WBASNs in enhancing communication between remote healthcare systems and patients within an IoT and Fog computing framework, enabling timely and reliable data delivery. In [12], Su et al. present an ICT-based RPM system that provides timely medical support and compare and review 11 healthcare IoT platforms. Harb et al. [13] studied atmospheric attenuation in pristine environments over a wide terahertz band by simulation software comparisons.

Mathew and others [14] present an approach for building an online patient-tracking system using a Raspberry Pi 3 that wirelessly transmits data to a worldwide diagnostic system. Several works highlight Remote Patient Monitoring (RPM) using wearable sensors, the concept of Healthcare 4.0 Hathaliya et al. [15], and return to the idea of a blockchain-based Healthcare Architecture. Regarding secure and reliable remote patient monitoring, Uddin et al. [16] proposed a patient management system based on blockchain technology, a small-scale consensus mechanism, and a decentralised medical software agent system. An SDN fingerprinting attack analysis is presented in Yew et al. [17], which indicates that SDN would be vulnerable to successful attacks through RTT and packet-pair dispersion. They suggest an action to take to reduce the risks or dangers effectively. Motwani et al. [18] present the SPMR framework for monitoring chronic diseases, highlighting the capabilities of local and cloud-based intelligence that enable better predictions and improved healthcare quality.

Meanwhile, advancements in ICT have been noted, and the task of securely integrating IoT into reliable Remote Patient Monitoring (RPM) in the healthcare domain has been proposed by Imtiaz et al. [19]. This section discusses IoT in the healthcare industry and the use of fog computing for effective patient monitoring using a validated algorithm (KNN), Moghadas et al. [20]. Griggs et al. [21] suggest secure data management and real-time patient monitoring via smart contracts on the blockchain. Based on the concept of the Internet of Things, R. Ani et al. [22] design a stroke risk monitoring system to detect, diagnose, and predict changes in factors. Kaur et al. [23] emphasise the importance of IoT in healthcare and propose a wearable system for remote healthcare monitoring that leverages the Raspberry Pi and Bluemix. Archip et al. [25] present a low-cost, modular prototype monitoring system that facilitates continuous patient evaluation after ICU discharge using IoT technology. El-Rashidy et al. [26] explain the need for Remote Patient Monitoring (RPM) in long-term diseases, as well as its benefits and challenges. They also highlight the different layers of complexity in RPM systems and the three main layers they comprise. The study also recognises some constraints and suggests additional research topics related to hardware, security, data transmission, and regulatory factors.

In order to provide real-time patient monitoring, Hassan et al. [27] propose a combination of the cloud and local model to form a hybrid context-aware model. The results validate the accuracy, fault tolerance and speed of the emergency detection of the model, particularly for patients with blood pressure disorders. Future tasks involve making the model more general to different diseases and contexts. Kumar G J et al. [28] suggest an IoT-supported health monitoring system for older persons, highlighting the best performance of J48 in determining the health status of older citizens. The robustness and implementation of a real application in an IoT environment will be future challenges. An edge-based CEP approach is proposed for RPM by Dhillon et al. [30], which shows several benefits, such as better data transfer ability. Further tasks include performance analysis, integration of more devices and load management. Uddin et al. [31] talk about an IoT patient monitoring system that enables patients' health condition monitoring remotely for better patient care. The application of fog computing in the Internet of Things (IoT) was developed by Verma et al. [32] for a better delivery of healthcare by efficiently monitoring patient health and real-time event processing.

Moghadas et al. [33] present a concept for implementing fog computing in the healthcare sector, reducing latency for cardiac arrhythmia monitoring through a combination of Arduino and KNN algorithms as IoT develops in the healthcare field. For the Internet of Things, Jeyaraj et al. [34] have described a deep learning approach to establish a physiological monitoring system for high-precision signal prediction in healthcare. They have designed a portable E-health recording system for continuously recording health parameters to a cloud storage, Shanin et al. [35]. The data integration, analysis, and secure sharing were proposed by Dridi et al. [36] based on the intelligent personalised Healthcare system – SM-IoT. To effectively collect, analyse, and secure health data, Plageras et al. [37] recommend using IoT, Cloud Computing, and Big Data. As the world's population continues to rise and agriculture faces challenges, Elijah et al. [38] state that data analytics and the Internet of Things are being embraced to enhance efficiency. Li et al. [39] proposed integrating Fog and Big Data to implement a Health monitoring system. Baig et al. [40] provide an overview of WPM, its challenges, elements, and user acceptance of WPM solutions in healthcare. Sharma et al. [41] present an IoT-based Smart Healthcare System for remote monitoring of COVID-19 patients using 1D biomedical signals and ontology techniques. Minhee et al. [42] explain the innovative use of IoT, cloud computing, and big data integration to provide patient care and control in healthcare services. When they say they are looking at the devices that monitor from the IoT, they also see how they can be integrated in the future, such as blockchain and AI, for providing personalised care. In this paper, both the Remote Patient Monitoring (RPM) functionality of the Smart House Healthcare Support System (ShHeS) and the benefits of IoT are improved and emphasised by Taiwo et al. [43]. Neethu et al. [44] describe the system's use of the Raspberry Pi 3 for real-time patient monitoring, enabling patients to avoid coming to the hospital. Alshamrani [45] emphasises the use of IoT and Artificial Intelligence (AI) to enhance health services in a smart city, including the applications and challenges involved. Juyal et al. [46] aim to enhance the diagnosis of skin diseases using AI and IoT, specifically through an 'Intelligent Skin Monitoring Device'. Raza et al. [47] proposed an IoT-based remote monitoring system for Parkinson's disease that enables efficient communication and reliable disease prediction. Last but not least, Shahjalal et al. [48] propose a remotely monitored smart home system based on LoRa technology, highlighting its wide coverage and cost-effectiveness. Baig et al. [40] and Uddin et al. [49] propose the Patient-Centric Agent (PCA)- based architecture, ensuring secure data transfer and privacy in Remote Patient Monitoring.

It is evident that in densely populated areas, healthcare demands are rising, necessitating efficient remote patient monitoring via IoT technology (Alshammari, [50]). Recent advancements in ICT have enabled innovative IoT-based healthcare solutions, enhancing remote patient monitoring and ensuring secure, efficient communications (Ahmed et al., [19]). This pandemic has provided a clear view of the potential applications of the Internet of Things in healthcare, where data management and remote patient follow-up are key challenges (Naveen Mukati et al., [51]). A detailed IoT-based asthma monitoring system has been developed and implemented to enable remote patient care, providing accurate details of related conditions, including environmental conditions (Islam et al., [52]). Moreover, certain machines now include features that facilitate post-COVID patient care, such as remote monitoring via IoT and machine learning, especially for vulnerable groups (Rahman et al. [53]). Along with a smart medicine box described in Singh et al. [54], sensors and cloud-based data can also help deliver home-based health services to patients. The Internet of Things (IoT) has also been shown to effectively enable comprehensive home-based health services through sensors, cloud-based data, and a smart medicine box (Singh et al., [54]). A health-tracking system, integrated with the Internet of Things, sensors, deep learning, and real-time feedback, has been proposed in the field of remote patient care (Reazul et al., [55]). However, there are concerns about the integrity of one cited study, specifically regarding human subjects protocols (Anonymous, Nafisa Shamim Rafa et al, [56]). An Internet of Things monitoring system has been highlighted for its significance and potential growth with advanced technology in the asthma study (Anonymous, 56).

The COVID-19 crisis has emphasised the need for advanced healthcare solutions, with an IoT-based monitoring system enabling efficient remote patient care and pandemic management (Wu et al., [57]). Another proposed IoT-based wearable system has been developed to monitor vital parameters, facilitating remote patient care with automatic alerts and data storage (Chowdhary et al., [58]). The rapid evolution of IoT in healthcare has been examined through a bibliometric analysis, highlighting key research trends (Rejeb et al., [59]). Karim Rejeb et al. [59] Moreover, IoT-powered health monitoring has been used to track mental and physical well-being, focusing on blood pressure, stress, and anxiety, leveraging wearable sensors and machine learning for real-time tracking, with automated artefact detection to remove movement-induced outlier points (Anonymous, Malik Bader Alazzam et al. [60]). The integration of IoT in healthcare has led to the development of a visualisation system for real-time patient monitoring, which has demonstrated improved user-friendliness, accuracy, and quality compared to traditional methods, thereby enhancing remote patient monitoring and overall patient outcomes (Khan et al., [61]). The shift from IoC to IoT has emphasised AI's role in disease detection; given that the proposed AI-enabled IoT-CPS algorithm performs well, it is imperative to enhance security (Ramasamy et al., [62]).

Mohammed et al. [24] proposed an IoT-based remote patient monitoring framework using web services and cloud computing. The system enabled real-time collection, storage, and remote access of patient health data, demonstrating the potential of cloud-assisted healthcare monitoring for improving patient care and accessibility. Hosseinzadeh et al.[29] developed an elderly health monitoring system that combined biological and behavioral indicators within an IoT environment. Their framework supported continuous monitoring of elderly individuals and enabled early detection of health abnormalities, thereby improving healthcare assistance and quality of life. Bugingo et al. [63] reviewed recent advances in seed health testing through the integration of molecular diagnostics, imaging technologies, and artificial intelligence techniques. Their study highlighted the effectiveness of AI-driven analysis in enhancing detection accuracy, quality assessment, and decision-making processes.

Table 1. Comparison with existing studies

Ref.	Monitoring	AI/ML	Fall Detection	Cloud Integration	Caregiver Alerts	Disease Prediction	Limitation
[14]	Yes	No	No	Yes	No	No	Only monitoring
[21]	Yes	No	No	Yes	No	No	Focus on blockchain security
[27]	Yes	Yes	No	Yes	No	Limited	Disease specific
[41]	Yes	Yes	No	Yes	No	Yes	COVID-focused
[47]	Yes	Yes	No	Yes	No	Parkinson only	
Proposed VitalCare-IoT	Yes	Yes	Yes	Yes	Yes	Yes	Integrated framework

Additionally, a cloud-based IoT system has been proposed for remote patient diagnosis, promoting safety, with the promise of improved accuracy and commercial viability in the future (Bhunia et al., 63]). Remote Patient Monitoring Systems (RPMS) have been emphasized as vital, especially amid the pandemic, with increasing mobility, networks, and standardization challenges. Recent RPMS research emphasizes applications and architectures, focusing on the quality of service, revealing RPMS growth until 2019, with a decline post-pandemic (Boikanyo et al., [64]). Additionally, it has been discovered that deep learning algorithms and IoT-based remote health monitoring help in patient early diagnosis and treatment, with the potential use of federated learning in the future (Mohana et al., [65]). Intelligent health monitoring systems leveraging IoT and AI have gained importance, particularly during COVID-19. The proposed system for heart patients demonstrates real-time monitoring and highly accurate disease classification. Additionally, an optimized CNN model yields superior results to other approaches, improving the likelihood that severely sick patients may survive (Almujally et al., [66]). The impact of ICT advancements has been discussed, emphasizing the potential of IoT and RFID integration in healthcare and the advantages of Remote Patient Monitoring (RPM) based on the Internet of Things for enhancing healthcare services. Finally, a proposed secure and privacy-preserving RPM system utilizing wearable devices and a comprehensive security scheme has been presented, with further research necessary to resolve security flaws in the Internet of Things apps (Ahmed et al., [19]). It seemed ridiculous to read in the literature that a low-cost, widely accessible remote patient monitoring system was required.

While many studies have discussed the use of healthcare monitoring systems using IoT technology, most of them are limited to only a few functionalities like vital sign monitoring, prediction of different diseases, cloud-based storage or secure healthcare communication. Very few studies offer a comprehensive framework that can facilitate continuous physiological monitoring, fall detection, machine learning-based health analytics, emergency alert generation, and multi-user interaction between patients, doctors, and caregivers. Moreover, some of the systems available are dependent on costly infrastructure, disease-specific models, and limited monitoring capabilities, which affect their usability for general remote patient monitoring scenarios.

The novelty of the proposed VitalCare-IoT framework is the combination of a wearable sensing device, edge-enabled IoT communication, cloud-assisted healthcare management and machine learning-driven health analytics into a single remote patient monitoring framework. While there are several existing systems which focus on individual healthcare capabilities, the proposed system aims to integrate all these functionalities into one single platform, including heart rate monitoring, blood pressure monitoring, fall detection, emergency notification, cloud-based data management and intelligent disease prediction. Moreover, the system allows patients, healthcare providers, and caregivers to communicate in real time, enabling timely intervention and patient monitoring. This built-in system increases accessibility of healthcare, patient safety, and the ability to detect possible health problems early on.

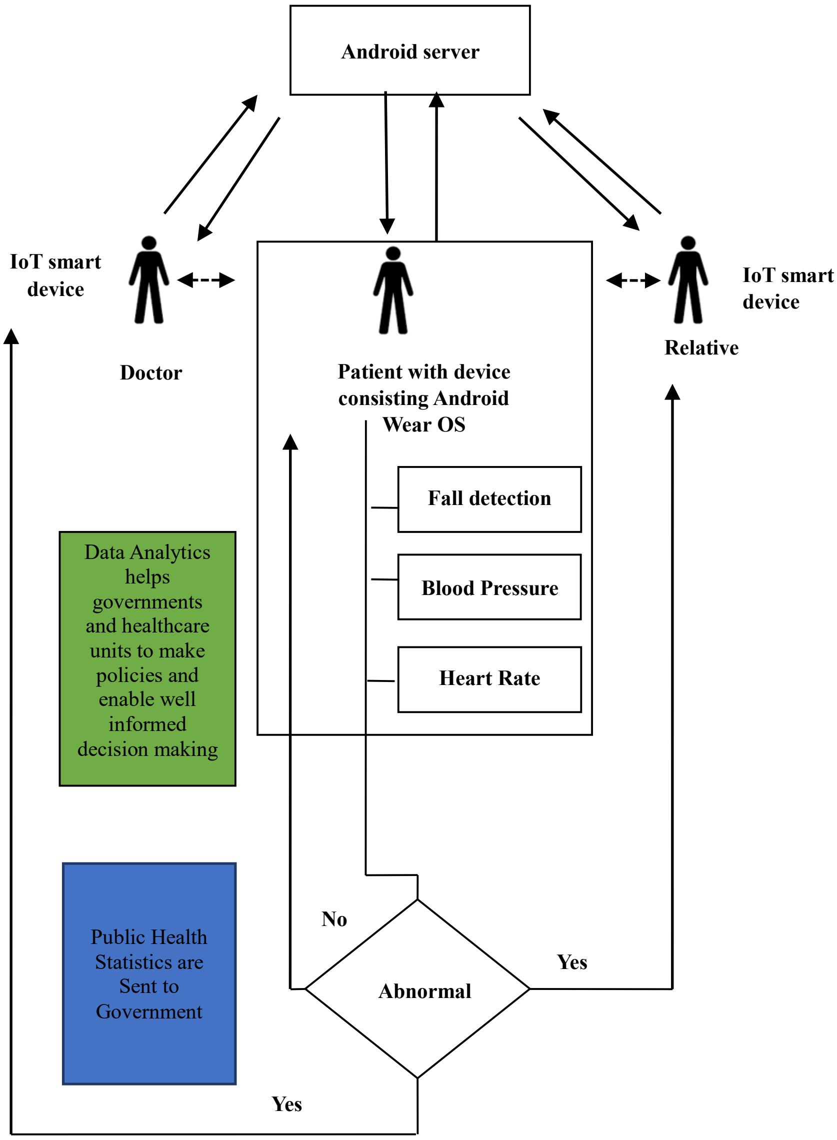

Fig. 1 An IoT use case for RPM motivating the proposed system

The literature reflects the advances that have been made in developing remote patient monitoring systems with IoT, based on the use of wearable sensors, cloud computing, edge intelligence, blockchain security, and machine learning techniques.

Previous works have managed to solve the individual aspects of physiological data collection, disease prediction, monitoring of patients, secure data transmission and real-time healthcare services. However, several of the reported methods are disease-specific, monitoring-specific or analytical-specific.

Moreover, not much focus has been paid towards the formulation of an integrated healthcare architecture that can support multiple functionalities such as continuous vital sign monitoring, fall detection, health assessment using machine learning, the generation of emergency notifications, as well as interaction with different stakeholders, including patients, doctors, and caregivers. These limitations indicate the need for a complete and cost-efficient remote patient monitoring framework, which can be realized in the form of a unified solution comprising sensing, communication, analytics and healthcare decision support.

3. Motivating Scenario

After reviewing the literature, it became clear that Remote Patient Monitoring (RPM) is still a work in progress. It needs to extend its reach to rural patients to save their lives, time, effort, and money. Using simple and cost-effective equipment, RPM technology could be accessible to the general public. This need is the driving force behind the research presented in this paper. For more details, please refer to Figure 1 for the motivating scenario. The IoT-integrated system allows remote patient monitoring and assists in disease diagnosis and treatment in real-time. Using wearable devices with sensors makes it possible to create a highly cost-effective RPM system.

Patients wearing smart watches or other wearable devices with sensors can help capture data and monitor vital signs remotely. The key vitals are heart rate and blood pressure, as ignoring abnormalities in these can lead to heart and brain strokes. Monitoring these vitals to enable timely diagnosis and potentially save lives is crucial. An Android server can receive data from the sensors for further processing. In this scenario, the doctor and the patient's relatives can also be involved in the IoT-integrated application.

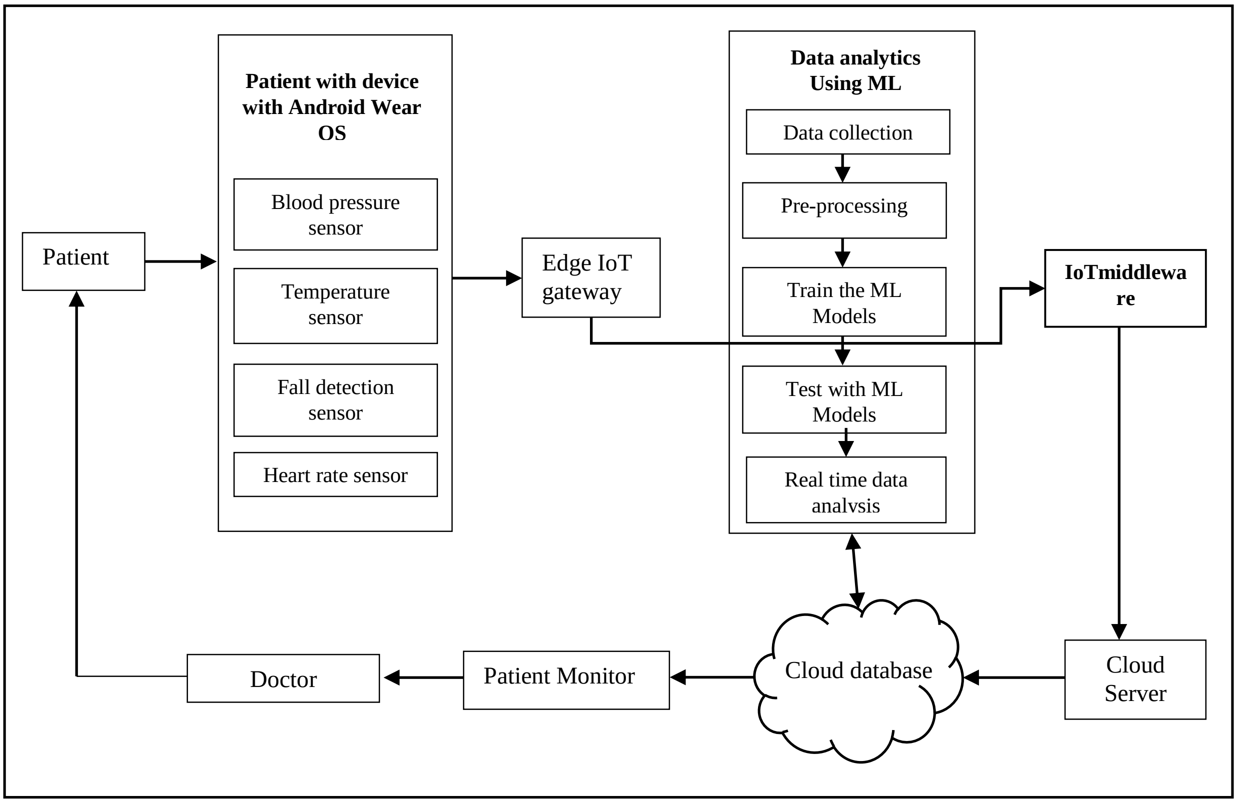

Fig. 2 Overview of the proposed system for remote patient monitoring

4. Proposed System

As seen in Figure 2, Have created a system for remotely monitoring patients. This system utilizes live sensor data from a patient for disease detection and informed decision-making through data analytics. The framework is designed as an IoT-based health monitoring system that uses Android Wear OS devices and machine learning for data analytics. In this system, the patient wears an Android Wear OS device equipped with many sensors for temperature, heart rate, and blood pressure. The data collected from these sensors is sent back to an edge IoT gateway, which then sends the information to a cloud database for storage. The cloud database is further connected to an online server and IoT middleware to handle and store data. In the data analytics phase, the collected data undergoes several stages, including data collection, pre-processing, training Machine Learning (ML) models, testing the ML models, and real-time data analysis.

The findings of the study are retained in the cloud database. This data is available to doctors via a patient monitor, giving them real-time patient health data. This system allows the possibility of monitoring and intervention at any time by health care facilities, thus improving the management of patients.

Android Wear is a version of the Android operating system that has been designed for wearables and the smartwatch segment. It was first launched in 2014 and renamed as Wear OS in 2017.

Android-based Wear OS offers a home for manufacturers to make wearable gadgets that will be able to communicate with Android cellphones and have a variety of functions, which include playing music on the Android cellphone, tracking fitness records, and pulling certain notifications directly. Wear OS devices typically feature touchscreens, support for voice commands, and various sensors to enhance the user experience.

A blood pressure sensor is an instrument that gauges the blood pressure inside the arteries. This sensor comes in two varieties: non-invasive (like the ones in digital blood pressure monitors that encircle the upper arm or wrist) and invasive (like the ones used in medical settings for accurate measurements).

Non-invasive blood pressure sensors use oscillometric or auscultatory methods to determine blood pressure, while invasive sensors are used in critical care settings and surgery for continuous monitoring.

When an object or its surroundings are heated, a temperature sensor takes readings and produces a signal. Temperature sensors are used in weather monitoring, industrial processes, HVAC systems, and medical devices.

There are several kinds of temperature sensors, each having a unique variety of uses and operations, such as thermocouples, thermistors, Resistance Temperature Detectors (RTDs), and infrared sensors.

A fall detection sensor is designed to detect when a person falls. It is commonly used in healthcare settings, particularly for older people or individuals at risk of falling. The sensor can alert someone if it senses a sudden change in movement or orientation, then help tools can be set in motion, after a fall, which is the most crucial moment.

The heart rate sensor measures a person's heart rate by identifying blood pulsation through the arteries. The sensors are used in wearable fitness trackers, medical devices or smartwatches. They track heart rate during physical activity, exercise or at rest and can provide important data on the health and fitness of the cardiovascular system. The cloud also has to communicate with the IoT device, and an Edge IoT gateway is used as a middleman. It sits on the network periphery to gather, analyze and upload data to the cloud.

The Edge IoT gateway provides Low Latency, low bandwidth, security and real-time analysis of data at the edge of the network. IoT middleware is the special software that connects the hardware with the applications of an IoT system.

This controls the devices and gathers data from the sensors, processes it and supports interactions with other software. By mapping the communication protocols and facilitating integration with other IoT devices and applications, IoT middleware allows deployments to be scalable, standardized, and secure, making it easy to integrate everything on the internet of things.

Machine learning is crucial in analyzing sensor data in remote patient monitoring for disease detection. Healthcare professionals can use machine learning to analyze the huge amount of sensor data gathered from patients at a distance, and then learn patterns and discover variations that can suggest a disease or health problem, for early detection and intervention.

Wearable devices like smartwatches, remote monitoring equipment, or even other medical devices will now constantly take measurements and information of patients' blood pressure, heart rate, blood sugar levels and degree of physical activity, as well as various health markers.

Modelling these data using machine learning techniques can then identify abnormal deviations from normal patterns that could indicate the appearance or development of any disease. Besides, machine learning can also be used for predictive modelling and predict potential medical conditions from historical data and real-time sensor readings.

Healthcare practitioners can implement a proactive approach via early intervention, individualized therapy and enhanced patient results. The adoption of machine learning in telemedicine for early disease detection provides substantial advantages in terms of disease diagnostics, individualised healthcare, and most importantly, better management of long-term chronic diseases.

4.1. Modules in the System

This section describes the functions related to different modules within the proposed system.

4.1.1. Patient Module

It has a few modules in the suggested framework. The patient module is only for the patient activities of the proposed remote patient monitoring system.

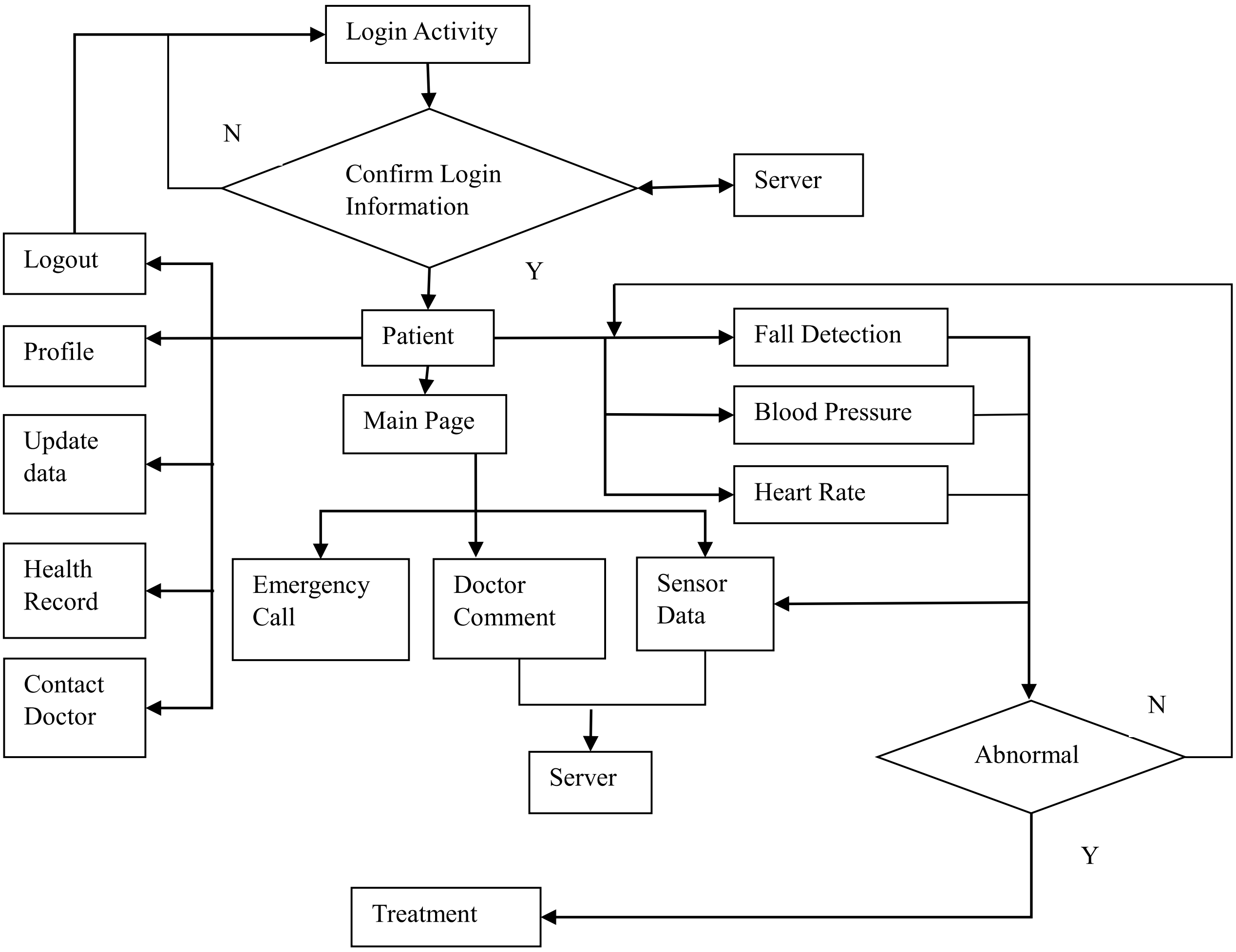

Fig. 3 Flowchart of patient module

As shown in Figure 3, a Patient Module was presented to make it possible for the second application of this study, which collects health-related data from the patient. The first step is your Login Activity, where the patient logs in. Else if the verification of login info fails, the patient is directed back to use the health system. After verifying the login information, it interacts with the server to authenticate credentials. Once login is successful, the reconciliations page pops up, and the patient moves to the home page.

From the main page, patients can access functions to “Profile”, “Update Data”, Health Record, and “Contact Doctor. Also, the patient can logout to from this interface. Specifically, the system has three main functions which enable monitoring of health-related indicators such as “Fall Detection,” “Blood Pressure”, and “Heart Rate”. These metrics constantly flow to the “Sensor Data” part and later on are administered to the caterer.

The data from the sensors is analyzed to determine whether there are any irregularities or abnormalities in the server. If the data belong to what is normal, no intervention occurs while monitoring continues. However, the system responds by triggering an emergency response to prevent something abnormal from happening. In an emergency, the patient can press “Emergency Call” or the doctor will write a comment in “Doctor Comment”. Now, the server performs this processing and leads them to “Treatment”, which is right.

This structured workflow, it ensures constant patient health monitoring, and any future presenting issues can be tackled immediately, combined to offer an all-in-one holistic healthcare management solution.

4.1.2. Relative Module

The proposed system is a relative module that handles the functionalities of patient attendants or relatives.

The Relative Module of the healthcare monitoring system is illustrated in Figure 4. It all starts with the “Login Activity” where a relative tries to log in for the patient. In case the relative fails to confirm the login information, they are redirected and requested to make a fresh attempt at logging in.

After a successful login, the relative gets logged in on the server side. Once the relative has logged in, they go to a main page where most of what you want to do lies. From the main, relatives can access sections like Profile, Health Record and Contact Doctor, which gives an overall picture of patients state details and allows communication with the doctor. The relative module is crucial in providing full access to the patient's medical records, ensuring that the patient's relatives or attendants are well-informed concerning the patient's state of health. The relative can also log out from this interface.

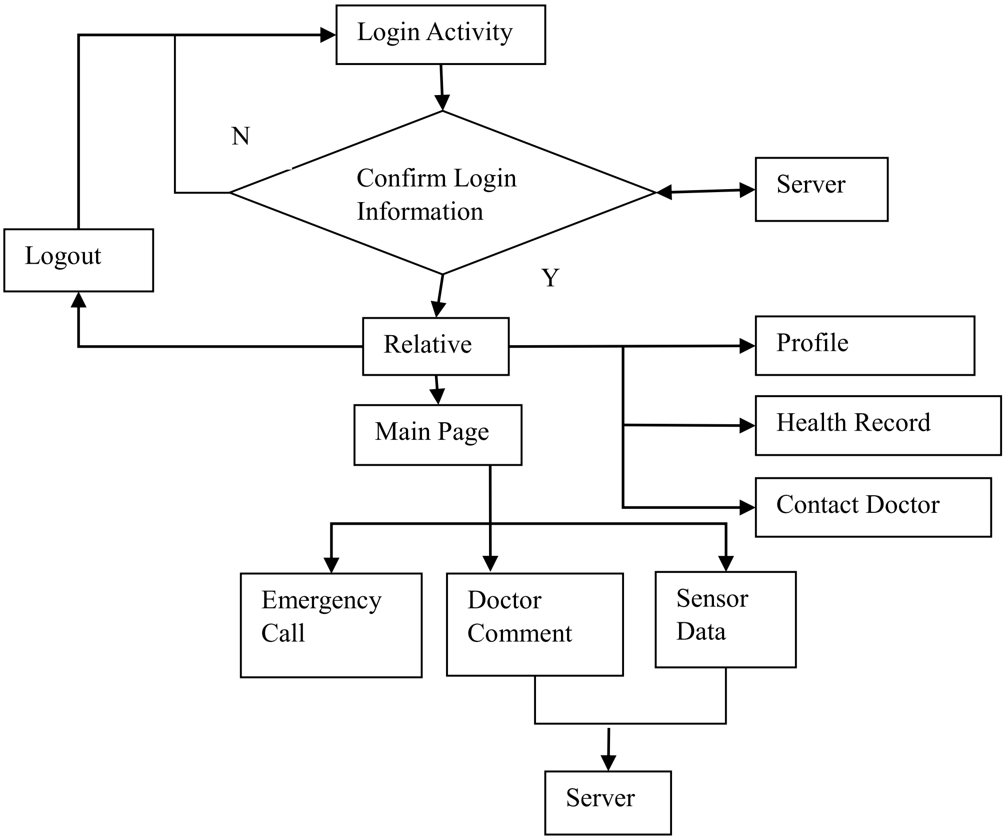

Fig. 4 Flowchart of the relative module

Key features from the main page include initiating an "Emergency Call" in critical situations and viewing "Doctor Comments" for professional medical advice. The system also receives and displays "Sensor Data," crucial for monitoring the well-being of the patient metrics. The sensor data is continuously sent to the server for analysis. This ensures that any anomalies in the patient's condition can be detected promptly, allowing for timely intervention. In summary, the Relative Module enables relatives to stay informed about the patient's health, access essential medical records, communicate with doctors, and take necessary actions in emergencies, providing a robust support system for patient care.

4.1.3. Doctor Module

The Doctor module associated with the remote patient monitoring system is meant to provide functionalities for healthcare professionals or physicians who monitor patients remotely.

Figure 5 depicts the Doctor Module in a healthcare monitoring system. It begins with the "Login Activity," where a doctor tries to log in. The doctor is asked to re-enter the credentials if the login information is invalid. After the server verifies, the access will be granted to the doctor, allowing them inside. After logging in, the doctor sees a "Health Record" that shows the important health data like "Fall Detection", "Blood Pressure", and "Heart Rate". This information is constantly monitored, and the system looks for discrepancies. The doctor can move on to routine monitoring if no anomalies are found. The system runs if anything irregular is detected, and then it can highlight the treatment protocol indicated.

In addition to this, under the main interface, doctors can receive the patients and relatives' "Emergency Calls," i.e. Be able to attend urgent healthcare needs immediately. The doctor can log out of the system whenever the doctor wants as well. The Doctor Module, hence, serves as a big field tool for the Doctors to get notified in advance of any human health indicators and take immediate action towards the emergencies, which provides benefit both patients since timely medical care can be taken.

4.2. Heart Rate Monitoring

As presented in the proposed system illustrated in Figure 2, the heart rate sensor is meant for remote patient monitoring in real-time. The sensor data is periodically kept in cloud storage. This data is subjected to continuous monitoring, and doctors and patients' relatives are notified of any abnormalities. Figure 6 illustrates the heart rate monitoring algorithm.

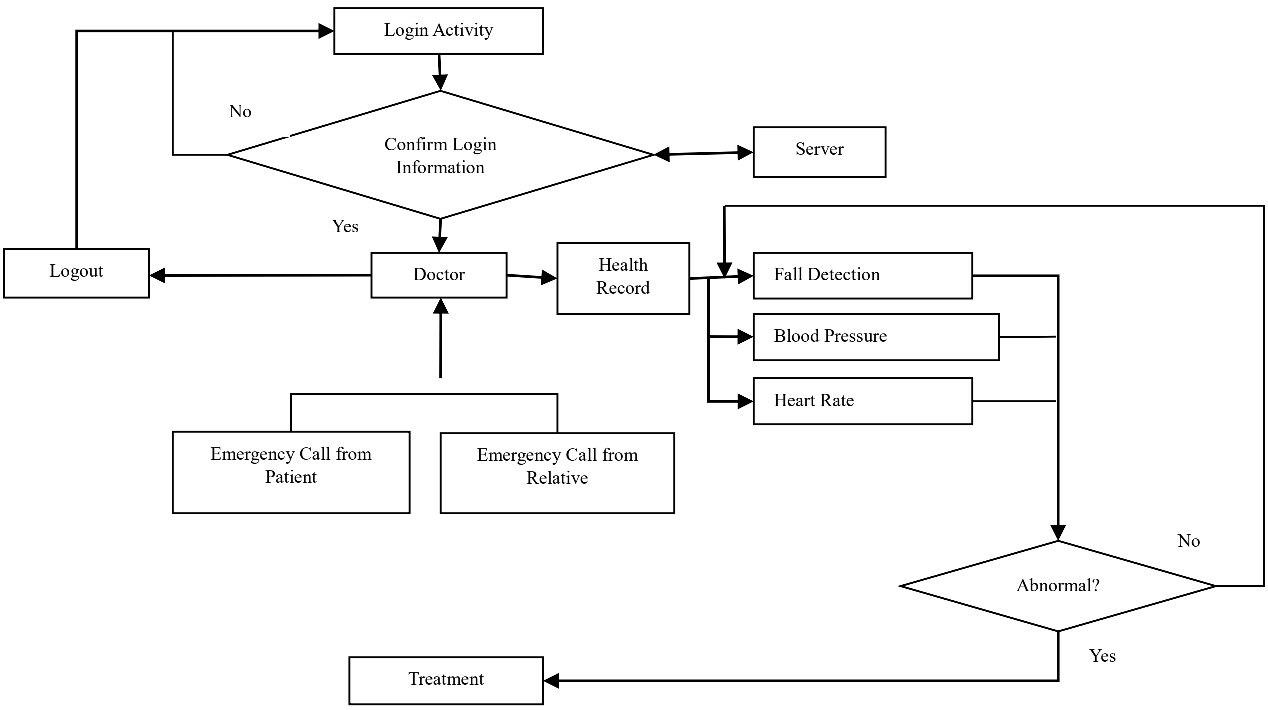

Fig. 5 Flowchart of the doctor module

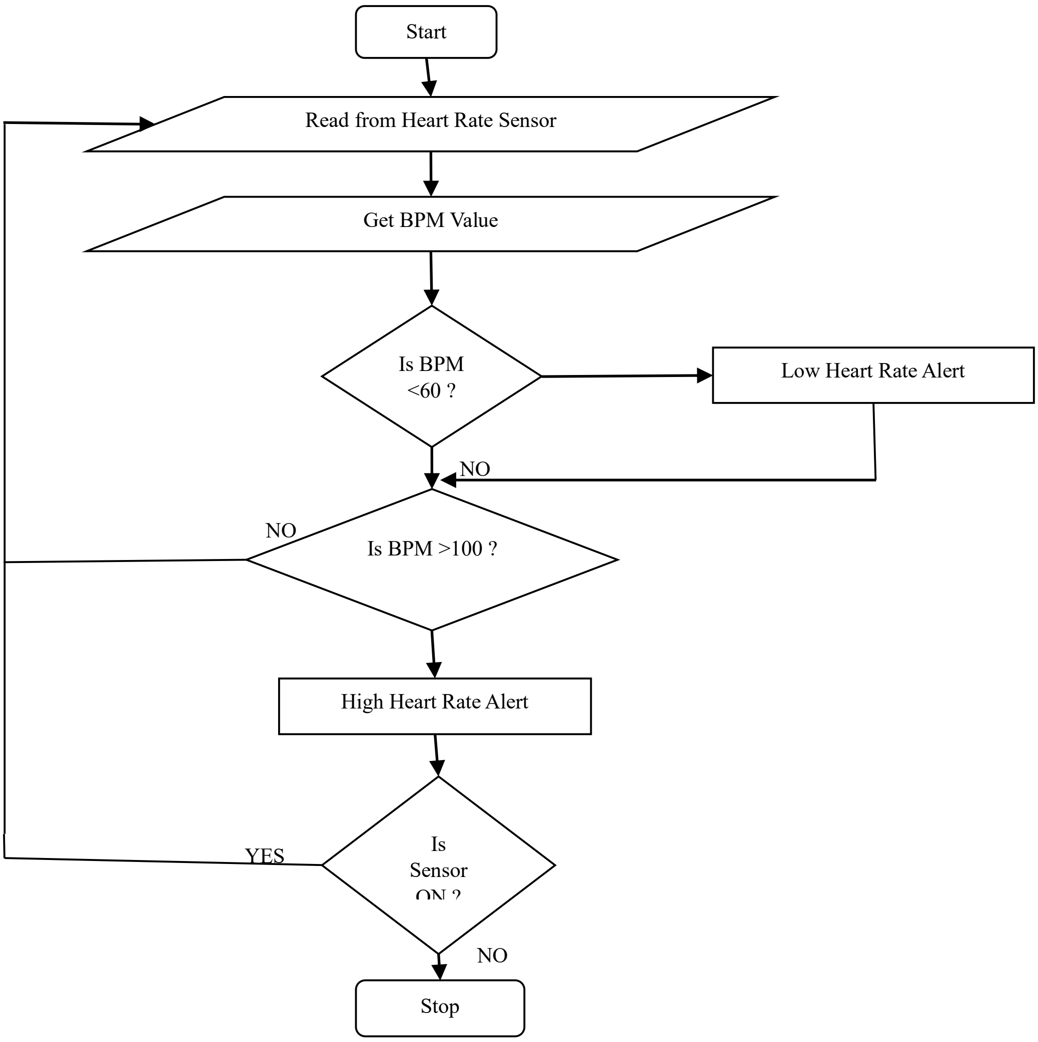

Fig. 6 Illustrates the heart rate monitoring algorithm

The sensed data through the heart rate sensor is monitored and notified. Beats Per Minute (BPM) is the measure considered. The temporal data is used to compute and analyze BPM.

If the BPM value is less than 60, it sends a low heart rate alert along with the BPM value. If the BPM exceeds 100, it causes a high heart rate alert.

4.3. Blood Pressure Monitoring

The data collected through the BP sensor is used to monitor the patient's blood pressure continuously. The data captured and stored in the cloud is used for analytics. Figure 3 shows the proposed algorithm for blood pressure monitoring. It exploits the two kinds of readings required by blood pressure as standardized by the World Health Organization (WHO).

Algorithm: Blood Pressure Monitoring

1. Start
2. Take blood pressure sensor input
3. IF ((systolic >=90 & systolic <=120) & (diastolic>=60 & diastolic<=80)) Then
4. Msg←Normal
5. ELSE IF ((systolic >=121 & systolic <=129) & (diastolic>=60 & diastolic<=80)) Then
6. Msg←Elevated
7. ELSE IF ((systolic >=130 & systolic <=139) & (diastolic>=81 & diastolic<=89)) Then
8. Msg←Stage 1 Hypertension
9. ELSE IF systolic >=140 & diastolic>=90 Then
10. Msg←Stage 2 Hypertension
11. ELSE IF systolic >180 &/OR diastolic <120 Then
12. Msg←Hypertensive crisis
13. END IF
14. Alert with Msg along with readings
15. IF sensor is ON Then
16. Repeat from Step 2
17. Stop

Algorithm 1: Illustrates the proposed algorithm pseudocode for blood pressure monitoring

Algorithm 1 considers both systolic and diastolic readings to diagnose hypertension, which may lead to a heart attack and brain stroke if not identified and treated early.

The algorithm has provisions to know the condition of BP in terms of stages 1 and 2 hypertension, hypertensive crisis, high, normal, and hypertensive.

4.4. Fall Detection

Two devices, an accelerometer and a gyroscope, are used to obtain values that help in the detection of falls by the patient being monitored. The accelerometer senses values of three axes, namely X, Y, and Z. The linear accelerate values along with "aX," "aY," and "aZ" stand for those axes. The values generated by the Gyroscope have values known as roll (gX), pitch (gY), and yaw (gZ). Equation 1 is used to compute accelerometer sensor readings to generate a vector.

$$AT_t = \sqrt{aX_t^2 + aY_t^2 + aZ_t^2} \tag{1}$$

Similarly, Equation 2 is used to find the max and min values of the vectors.

$$MAX[AT_t..AT_{t-n}]\ danMIN[AT_t..AT_{tn}] \tag{2}$$

Afterwards, Equation 3 is used to find the angle of acceleration, where g is the constant of gravity, which is 9.8 m/s^2.

$$angle_{(x,y,z)} = \text{arccos}\frac{acc(x,y,z)}{g} x180 \tag{3}$$

As presented in Figure 7, the fall detection process is split into four phases. The max and min values of the vectors are computed as a starting step. The angle value is computed in the second step to determine the patient's falling probability.

In the third step, a threshold value is compared to determine the sudden acceleration of the patient. Then, in the last step, the direction of the patient's fall is determined.

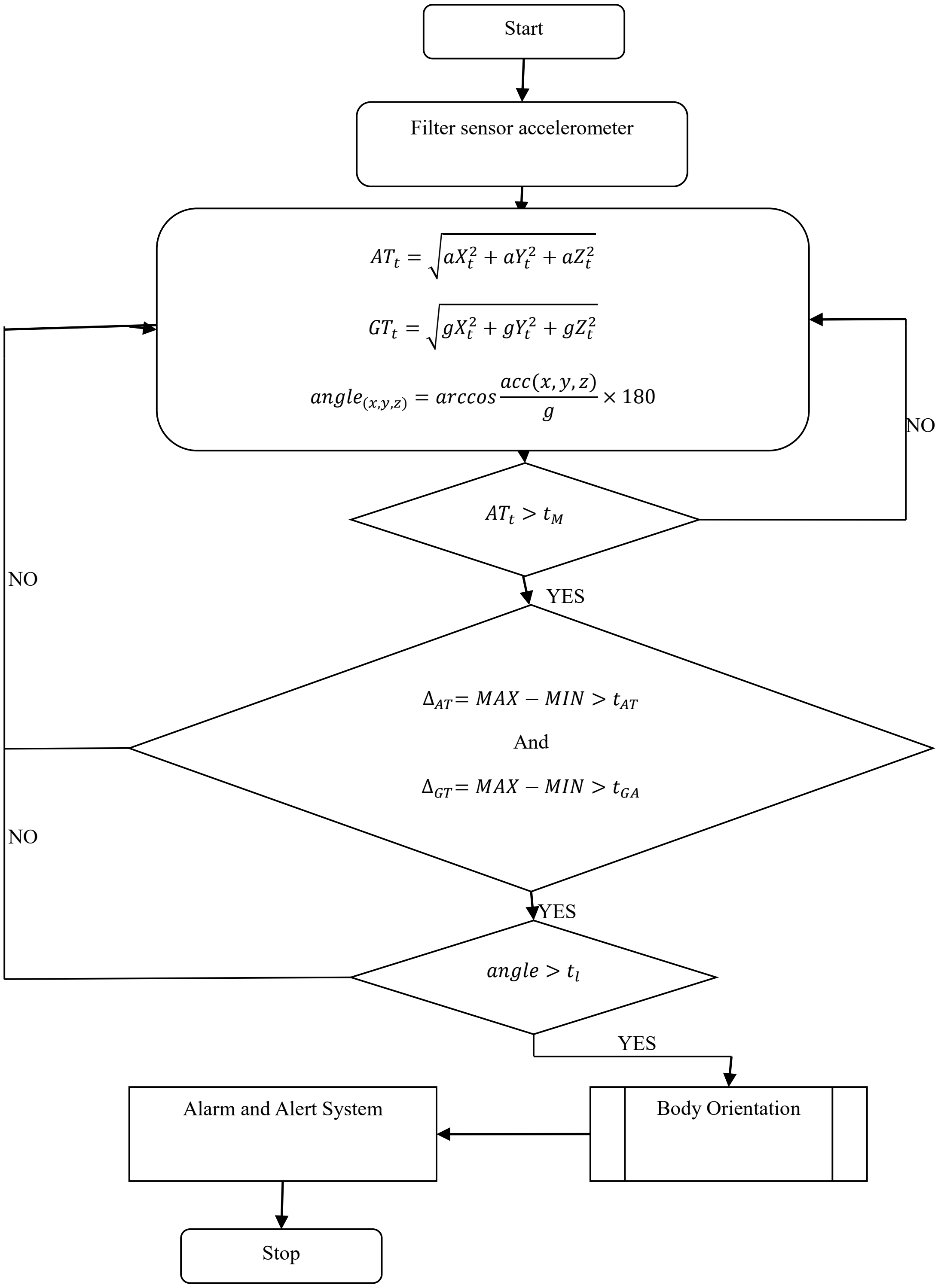

Fig. 7 Illustrates the fall detection algorithm proposed

4.5. Performance Evaluation

The performance of the proposed system and contemporary techniques regarding heart disease prediction is evaluated using metrics derived from the confusion matrix shown in Figure 8. Training data collected from [41] is used to train models.

The evaluation has four cases based on the prediction value and ground truth. True positive indicates a positive (heart abnormality) sample detected by the model as positive. True negatives suggest that a negative (no heart abnormality) sample detected by the model is unfavorable. A false positive means a negative (no heart abnormality) sample is detected by the model as positive. A false negative indicates a positive (heart abnormality) sample detected by the model as unfavorable. Based on these cases, different performance metrics are available, as shown in Equations 4 through 9.

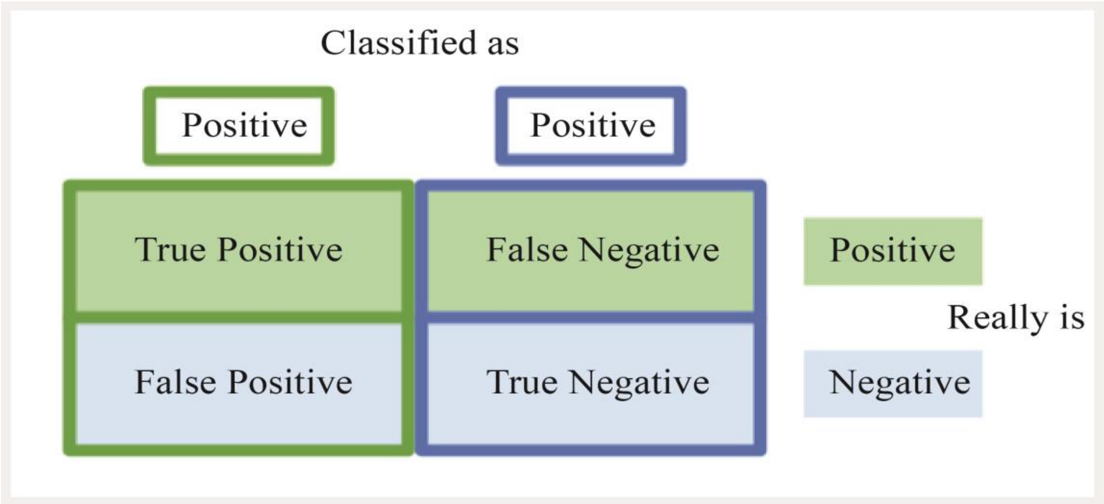

Fig. 8 Confusion matrix

$$\text{Specificity}=\frac{TN}{TN+FP} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (6)$$

$$\text{F1-score} = 2 * \frac{(precision * recall)}{(precisione+recall)} \quad (7)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

$$\text{AUC} = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \quad (9)$$

These metrics give rise to a number from 0 to 1. A higher value in heart disease prediction indicates superior performance.

5. Results and Discussion

A smartphone with the Android operating system was used for the empirical study. A patient is involved in the evaluation of the system. The height of the patient is 170 cm. Other values considered for empirical study include $t_M = 9$, $t_l = 60$, $t_{GT} = 3$ and $t_{AT} = 4.2$.

For fall detection, data captured from the accelerometer and gyroscope were used. These sensors were embedded in Android mobile devices.

Heart rate and blood pressure were captured with a smartwatch with an Android OS. That system could detect all kinds of falls, such as falls to the left, right, forward, and backward.

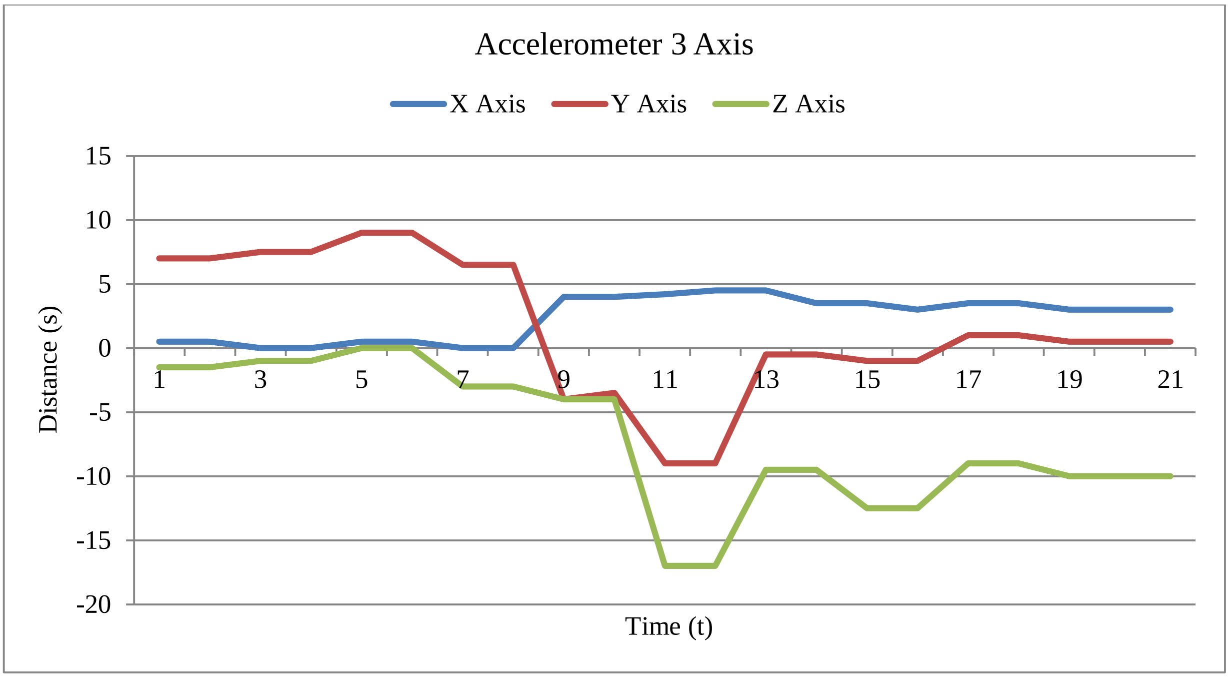

Fig. 9 Raw data of the accelerometer

As presented in Figure 9, accelerometer data about three axes over time versus distance are provided.

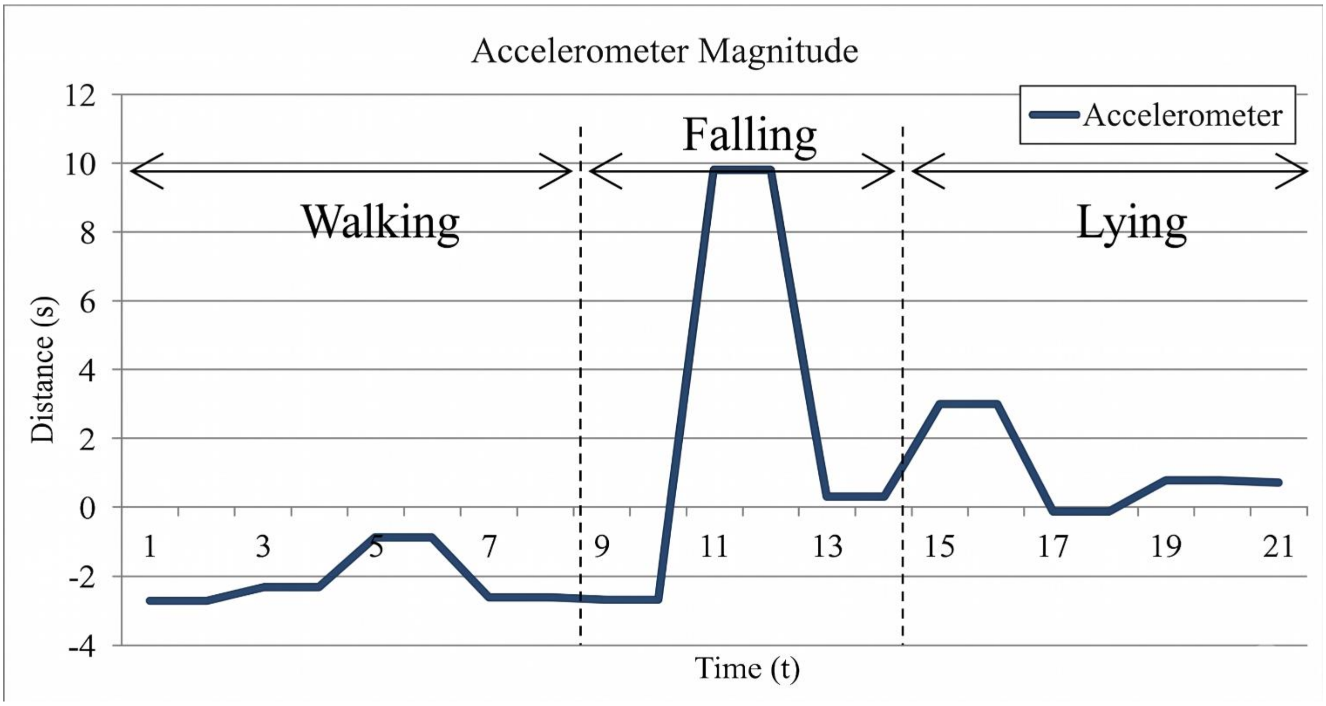

Fig. 10 Magnitude data of the accelerator

As presented in Figure 10, accelerometer magnitude data over time versus distance are provided to determine falling.

Figure 11 presents raw data from the gyroscope for three axes and time versus radians.

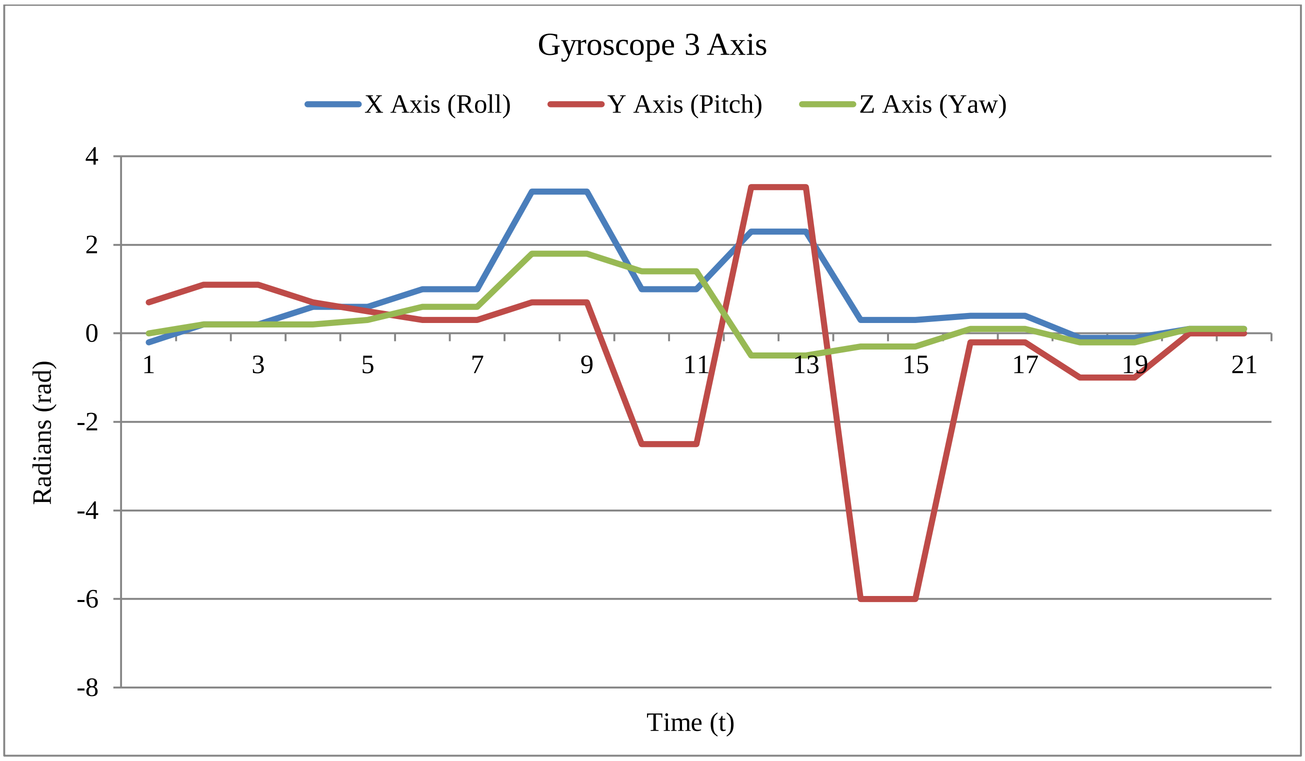

Fig. 11 Raw data of gyroscope

As presented in Figure 12, the magnitude data of the gyroscope over time versus radians are provided to determine falling. Detection of falling by the system triggers automatic notification of the same to the doctor and the patient's relative. The system detected falls and notified the patient's relatives and doctors with the highest accuracy, 96.67%. The system detected abnormalities in terms of temperature and heart rate. The proposed system is trained with the dataset, and the sensor data collected is used to identify heart problems. This suggested model, known as the Hybrid Bio-Sensor Model (HBM), outperformed the models' current condition regarding ACC.

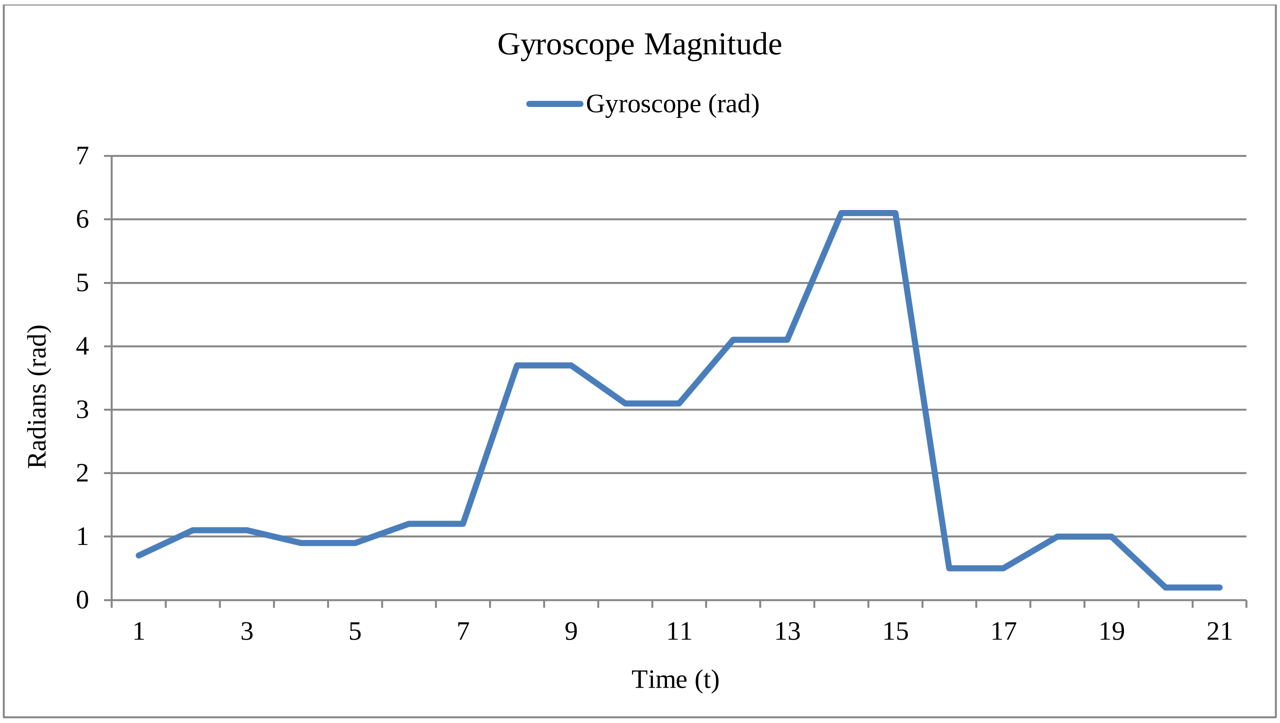

Fig. 12 Magnitude data of the gyroscope

Table 2. Performance in heart disease prediction

Prediction Model	AUC (%)
Enhanced DNN [24]	98.25
AI-enabled IoT-CPS [62]	81.5
RPMM (CNN + LSTM Ensemble) [67]	98.2
EE-HDMM[68]	97.8
HBM (Proposed)	**99**

Table 2 presents the AUC-based performance comparison of the proposed HBM model against four existing heart disease prediction models from the literature. The Enhanced DNN [24] achieved an AUC of 98.25%, while the AI-enabled IoT-CPS [62] recorded 81.5%. The RPMM model using a CNN+LSTM Ensemble [67] attained 98.2%, and the EE-HDMM [68] achieved 97.8%. The proposed HBM outperformed all compared models with the highest AUC of 99%, confirming its superior discriminative capability in heart disease classification.

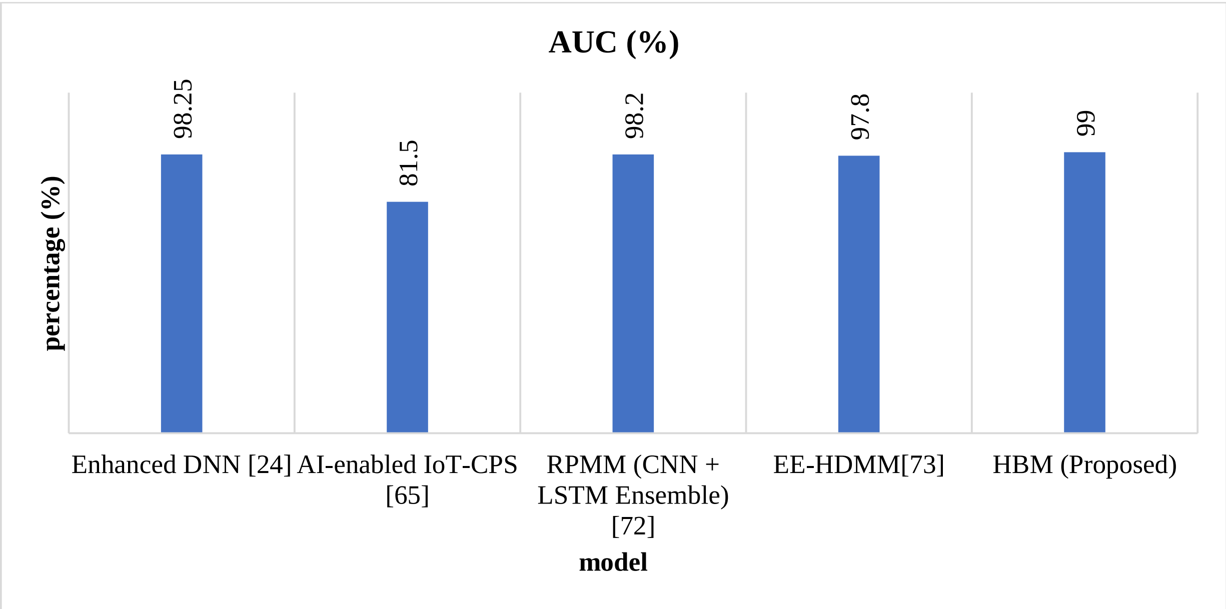

Fig. 13 Shows heart disease prediction performance in terms of AUC

The AUC performance comparison of all the models tested is shown in a visual representation in Figure 13. The bar chart clearly shows that the proposed HBM is able to gain the highest AUC among the five models as compared with the deep learning ensemble models and IoT-CPS-based models. This is further evidence that the hybridized bio-sensor approach is effective in increasing the reliability of prediction in real-world remote monitoring.

Table 3. Performance comparison among heart disease prediction models

Prediction Model	Ref.	Precision (%)	Specificity (%)	Sensitivity / Recall (%)	F1-Score (%)	Accuracy (%)	Error (%)
HBM (Proposed)	**Ours**	**96.54**	**97.88**	**97.89**	**98.79**	**99.45**	**0.55**
Deep Learning IoT (CNN + Attention) for ECG Arrhythmia	[55]	98	-	98	98	98.2	1.8
CNN-based IoT Smart Monitoring (Acute Heart Failure)	[66]	93.98	-	95.65	94.81	94.62	5.38
AI-enabled IoT-CPS	[62]	-	-	86.5	-	81.5	18.5
MDCA Fusion + SVM	[41]	-	95	98	-	96.33	3.0
RPMM (CNN + LSTM Ensemble)	[67]	96.8	-	96.7	96.7	97.33	2.77
EE-HDMM	[68]	-	-	94	-	97	3
Proposed Edge–Fog ECG Framework (Random Forest)	[69]	86.34	-	60.54	71.84	91.96	8.04
Cloud-Based Smart Healthcare Monitoring Framework (RF + LSTM)	[70]	-	97.2	95.4	-	96.8	3.2

Table 3 shows the multi-metric performance comparison of the proposed HBM model with a wide range of state-of-the-art heart disease prediction models, which include different types of architectures like deep learning, fusion-based classifiers, edge-fog systems, and cloud-based monitoring. The Deep Learning IoT model based on CNN with Attention for ECG Arrhythmia [55] recorded the highest precision and sensitivity (98%) and an accuracy of 98.2% among the compared models. In the case of Acute Heart Failure, the IoT Smart Monitoring system based on CNN achieved a precision of 93.98% and accuracy of 94.62% [66]. In the case of the MDCA Fusion+SVM approach [41], the specificity and the accuracy were 95% and 96.33%, respectively, and for the RPMM CNN+LSTM Ensemble [67], the precision and accuracy values were 96.8% and 97.33%, respectively. The EE-HDMM [68] model had a sensitivity of 94% and an accuracy of 97%, whereas Edge-Fog ECG Random Forest [69] had an accuracy of 91.96%, and Cloud-Based Smart Healthcare RF+LSTM [70] had an accuracy of 96.8%. It is observed that the proposed HBM is always superior to all the compared approaches as it gives the highest precision 96.54%, specificity 97.88%, sensitivity 97.89%, F1 score 98.79% and accuracy 99.45% with a minimum error rate 0.55%. The results demonstrate the superior and comprehensive performance of the integrated multi-sensor and machine-learning-based approach of VitalCare-IoT in all the standard evaluation metrics.

Most of the evaluation metrics showed that the proposed HBM always performed better than the compared methods. In particular, the improvement in accuracy and F1-score demonstrates the effectiveness of combining multi-sensor physiological information with machine learning-driven analytics.

The outcomes indicated that the suggested framework can decrease the forecast error without making a huge compromise on sensitivity and specificity for use in genuine remote patient monitoring applications.

5.1. Discussion of Superior Performance

The proposed Hybrid Bio-Sensor Model (HBM) outperformed the current state-of-the-art models in terms of accuracy, precision, sensitivity, F1-score and AUC. Several important characteristics of the proposed framework can be used to explain the improved performance.

First, the proposed system integrates the various physiological signals from wearable sensors such as heart rate, blood pressure, temperature, and fall detection, etc. The use of more than one health parameter will give a more complete picture of the patient's health status, rather than the use of a single physiological parameter. This multi-sensor approach enhances the system's ability to more accurately detect abnormal health situations.

Secondly, the envisioned framework integrates continuous data acquisition from IoT devices and cloud-based data analysis, which allows actual patient data to be collected in real-time. By continuously monitoring, information loss is reduced, and the physiological trends obtained are more up-to-date, which can assist in more reliable health assessment and early abnormality detection.

Third is the use of machine learning-based analysis for discovering hidden relationships between physiological data. Conventional threshold-based monitoring methods cannot capture complex patterns associated with possible health abnormalities, which can lead to better classification performance using the learning-based component.

Add to this the fact that wearable sensing devices, edge communications, cloud, and intelligent analytics are all connected under one roof, which further reduces the delay in the data being processed, and the importance of timely healthcare intervention. Real-time alerts to doctors and caregivers further improve the usefulness of the proposed monitoring system.

Table 3 shows that the proposed HBM obtained an accuracy of 99.45%, F1-score of 98.79%, sensitivity of 97.89%, and precision of 96.54%, which is superior compared to some of the existing approaches reported in the literature. These enhancements suggest that the proposed framework has the potential to offer more accurate health monitoring, disease prediction, and ensure continuous patient observation and quick emergency response.

6. Conclusion and Future Work

We have developed a simple yet effective system for monitoring remote patients. This system serves a dual purpose: collecting patient data and using data analytics tools to detect potential diseases. Cloud-based IoT middleware stores the data, which is then analyzed using machine learning algorithms to diagnose diseases potentially. Several algorithms have been proposed for monitoring patient vitals and notifying the patient, caregivers, or healthcare professionals. The system features user-friendly mobile and web interfaces for patients, doctors, relatives or caregivers. The proposed system uses machine learning for disease prediction. The proposed system has been compared with many state-of-the-art machine learning models, and it was found that the proposed approach exhibits the highest accuracy at 99.45% with a minimal error rate of 0.55, outperforming existing methods. It can also be integrated with existing healthcare applications to attain an affordable remote patient monitoring system. It intends to use the sensors available in the healthcare industry to expand the capabilities of the remote patient monitoring system in the future so that it can monitor more potential ailments.

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