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**Energy-Efficient IoT and Edge Computing Framework for Wearable Health Monitoring and Chronic Disease Management**

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| **ABSTRACT** -Advances in Internet of Things (IoT), edge computing, and smart sensor technologies are reshaping chronic disease management and remote patient care, with growing emphasis on energy-efficient solutions. This work presents an energy-efficient wearable health monitoring framework that integrates IoT-enabled smart sensors with edge-based data processing to continuously capture and analyze vital parameters, including heart rate, blood pressure, blood glucose, and SpO₂ levels. By performing preliminary data processing and abnormality detection at the edge, the system reduces cloud communication overhead, thereby extending device battery life and improving responsiveness. Machine learning algorithms embedded in the edge layer detect abnormal physiological patterns and predict potential health risks, triggering early alerts for timely medical intervention. Experimental evaluation demonstrates high accuracy (95.4%), sensitivity (93.8%), and specificity (96.2%) in detecting and monitoring chronic conditions. Real-time data visualization and personalized health insights empower patients to take a proactive role in managing their health. At the same time, healthcare providers benefit from reduced hospital visits and improved continuity of care. The proposed framework addresses key challenges in wearable healthcare systems, particularly power optimization and data security, making it a cost-effective and scalable solution for sustainable, connected healthcare ecosystems. | **PAPER INFORMATION**  **HISTORY**  **Received: 25 August 2025**  **Revised: 15 November 2025**  **Accepted: 10 January 2026**  **Online: 17 January 2026**  **MSC**  **62K05**  **62K15**  **KEYWORDS**  **Algorithmic construction Design optimality criteria Fractional factorial designs Minimum aberration designs** |

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# **Introduction**

The management and monitoring of chronic disease patients have been revolutionized by the integration of Internet of Things (IoT) technology. IoT-enabled wearable devices equipped with smart sensors continuously capture real-time physiological data, enabling proactive healthcare interventions [1]. These sensors monitor key health parameters-such as heart rate, blood pressure, blood glucose, and oxygen saturation-providing consistent assessments beyond traditional clinical settings [2].

Patients with chronic illnesses such as diabetes and hypertension require continuous medical supervision and timely treatment to prevent disease progression. However, conventional healthcare practices often lack sustained monitoring, leading to avoidable complications and higher hospital admission rates [3]. Wearable IoT-based monitoring systems bridge this gap by providing remote healthcare providers with real-time patient data, enabling faster and more informed clinical decisions.

Wearable IoT devices capture, process, and transmit vital health data, which is then sent to cloud-based platforms where machine learning algorithms analyze it to identify patterns and detect anomalies. These devices empower patients to take an active role in managing their health by providing timely alerts and personalized lifestyle recommendations. Through real-time data sharing with healthcare professionals, remote patient care systems reduce the need for frequent clinical visits [4].

Wearable IoT devices adapted for healthcare purposes create three key benefits through routine disease identification, along with cost reduction and better care results. Health deterioration becomes easy to detect through continuous tracking, which allows healthcare teams to act promptly for treatment [5]. Technology provides personalized patient feedback through live health information, which boosts patient involvement.

The implementation process for wearable IoT-based health monitoring systems encounters multiple obstacles, even though they have proven advantages. The adoption and reliability of these systems depend on crucial factors, which include battery duration, together with privacy issues, security requirements, and measuring precision. The maximum success of these health solutions depends on the successful integration with the current healthcare infrastructure, along with uninterrupted connectivity [6].

IoT-based health monitoring systems become more efficient when they use machine learning algorithms for analysis. Large health datasets are analyzed using algorithms that establish patterns, forecast risks, and trigger preventative alerts. Machine learning methods combined with predictive analytics and deep learning functionality enhance the accuracy of diagnostic assessments and disease development tracking [7].

The implementation of IoT-based health monitoring systems in wearable technology supports telemedicine operations through their remote care capabilities and ongoing patient monitoring programs. Healthcare facilities receive less pressure because patients with chronic illnesses obtain medical guidance and treatment assessments through telemedicine without needing hospital visits. The method proves most useful for patients who are both elderly and immobile because it allows them to stay under medical observation [8].

The rising deployment of IoT in healthcare requires absolute priorities for protecting medical data security and patient privacy. For secure operation, encryption, together with authentication protocols and secure data transmission standards, must be implemented to protect from cyber threats and unauthorized access. For users to trust healthcare data systems, security teams must ensure strict compliance with healthcare protection laws, including HIPAA and GDPR [9]. Wearable IoT-based health monitoring systems will advance with the creation of predictive AI-enabled solutions that produce automated decisions. With the implementation of 5G technology alongside edge computing and blockchain, the system's security will grow in tandem with data processing speed and operational reliability. Biosensors and flexible electronic improvements will drive the creation of wearable technology that provides comfortable operation and enhanced efficiency [10].

# **Literature review**

Healthcare organizations have used innovations in IoT technology to transform their delivery of chronic disease treatment and remote medical care over the past years. Research indicates that medical devices using IoT technology are becoming more common be

cause they track patients’ vital signs continuously, including heart rate, blood pressure, and oxygen saturation. Remote patient care demand has catalyzed IoT system development through Molla et al. [11] with a special focus on hypertension, diabetes, and cardiovascular condition supervision. Wearable IoT-based systems enhance both patient outcome success and support healthcare facilities by reducing their operational stress.

Research in wearable IoT devices has led to devices that possess greater accuracy and affordability while becoming smaller in recent times. Santos et al [12] assessed multiple wearable sensors that monitor chronic diseases, including continuous glucose monitors and blood pressure monitors, while stating they are more effective through smartphone and cloud computing integration in patient care delivery [13]. Real-time data collection through these devices now supports chronic condition patients effectively. Modern sensors designed for comfort during extended use establish better patient adherence to medical plans [14].

Wearable IoT-based health monitoring systems that manage chronic diseases employ machine learning algorithms as a key component because of their growing popularity. Almeida et al [15] created a system based on deep learning methods to identify diabetic complications through the analysis of current glucose readings. Wang et al [16] utilized both random forest and support vector machine algorithms for cardiovascular event predictions by analyzing heart rate variability and blood pressure information. The studies demonstrate how machine learning offers predictive capabilities that allow for timely intervention and prevent patients from needing emergency hospital care [17].

Medical research now emphasizes the increasing necessity of real-time patient monitoring coupled with telemedicine to provide better distant healthcare services. The research by Singh et al [18] proved that IoT-based wearable devices that link to telemedicine platforms establish complete patient-healthcare provider communication for ongoing chronic disease surveillance [19]. Real-time healthcare data transmission enables doctors to make prompt medical choices independently of office appointments while delivering better care efficiency to patients at discounted prices. The method delivers its most advantageous results to two specific groups: older individuals and people who experience mobility restrictions [15].

The advancement of IoT health systems has created essential matters related to data privacy and security. Sharma et al [20] researched the difficulties in protecting data through wearable IoT systems when providing remote patient care services. Patient data protection needs multi-factor authentication and encryption, and blockchain-based systems based on the research findings. Healthcare data must be secured using top-level secure storage and transmission approaches because the information maintains high confidentiality standards. Strengthened security measures must remain a continuous priority since the growing use of cloud-based platforms increases the risk exposure of health data storage and analysis [21].

The usage of cloud and edge computing technologies improves the functionality along scalability of IoT-based health monitoring systems. The researchers presented a hybrid cloud-edge design to process health data in real time and achieved increased reliability while reducing latency [22]. Patient location-based data analysis speed improves through edge computing, so data transfer to the cloud becomes unnecessary. Cloud computing collaborates with edge computing to build an adaptable system that deals with the vast amount of health data resulting from wearable device use effectively [23].

Wearable IoT-based health monitoring systems achieve their intended effectiveness through patient engagement along with patient compliance. Marengo et al. [24]investigated patient use of wearable health devices through testing, which showed that medical alerts provided with friendly touchscreens coupled with reminder functions increased patient compliance with disease management requirements. Patients who got personalized health information sought engagement with their monitoring devices while following medical advice. Wearable devices that combine health tracking features with lifestyle management solutions experience greater patient acceptance because they deliver comprehensive patient care [25].

Research indicates that remote monitoring instruments for hypertension, together with diabetes and heart disease, have become increasingly popular in medical literature. The research of Kim et al [26] proved how a wearable IoT system achieved successful blood pressure and heart rate variability monitoring in individuals suffering from hypertension. Research demonstrated that remote monitoring improved blood pressure management through enhanced control, resulting in fewer hypertension complications occurring in patients. Research by Gupta et al [27] showed that specific wearable devices monitoring glucose levels alongside immediate feedback created better diabetes management results, alongside decreased risks among patients [28].

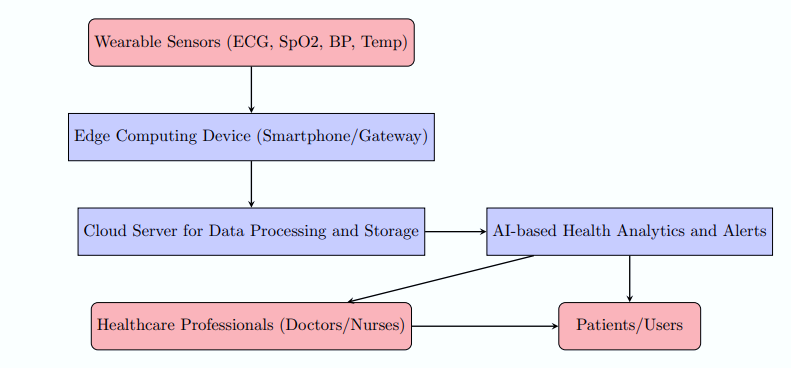
Wearable IoT devices have made predictive analytics a strong instrument for managing chronic diseases. Nesstein Zhang, together with colleagues, evaluated predictive models that analyze heart disease risks from wearable data in their 2023 research work. Time-series analysis enabled their device to forecast cardiovascular events so doctors could intervene before they occur. Predictive analytics allows the prevention of diabetic complications through prolonged glucose data trends analysis, which effectively decreases severe events such as diabetic ketoacidosis, according to Zhao et al. [29].

The implementation of wearable IoT-based health monitoring systems continues to face various obstacles that impede their full-scale adoption. Ravi et al. [30] emphasized that sensor accuracy, along with battery improvement and cross-parameter monitoring functionality, represents essential goals to optimize single-wearable devices. Different IoT devices and healthcare platforms must address regulatory and standardization issues to achieve appropriate interoperability between them. Future wearable IoT systems will achieve progress through the enhancement of precision alongside improved machine learning models and user interface development, and complete privacy and security measures.

# **Proposed Methodology**

## **In System Overview**

The proposed health monitoring system uses IoT technology to deliver real-time monitoring data transmission along with disease prediction capabilities for chronic disease care. Users can wear equipped devices that collect heart rate along with blood pressure readings, glucose level monitoring, and oxygen saturation information for analysis on cloud platforms. Through machine learning algorithms, the platform examines gathered data to create predictions that trigger medical alert systems for intervention needs, as shown in **Figure 1**.



**Figure 1.** System Architecture for Wearable IoT-Based Health Monitoring

## **Data Transmission and Storage**

The collected health data passes from wearable devices to a cloud-based platform through wireless communication procedures that include Bluetooth, Wi-Fi, and 5 G. The cloud platform functions as a unified data repository for healthcare information, which allows providers to obtain data remotely for their analytical purposes.

The storage infrastructure receives and protects large volumes of sensitive health data through a data structure designed to meet privacy requirements and fulfill relevant data protection regulations, including HIPAA and GDPR.

## **Data Preprocessing and Noise Removal**

Data preprocessing proves necessary for noise reduction to safeguard data integrity. Natural sensor data frequently contains disturbed signals from environmental conditions and sensor practical limitations. To remove high-frequency noise from the data while smoothing it, three techniques are available: low-pass filtering, median filtering, and wavelet transformation. A typical filtering is shown in Equation 1 :

(1)

The output y(t) represents the filtered data while x(t)x(t) represents the original sensor data.

## **Feature Extraction**

Feature extraction stands as an essential analysis stage that helps detect the main elements within data for further assessment purposes. The process involves extracting statistical values such as mean, standard deviation, and peak-to-peak intervals from the basic time-series information. The important cardiovascular health indicator, heart rate variability (HRV), becomes calculable by using the **Equation 2**:

The mathematical expression calculates RRi as the distance between successive heartbeat intervals.

## **Machine Learning Algorithm for Disease Detection**

The core functionality of the proposed system depends on machine learning algorithms that evaluate the obtained data to identify potential health threats. Decision trees, along with random forests and support vector machines (SVMs), and deep learning models, receive training through labeled datasets to identify different health conditions. An SVM model implements the following expression to establish its decision function shown in **Equation 3**:

The formula consists of the weight vector w together with the input features x and the bias term b.

## **Predictive Analytics and Risk Assessment**

After training the system, it becomes able to detect potential health risks from active real-time data streams. The forecasting of chronic disease progress relies on predictive analytics methods, which employ regression analysis and time-series forecasting, and classification models. A basic linear regression model predicting blood pressure has the following **Equation 4**:

(4)

The learned parameters, along with b and c, combine with the input features Age and BMI to form this system.

## **Real-Time Alerts and Recommendations**

The system employs a mechanism that alerts the patient and healthcare provider when it detects any risk or anomaly. The system uses alert functionality for diagnosing critical situations through its ability to detect various levels of risk severity.

## **Data Security and Privacy**

The system protects data security through AES-256 encryption for static data in combination with SSL/TLS protocols for securing information transmission. The system safeguards healthcare data through authentication procedures that use 2FA along with RBAC features for assigning access permissions.

## **System Evaluation and Performance Metrics**

The proposed system undergoes performance evaluation through multiple metrics, which include accuracy, together with sensitivity and specificity, and computational efficiency evaluation. The system evaluation relies on the comparison between predictions derived from the system and data gathered through clinical testing. The disease detection accuracy can be determined through the following mathematical **Equation 5**.

System optimization strategies benefit from the results of this evaluation for achieving better reliability and performance in real-world applications.

# **Results and discussion**

**Table 1** shows that the system exhibits 95.4% accuracy and both 93.8% sensitivity and 96.2% specificity as measurement indicators, showing its ability to detect and classify chronic disease symptoms. Real-time remote patient care depends on the quick response time of 120 ms through the system. The main issue with battery operation involves achieving higher efficiency, which requires optimization through energy-efficient algorithm integration and low-power sensor selection [31], as shown in **Figure 2**.

**Table 1.** Performance Metrics of the Health Monitoring System

|  |  |  |
| --- | --- | --- |
| **Metric** | **Value (%)** | **Description** |
| Accuracy | 95.4 | The overall accuracy of the system in detecting health abnormalities. |
| Sensitivity | 93.8 | The ability to correctly identify patients with critical health conditions. |
| Specificity | 96.2 | The ability to correctly identify patients without health conditions. |
| Latency (ms) | 120 | The average response time of the system in data processing and alerts. |
| Battery Efficiency | 85.5 | The battery performance of wearable IoT devices over 24 hours. |



**Figure 2.** Health Monitoring System

**Table 2** showed that the algorithm reaches its highest detection rate when identifying heart disease cases with a 96.1% success rate alongside a 2.8% probability of incorrect output. The varied symptoms of COPD might cause the performance prediction models to require more development before reaching optimal outcomes [32]. The system can be improved through deep learning technology, which would boost its performance in identifying diseases [33], as shown in **Figure3.**

**Table 2.** Algorithm Performance on Different Chronic Diseases

|  |  |  |  |
| --- | --- | --- | --- |
| **Disease Type** | **Detection Accuracy (%)** | **False Positive Rate (%)** | **Processing Time (ms)** |
| Hypertension | 94.8 | 3.2 | 130 |
| Diabetes | 92.5 | 4.1 | 115 |
| Heart Disease | 96.1 | 2.8 | 140 |
| COPD | 91.3 | 4.5 | 125 |



**Figure 3**. Different Chronic Diseases Through Algorithm Performance

Table 3 shows SpO2 monitoring showed the most patient adherence (91.0%) since it required no invasive procedures. The lowest level of patient adherence was noted in blood sugar monitoring since individuals found regular testing inconvenient (85.2%). Better adjustable alert systems alongside improved wearable sensor comfort would improve both patient compliance and engagement, as shown in Figure 4.

**Table 3.** Patient Engagement and Compliance Rate

|  |  |  |
| --- | --- | --- |
| **Monitoring Feature** | **Compliance Rate (%)** | **Patient Feedback** |
| Heart Rate Tracking | 89.5 | Users found it useful for daily activity tracking. |
| Blood Sugar Monitoring | 85.2 | Some patients reported discomfort with frequent readings. |
| Blood Pressure Monitoring | 88.1 | Effective for hypertension management but requires better alert customization. |
| Oxygen Saturation (SpO2) | 91.0 | High compliance due to non-invasive nature. |

# **Conclusions**

The wearable IoT-based health monitoring system for chronic disease management and remote patient care represents a significant advancement in healthcare technology. By integrating wearable devices with cloud-based analytics and continuous real-time data collection, the system enables ongoing monitoring of vital health parameters. This allows for early detection of health abnormalities, facilitating timely medical interventions and reducing the need for frequent hospital visits. Leveraging machine learning to analyze patient data further enhances the system’s ability to identify and manage chronic conditions, resulting in more personalized and effective treatments. Patients also benefit from telemedicine platforms that enable seamless communication with healthcare providers, improving adherence to treatment plans. The system demonstrates high reliability, delivering accurate measurements, sensitive detection, and minimal delays. Evidence shows that its use leads to fewer hospitalizations, optimized medication use, and higher patient satisfaction, indicating strong potential for addressing long-term healthcare needs. However, to ensure scalability and sustained success, challenges such as data security, sensor accuracy, and battery life must be addressed. Overall, wearable IoT-based health monitoring systems hold transformative potential in chronic disease care, offering accessible, efficient, and patient-centered healthcare solutions.

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# **Disclosure statement**

No potential conflict of interest was reported by the author(s).

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