Low-Cost, Low-Power IOT System for Real-Time Vital Signs Monitoring and Early Detection of Health Abnormalities in the Elderly, With Enhanced Privacy.

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Abstract

With the rapid advancement of Internet of things (IoT) technologies, smart and connected healthcare systems have emerge as a promising solution for continuous and remote patient monitoring. This is particularly critical for elderly populations and patients with chronic conditions, where frequent hospital visits are costly and hectic. In this paper, we propose an experimentally validated Low-cost, low-power IoT-based remote health monitoring system designed for continuous acquisition of vital physiological parameters, including electrocardiogram (ECG), heart rate, blood Oxygen saturation (SpO_2), and body temperature. The proposed architecture integrates wearable wireless sensors, energy-efficient clustering mechanisms, secure data transmission, and cloud-based storage and analytics. To address the limitations of existing systems, our methodology combines a hardware prototype with network-level simulations conducted using NS-3 and MATLAB to evaluate latency, energy consumption, packet delivery ratio, and scalability. Security and privacy of patient data are guaranteed through a lightweight encryption framework suitable for resource-constrained IoT devices, with comparative analysis against computationally expensive homomorphic encryption schemes. Experimental results demonstrates that the proposed systems achieve reduced latency, improved energy efficiency and reliable data confidentiality. The findings confirm the suitability of the architecture for real-time remote healthcare monitoring in smart city and rural healthcare environments.

Keywords: **Internet of Things, Remote Healthcare Monitoring, Wireless Sensor Networks, security, Energy Efficiency, Wearable sensors.**

I. Introduction

The rapid evolution of the Internet of Things (IoT) has significantly transformed healthcare delivery models by enabling continuous, real-time, and remote monitoring of patients. This paradigm shift is particularly critical in the context of aging populations and the increasing prevalence of chronic diseases, which place substantial pressure on healthcare infrastructures worldwide. Elderly patients often require frequent physiological monitoring, yet repeated hospital visits are costly, inconvenient, and sometimes impractical, especially in rural or resource-constrained environments.

IoT-based remote healthcare monitoring systems offer a promising solution by integrating wearable sensors, wireless communication technologies, and cloud-based analytics to enable continuous observation of vital physiological parameters such as electrocardiogram (ECG), heart rate (HR), blood oxygen saturation (SpO_2), and body temperature. These systems have the potential to improve quality of care, facilitate early detection of health abnormalities, reduce hospital overcrowding, and lower overall healthcare costs.

Despite significant research efforts in IoT-enabled healthcare, several critical challenges remain unresolved. First, many existing solutions emphasize functional prototypes without rigorous quantitative evaluation of network performance metrics such as energy

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consumption, latency, packet delivery ratio, and scalability. This limitation is particularly problematic for wearable and body area network (BAN) applications, where devices are severely constrained in terms of power, computation, and memory. Second, security and privacy mechanisms proposed in their literature often rely on computationally intensive cryptographic techniques, such as homomorphic encryption, which are impractical for low-power IoT devices. Third, validation methodologies across studies are inconsistent, making objective comparison and benchmarking difficult. Finally, cost and deployment feasibility are rarely addressed, despite being essential factors for large-scale adoption in developing regions.

To address these gaps, this paper proposes a low-cost, low-power IoT-based remote healthcare monitoring system specifically designed for elderly care. The proposed solution integrates wearable physiological sensors, an energy-efficient wireless sensor network architecture, a secure data transmission framework, and cloud-based storage and analytics. Unlike many prior works, this study adopts a comprehensive evaluation approach combining hardware prototyping with network-level simulations to quantitatively assess system performance.

The key hypothesis underlying this work is that the adoption of an energy-aware clustering protocol, combined with lightweight cryptographic mechanisms, can significantly improve network lifetime and real-time performance without compromising data confidentiality. To validate this hypothesis, the proposed system is evaluated using both NS-3 and MATLAB simulations, alongside experimental measurements obtained from a functional prototype.

The main contributions of this work are threefold:

1. The design of a scalable and energy-efficient IoT healthcare monitoring architecture suitable for continuous vital-sign monitoring.

2. A quantitative performance evaluation of the proposed system in terms of energy consumption, latency, packet delivery ratio, and security overhead.

3. A comparative analysis highlighting how the proposed approach addresses key limitations observed in existing IoT-based healthcare monitoring systems.

The remainder of this paper is organized as follows: Section II reviews related work and identifies existing gaps; Section III presents the proposed system architecture and methodology; Section IV discusses experimental results; and Section V concludes the paper with recommendations for future research.

Fig. 1. General Archiitecture of the IoT-Based Remote Healthcare Monitoring System

II. Background and Related Works

The term Internet of Things (IoT) was invented by Kevin Ashton in 1999 and refers to data on the Internet that are connected to evolving global service architecture [1,2]. IoT is the product of advanced research on information and communications technology. When properly used, it can potentially enhance urban residents' quality of life. With the exponential growth in the world's population as well as the prevalence of chronic diseases, there is a rising demand for designing cost-effective healthcare systems that can efficiently manage and provide a wide range of medical services while reducing overall expenses [3,4,5,6]. The IoT healthcare-monitoring system aims to accurately track people and connect various services and things in the world through the Internet for the purpose of collecting, sharing, monitoring, storing, and analysing the data generated by these things [7]. However, although IoT is a new paradigm it creates the possibility where all physically connected objects in intelligent applications, such as smart city, smart home, and smart healthcare, are addressed and controlled remotely. Identifying disorders and monitoring patients are of ought most importance in the healthcare sector which can significantly be improved with the use of wireless Sensor Networks and the readily available data obtained from these connected devices. IoT systems will give the physicians the possibility to keep an eye on their patients remotely and schedule their appointments more efficiently. Patients also can improve their home healthcare to reduce their need for doctor visits and the likelihood of receiving unnecessary or inappropriate medical treatments in hospitals or clinics. For this reason, the quality of medical care and the overall safety of patients may improve, while the overall cost of care may decrease. The IoT holds significant potential in healthcare [7,11]. This work is aimed at designing an IoT-based remote health monitoring system, implement a prototype, evaluate its performance using NS-3/ MATLAB and compare the system with existing approaches.

According to [14], an IoT-connected healthcare system typically consists of three main components: (i) wearable sensor devices responsible for monitoring patients' vital signs and collecting physiological data; (ii) a gateway that enables secure connectivity between the wearable devices and the Internet; and (iii) a cloud-based server that provides data storage, processing, and advanced analytical capabilities. The gateway and the cloud server are the basic IoT infrastructure, while wearable sensors are indispensable components in an IoT-connected healthcare platform for remote health monitoring applications. An elaboration on wearable devices can be seen in the section below.

II.1. Wearable devices

The vital signs of the human body can reflect people's basic health status [16]. There have been many wearable sensors proposed by researchers for measurements of health data. In [15], a comprehensive review of wearable sensors for remote healthcare applications is presented, such as cardiovascular monitoring, body activity and temperature, Galvanic Skin Response (GSR), blood oxygen saturation (SpO2), etc. For example, Asada et al. propose a wearable ring-shaped sensor for HR measurements based on the photoplethysmography (PPG), which analyzes technical and clinical issues during long-term continuous HR monitoring [8]. Wearable motion sensors are employed for behavioural anomaly detection of the elderly in a smart assisted living home [9]. The proposed probabilistic framework based on wearable sensors can recognize anomalies of daily activities to improve the living status of elderly people. In [17], a small magnetometer-based sensor is designed to measure RR and the apnoea time during sleep. The sensor data are transmitted to a smartphone gateway and compared with a commercial airflow sensor. As for BP measurements, the traditional sphygmomanometer with a cuff is not suitable for wearable BP monitoring due to its cumbersome size and limited measurement intervals. In recent years, several promising methods for wearable BP monitoring are proposed based on the pulse transit time (PTT) and pulse arrival time (PAT). Most of the wearable BP estimation works measures ECG (on the body) and PPG (on the finger or earlobe) using separate devices [18], [19], [20], which is not user-friendly for long-term monitoring scenarios. Thomas et al. propose a wristwatch design for BP measurements in [14]. With the watch worn on the left wrist, a user just needs to touch the electrode with his right hand for electrocardiogram (ECG) and PPG signal acquisition. The corresponding BP values can be calculated using an appropriate regression model for the PAT derived from the measured ECG and PPG signals. Although the bio-watch simplifies the hardware design, it is not able to measure continuous long-term BP values as both hands are required for measurements. In the proposed work, both ECG and PPG sensors are integrated on a chest-based sensor patch, which can be used for long-term continuous BP estimation. Different from traditional wrist- and finger-based wearable devices, the proposed chest-based sensor patch can be hidden under clothes without disturbance in daily life activities.

II.2 Cross-examination of existing tools

The wearable device developed by Wu et al. [14] monitors various physiological parameters, including body temperature (BT), electrocardiograph (ECG), and heart rate (HR). Using Pulse Arrival Time (PAT) to measure ECG and PPG, it is possible to estimate blood pressure (BP). The interaction between humans and remote monitoring programs is straightforward because all the components are designed within a rigid framework. In addition, the power consumption of the devices is low, and they can communicate wirelessly to make tailored measurements of a specific physiological signal. The physiological measurements can be wirelessly transmitted to a gateway using a BLE module. The data are encrypted at the sensor patch and gateways to maintain privacy, ensuring transmission security. The wearable sensor system is connected to the cloud using a smartphone and a Raspberry Pi module as a gateway; the data can be retrieved and analyzed from the cloud. Despite its low energy consumption, BLE technology is unsuitable for wireless communication over long distances and high data rates.

Gupta outlines a healthcare-monitoring system using the IoT for obese patients [21]. The prototype is a fully functional device that measures body characteristics such as HR, SpO2, BP, and BT. This device is ideal for regular monitoring of body conditions. The system uses an Arduino board to store medical data for multiple patients simultaneously, and then, sends the information to healthcare providers via a Wi-Fi module for remote monitoring. Clinicians can use the recorded data to examine patients' health patterns over time in order to detect any changes that may indicate an underlying, undetected health problem. Consequently, long-distance communication can be a challenge with this system.

Islam et al. [17] developed an intelligent monitoring system for use in a hospital. It not only collects data on patients' BT, HR, and other vital signs but also monitors environmental factors in the hospital room, such as CO, CO_2, and humidity. The success rate of modern healthcare systems is ~95% agreement between monitored and actual data in all cases. Medical staff can view the data in real-time, either on-site or remotely. Hypothetically, the technology would be helpful during medical crises and epidemics, as medical personnel would have almost instant access to raw data. The prototype created is incredibly easy to design and use. Such devices could be helpful in managing infectious-disease outbreaks, such as COVID-19. Potentially, this system could save more lives by improving the efficiency of the existing healthcare system. However, at this stage, the system still lacks some epidemic-related sensors that need to be evaluated once implemented.

Hamim et al. [19] present an IoT-based healthcare-monitoring system for patients and older adults based on an Android application. The sensors in this prototype collect BT, HR, and Galvanic Skin Response (GSR) data that are fed into a single system, the Arduino Uno platform. Raspberry Pi transfers the data to cloud storage. Android Studio was used to develop the Android app, in which health parameters collected from patients can be visualized. Doctors can use the application to prescribe necessary prescriptions and track the patient's health over time.

To assist physicians, diagnose and monitor their patients' health status, Alamsyah and Ikhlayel developed a monitoring system based on an IoT that can detect vital signs [22]. The system uses sensors to collect vital signs such as HR, BP, and BT. The data from the sensors are gathered and processed by Raspberry Pi before being uploaded to the cloud. The data can be retrieved remotely through a mobile app that allows easy access for medical staff. The results of retrieving vital-sign data show that the instrument was developed and the system was tested and evaluated reasonably.

Another IoT-based vital-sign-monitoring system is described in [24] by Sahu et al. Similar to other systems, vital signs are monitored in real-time, and the data that are collected are locally stored, and then, transferred to the cloud, from where they can be evaluated. The system detects abnormalities, sends alerts, and calculates early-warning scores. By storing the data on a personal server, the Android app reduces the burden placed on central medical servers and minimizes the server's maintenance costs. The system is compact, portable, and easy for patients to use. Additionally, the system has been tested and evaluated against most other systems in the field.

A. D. Acharya and S. N. Patil designed and implemented an IoT-based smart medical kit for critical medical conditions [25]. This kit can provide a versatile connection to data from the IoT and can support emergency medical services such as intensive care units. The model collects, stores, analyzes, and distributes Big Data in real-time, enabling users to lower their health risks and reduce healthcare costs. This research aimed to reduce patient anxiety about regular doctor visits. With the help of this project proposal, patients' and doctors' time will be saved, allowing doctors to help patients in critical condition as much as possible.

Kishor and Chakraborty designed a healthcare model using seven classifying algorithms [27]. Nine different disease related datasets were organized based on classifications. AUC, accuracy, sensitivity, and specificity were the four variables used to measure the classifiers' performance. The three phases of this work were data collection, pre-processing and computation, and determining the results' visibility to physicians or end-users, with the results stored on a cloud server. This study compared machine learning-based health models with previously developed work. Unlike other classifiers, the RF classifier has the highest accuracy, sensitivity, specificity, and AUC for a variety of common diseases, according to the study authors. This model can be extended for various purposes, such as weather forecasting, military, and food availability prediction.

In another study that is very similar to [27], Souri et al. suggested an IoT-based system for monitoring student health [28]. This model aimed to monitor students' valuable metrics and identify behavioural and biological changes in students using cutting-edge student-support technologies. This approach consists of three levels: identifying the required data for the student using biological and behavioural factors, capturing the information using biosensors and intelligent IoT devices, and pre-processing the data. In this process, four classifiers were employed to assess the validity of the proposed model. The experiment results showed that the classification algorithms performed superbly in terms of precision, recall, accuracy, and F-score. The authors stated that SVM achieved the highest possible performance in predicting diseases in the proposed scenario. This system requires a local repository to reduce the time needed for emergency services, which saves bandwidth within the system. The response time of this system is not fast enough.

Gera et al. [6] concentrated on an IoT-based Cloud Talk platform-connected patient-health-monitoring system. This system streamlines the conventional workflow by providing all systems—including medical examinations, facilities, and tests—in one location. This system is capable of being implemented in a real-world setting because it consists of five fundamental components that are able to carry out a variety of tasks, such as collecting patient data from wearable IoT sensors, uploading the report to a cloud platform, analyzing the findings, and providing medical check-ups, diagnostics, and facilities to patients. In addition to these benefits, the system facilitates better decision-making and makes navigating the conventional workflow of the normal healthcare system simpler. In addition, it acts as a point of contact for the patient, the doctor, the pharmacist, and the diagnostician. There are restrictions on the system's ability to manage patient healthcare.

An IoT-based healthcare-monitoring system with numerous sensors and an intelligent security system was presented by Hashim et al. in [32]. The system uses many sensors to collect vital signs such as humidity and room temperature using a DHT11 sensor, HR using a pulse sensor, and BT using an infrared thermometer. Data from the sensors that used the Arduino to gather information on the condition of the patient are sent to ThingSpeak and stored using the Wi-Fi module. The collected data are displayed on the LCD (cloud platform). When the sensor detects an abnormal reading, an SMS is sent to the smartphone using a GSM module to contact the patient's family or doctor promptly. The performance of the temperature and pulse sensors was evaluated using various experiments. According to the authors, the percentage error of the infrared thermometer sensor is 1.2% lower than that of the current model. The user and physician can view the results when uploaded to ThingSpeak, but this system cannot monitor the patient remotely in real-time.

SoonHyeong et al. [30] proposed an intelligent health-related monitoring system that detects abnormal movements such as falls based on sensor readings from accelerometers. After detecting abnormal movements, the system analyzes basic bio-signals such as a person's BP, HR, and BT. Users, caregivers, and professionals can check that the patient has measured biometric data anytime, anywhere, using a smartphone. This monitoring system includes a JAVA-based Android service environment. The performance of this monitoring system was evaluated using datasets with information from fifty different individuals. In this model, blockchain technology is used to protect individuals' medical data by increasing the data's reliability while maintaining its confidentiality. With the help of a sensor chip, technology that is part of the IoT, the accumulation of personal medical information is stored and monitored in real-time. The transmission of sensitive medical data occurs in real-time via a mobile device only, such as a smartphone.

Piyush et al. [31] present a positive strategy for monitoring the daily life of Alzheimer's patients and providing quality care to those affected by the disease. This work is based on data collected from sensors connected to the IoT that determine various parameters of the patient's body, such as temperature, BP, pacing, and walking speed, to name a few. The Atmega microcontroller is used for collecting all this sensory data and information. All the collected information is transmitted to a cloud server using parallel communication to analyze the data. It is possible to retrieve the patient's desired parameters, which helps provide real-time patient support. In addition, this work cannot predict the patient's condition before the emergency becomes more serious.

Ref	Sensors Used	Communication method	Security Method	Experimental Validation	Limitation
Wu et al. [14]	ECG, PPG, BT, HR	BLE	Encryption at gateway	Prototype testing	Limited communication range
Gupta [21]	HR, SPo_2, BP, BT	Wi-Fi	Basic Encryption	Prototype only	Scalability and long-distance issues
Islam et al. [17]	BT, HR, CO, CO_2	Wi-Fi	None specified	Lab Testing	Limited epidemic-related sensors
Hamim et al. [19]	BT, HR, GSR	Wi-Fi	None specified	App-based validation	No network performance evaluation
Alamsyah et al. [22]	HR, BP, BT	Wi-Fi	Basic authentication	Prototype tested	No energy analysis
Hashim et al. [32]	HR, BT, Humidity	Wi-Fi + GSM	None Specified	Sensor accuracy test	No real-time remote Monitoring
Soon Hyeong et al. [30]	BP, HR, BT, Motion	Mobile Network	Blockchain	Dataset testing	High computational overhead
Proposed system	ECG, HR, SpO_2, BT	WSN + Gateway	AES+ secure Channel	NS-3 + MATLAB + prototype	-

Table 1: Comparative analysis Table

II.3 Explicit Contributions and deduced Scientific Gaps

II.3.1: Explicit Contributions

The main contributions of this work are as follows

i. **Architecture Design**
A scalable IoT-based healthcare monitoring architecture integrating wearable sensors, microcontrollers, energy-efficient routing, and cloud services.

ii. **Energy-Efficient communication;**
The adoption and evaluation of HEED clustering protocol to extend network lifetime compared to LEACH-based approaches.

iii. **Experimental Validation;**
Performance evaluation using simulations (NS-3, MATLAB) and prototype testing, focusing on energy consumption, latency, packet delivery ratio and systems reliability.

iv. **Comparative Analysis;**
A structured comparison with existing IoT healthcare systems highlighting unresolved gaps.

II.3.2 Deduced Scientific Gaps

From the reviewed literature, the following experimental and methodological gaps were identified;

Identified Gaps	Evidence from Literature
Lack of quantitative network evaluation	Most systems report functionality without latency or energy metrics
Unrealistic security assumptions	Use of heavy cryptographic methods unsuitable for constrained IoT nodes
Inconsistent Validation methods	No standardized benchmarking across systems
Absence of cost analysis	Hardware and operational costs rarely discussed

Table 2 : gap matrix

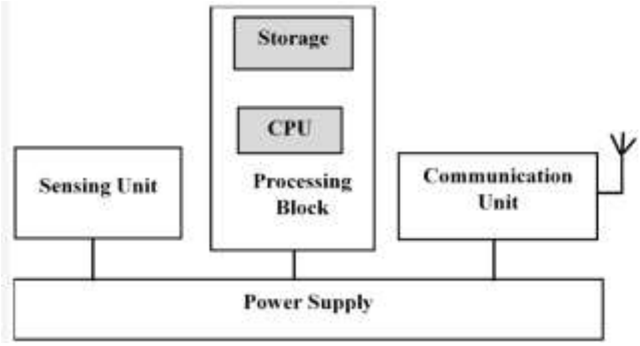

Fig 2: General architecture of the IoT-based remote healthcare monitoring system

III Proposed System Architecture and Methodology

III.I System Architecture

Fig. 3. Components of a Wearable Sensor Node

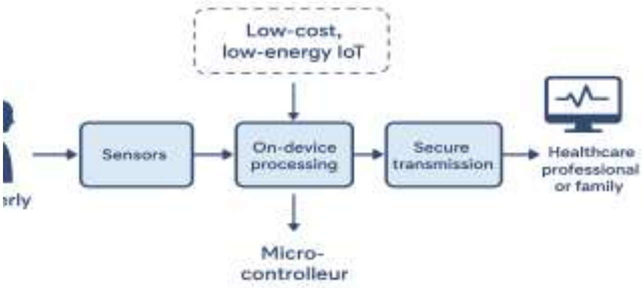

Fig 4: Proposed IoT system architecture

The proposed conceptual model made up of four layers is depicted in the **Fig 4.** Above.

i. **Sensing Layer:**
A custom chest-worn patch housing an ECG sensor, a pulse worn Oximeter (PPG/SpO_2), and a temperature sensor.

ii. **Network and Gateway Layer:** Data is aggregated within BAN using HEED protocol for energy efficiency and transmitted via a secure Bluetooth Low Energy (BLE) link to a smartphone gateway.

iii. **Secure Cloud Layer:** The gateway forwards encrypted data to a cloud server (e.g. AWS IoT, Thingspeak) via HTTPS. Data is decrypted, stored in a database, and processed for anomalies.

iv. **Application Layer**: A web/mobile dashboard provides real-time visualization and alerts for patients and authorized medical personnel.

III.2 Methodology for Design and Validation

This research adopts a **Design Science Research (DSR)** methodology, complemented by experimental validation through simulation and prototyping. The methodology is structured into four main phases: system design, simulation-based evaluation, prototype implementation, and performance analysis. This multi-layered approach ensures both theoretical rigor and practical feasibility.

III.2.1 System Design Phase

The first phase focuses on the co-design of hardware and software components required for continuous remote health monitoring. The system architecture follows a layered IoT model consisting of sensing, network and gateway, cloud, and application layers.

At the sensing layer, wearable physiological sensors are integrated into a chest-worn sensor patch capable of continuously acquiring ECG, HR, SpO_2, and body temperature data. The choice of a chest-based configuration ensures improved signal quality and user comfort for long-term monitoring. Sensor nodes are designed using low-power microcontrollers (e.g., ESP32-class devices) to meet energy and computational constraints.

At the network layer, sensor nodes form a body area network (BAN) in which data aggregation and communication are optimized using an energy-efficient clustering protocol. The Hybrid Energy-Efficient Distributed (HEED) protocol is selected due to its residual-energy-based cluster head selection and uniform cluster distribution, which contribute to prolonged network lifetime and reduced communication overhead.

Aggregated data are transmitted to a smartphone-based gateway via a secure Bluetooth Low Energy (BLE) link.

At the cloud layer, encrypted physiological data are forwarded from the gateway to a cloud server using secure HTTPS communication. Cloud services provide data storage, preprocessing, and anomaly detection, while ensuring controlled access for authorized healthcare personnel.

The application layer includes a web or mobile dashboard that enables real-time visualization of physiological parameters and generates alerts when predefined thresholds are exceeded.

III.2.2 Simulation-Based Evaluation Phase

To quantitatively assess network performance, simulation experiments are conducted using NS-3 and MATLAB. NS-3 is employed to model wireless communication behavior, latency, packet delivery ratio, and scalability under varying network densities, while MATLAB is used to analyze energy consumption, clustering efficiency, and network lifetime.

A network comprising 50 to 200 sensor nodes is simulated to emulate multi-patient monitoring scenarios in healthcare facilities or assisted living environments. The HEED protocol is evaluated and compared against the LEACH protocol under identical simulation parameters, including transmission power, packet size, and node deployment area. Performance metrics collected during this phase include:

- Average energy consumption per node,
- Network lifetime,
- End-to-end latency,
- Packet delivery ratio (PDR).

IV Results, Conclusion and Discussions

IV.1 Results

IV.1.1 Simulation Environment and Experimental Setup

Network-level performance evaluation was conducted using the NS-3 simulator, while MATLAB was employed for energy consumption analysis and clustering efficiency evaluation. The simulated environment consisted of a wireless sensor network comprising between 50 and 200 sensor nodes, representing a multi-patient remote healthcare monitoring scenario such as assisted living facilities or distributed home-care environments.

All simulations were performed under identical conditions for fair comparison. Key parameters, including transmission power, packet size, data generation rate, and node deployment area, were kept constant across protocols. The performance of the proposed HEED-based clustering approach was benchmarked against the LEACH protocol, which is widely used in energy-efficient wireless sensor networks.

The selected performance metrics—energy consumption, network lifetime, end-to-end latency, packet delivery ratio (PDR), and security overhead—are directly aligned with the operational requirements of real-time IoT healthcare systems.

IV.1.2 Energy Consumption and Network Lifetime Analysis

Energy efficiency is a critical requirement for wearable healthcare devices due to limited battery capacity and the need for long-term continuous monitoring. Simulation results indicate that the proposed HEED-based clustering mechanism consistently outperforms the LEACH protocol in terms of energy consumption across all network sizes.

On average, the HEED protocol achieves an improvement of approximately 10–15% in network lifetime compared to LEACH. This improvement can be attributed to three main factors: (i) residual-energy-based cluster head selection, which prevents premature energy depletion of specific nodes; (ii) more uniform distribution of cluster heads, which reduces communication imbalance; and (iii) lower re-clustering overhead during network operation.

These findings demonstrate that energy-aware clustering protocols are particularly well suited for healthcare monitoring applications, where uninterrupted data acquisition is essential for patient safety.

IV.1.3 End-to-End Latency and Packet Delivery Performance

End-to-end latency is a key performance indicator in real-time health monitoring systems, especially for physiological signals such as ECG, where delayed data delivery may compromise clinical relevance. Simulation results show that the proposed system maintains an average end-to-end latency below 150 ms, even as network density increases.

This latency level falls within acceptable bounds for non-critical real-time medical monitoring applications and demonstrates the suitability of the proposed architecture for continuous vital-sign transmission. The relatively low latency is primarily due to efficient data aggregation at the cluster level and reduced retransmission overhead.

Furthermore, the packet delivery ratio remains consistently above 96% across all simulated scenarios. This high PDR indicates robust communication reliability and confirms the scalability of the proposed system under increased network load. High data delivery reliability is particularly important in healthcare environments, where packet loss may lead to incomplete or misleading clinical information.

IV.1.4 Security Overhead and Encryption Performance

Security and privacy are fundamental requirements for IoT-based healthcare systems, as physiological data are highly sensitive. The implemented lightweight encryption framework based on symmetric cryptography was evaluated in terms of computational delay and energy overhead.

Experimental results show that the AES-based encryption mechanism introduces negligible processing delay and minimal additional energy consumption. In contrast, comparative analysis indicates that full homomorphic encryption schemes impose excessive computational complexity and energy overhead, making them unsuitable for resource-constrained wearable devices.

The results confirm that lightweight cryptographic solutions provide a practical balance between data confidentiality and system performance, ensuring secure communication without compromising real-time monitoring requirements.

IV.1.5 Prototype Validation and Measurement Accuracy

A functional hardware prototype was developed to validate the feasibility of the proposed system under real-world conditions. Experimental measurements demonstrate stable system operation during continuous monitoring sessions.

Sensor readings for heart rate, SpO_2, and body temperature were compared against calibrated commercial medical devices. The observed deviations were within acceptable clinical tolerances, indicating that the selected sensors and signal acquisition methods are suitable for continuous monitoring applications.

End-to-end latency measurements obtained from the prototype implementation are consistent with simulation results, further validating the accuracy of the simulation-based evaluation.

IV.2 Conclusion

This paper presented a low-cost and energy-efficient IoT-based remote healthcare monitoring system designed for continuous monitoring of vital physiological parameters. Unlike many existing works, that remain conceptual, the proposed system was evaluated through both prototype implementation and simulation-based experiments. The use of energy-efficient clustering protocols significantly improves network lifetime, while performance metrics demonstrate acceptable latency and reliable data delivery.

Furthermore, this study critically examined the feasibility of advanced cryptographic techniques for IoT healthcare systems and proposed a more practical security framework suitable resource-constrained device. The results indicate that the proposed architecture is scalable, secure and suitable for real-world deployment to ameliorate healthcare.

IV.3 Discussion

The experimental and simulation results collectively demonstrate that the proposed IoT-based healthcare monitoring system successfully addresses several limitations identified in existing solutions. Unlike many prior works that focus primarily on system functionality, this study provides quantitative evidence of performance improvements in energy efficiency, communication reliability, and security overhead.

The integration of an energy-efficient clustering protocol significantly extends network lifetime, which is essential for wearable healthcare applications. Moreover, the achieved latency and packet delivery performance satisfy the requirements of real-time physiological monitoring. The security evaluation further confirms that practical encryption mechanisms can be deployed without imposing prohibitive computational costs.

Nevertheless, some limitations remain. The evaluation is conducted under controlled experimental conditions, and large-scale real-world deployment may introduce additional challenges related to network interference, user mobility, and heterogeneous device behavior. Furthermore, while the system supports early detection through threshold-based alerts, more advanced clinical decision-making mechanisms, such as machine learning-based anomaly detection, remain an open area for future research.

V. Summary of Key Findings

- The HEED-based clustering approach improves network lifetime by approximately 10–15% compared to LEACH.
- Average end-to-end latency remains below 150 ms, meeting real-time healthcare monitoring requirements.
- Packet delivery ratio consistently exceeds 96%, demonstrating robust communication reliability.
- Lightweight encryption introduces minimal computational and energy overhead while ensuring data confidentiality.
- Prototype validation confirms the feasibility and consistency of simulation results.

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