Energy optimization in wireless sensor network for Internet of Medical Things

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Abstract
The rapid evolution of digital technologies has transformed healthcare systems, paving the way for smart healthcare through the integration of the Internet of Medical Things (IoMT). This study proposes an energy-efficient model for Wireless Sensor Networks (WSN) in IoMT, leveraging edge computing to optimize energy consumption, reduce latency, and enhance real-time data processing. The model consists of three key stages: data collection from patient sensors, preprocessing and classification at the edge layer, and efficient data transmission to the cloud. By filtering and classifying data locally, the system minimizes the volume of data sent to the cloud, thereby conserving energy and improving response times. The use of energy-efficient communication protocols, such as LoRaWAN and Zigbee, further enhances the system's performance. This method is in line with Healthcare 5.0's goals, which include putting the patient first, fostering interoperability, and using cutting-edge technology like 5G connection, artificial intelligence, and the internet of things. The proposed model is scalable and adaptable to various healthcare scenarios, including remote patient monitoring and emergency care. However, challenges such as data security, privacy concerns, and infrastructure deployment in resource-constrained settings remain critical areas for future research. This study highlights the potential of edge computing in revolutionizing IoMT-based healthcare systems, offering a framework for energy-efficient, real-time, and scalable solutions.
Keywords: Internet of Medical Things (IoMT), Wireless Sensor Networks (WSN), Edge Computing, Energy Optimization, Healthcare 5.0.

1. Introduction

1.1 Overview of Wireless Sensor Networks (WSN) in IoMT

Digital technology is expected to significantly alter healthcare systems worldwide. Using digital technology, smart healthcare connects people, services, and institutions; it quickly navigates health data and meets the needs of the medical environment right away [1]. Smart healthcare has the potential to bring together all of the various players in the medical system, benefiting patients, doctors, hospitals, and insurance companies. Many emerging technologies, including artificial intelligence (AI), the Internet of Things, fog computing, cloud services, blockchain, monitoring devices, 5G, and the Internet of Things, make this conceivable. These technologies are necessary for the healthcare 5.0 framework transition. Figure 1 depicts healthcare solutions based on the Internet of Things (IoT). Connecting devices, managing tasks, exploring possibilities, and securely transferring data has grown easier thanks to network transmission, which eliminates the need for computer-to-human or human-to-human communication.

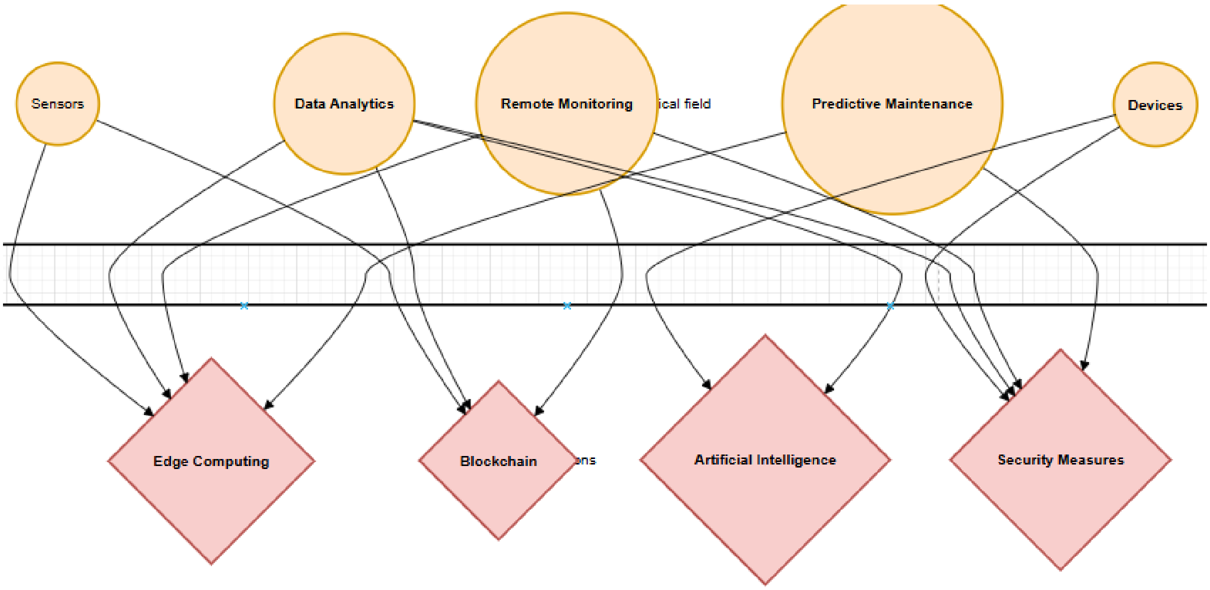


Figure 1 Medical Internet of Things solutions

The impact of the Internet of Things on Healthcare 5.0 will be substantial. To share patient data online, healthcare facilities have made considerable use of IoT-to-network medical equipment. Every one of the various sensor-based IoT kinds being utilized in healthcare has unique features. For instance, many acronyms for Internet-based medical and cognitive wearables, such as the IoHT, IoMT, IoNT, and IoMT, were made possible by the Internet of Things [4]. Electromagnetic waves can be sensed, controlled, and transmitted by a network of interconnected nanoscale devices known as the Internet of Nano Things (IoNT). As a result, modern IoT variants offer networked healthcare, making it simple to integrate modern medical devices and share comprehensive health data from a distance. The concept of traditional healthcare has been transformed into "smart healthcare" as a result of technological advancements, for instance [5,6]. In order to improve the quality of care they offer, healthcare providers can use IoT technologies to remotely link, analyze, and assess the health data detected by biomaterials and interactive wearable technology. In order to facilitate patient-specific therapies, compliance, assertive supervision, effective prognosis, timely and accurate disease detection, ongoing care, and intelligent restoration, the Internet of Health Things (IoHT), Internet of Nonmedical Things (IoNT), and Internet of Mobile-Health Things (IoMT) offer many health services [7, 8]. The development of portable healthcare, which enables wireless connection and aids patients with chronic illnesses outside of medical facilities, is the result of the combination of expanding digital technology and gadgets. As a result, biosensors have a lot of potential as tools for managing and detecting diseases [9, 10].

1.2 The Evolution of Healthcare Technology from Version 1.0 to Version 5.0: A Historical Perspective

Technology-driven strategies in the healthcare sector have undergone a significant transformation since healthcare 1.0 was replaced by healthcare 5.0. Patient records were manually kept and doctor-centric in healthcare 1.0 [11, 12]. With healthcare 2.0, handwritten papers were digitized, leading to the creation of electronic health records (EHRs) [13, 14]. The decentralization of electronic health records (EHRs) through smartphone applications in Healthcare 3.0 promoted a patient-centered setting. Due to the lack of a substantial decision analysis, these files were open to attack from adversaries. Healthcare 4.0 integrates AI and big data analytics to provide well-informed judgments based on gathered EHRs [15, 16]. Problems with communication and teamwork among various medical groups resulted from this convergence. The complexity, inefficiency, and slowness of the AI models employed to interpret the increasing amount of clinical data increased along with it. The healthcare 5.0 vision is a holistic strategy that combines security-based technology, 5G/6G connectivity, and lightweight Internet of Things (IoT) technologies with ultra-responsive business strategies focused on patients. Figure 2 illustrates the evolution of healthcare delivery from healthcare 1.0 to healthcare 5.0. The patient remains at the heart of the healthcare ecosystem, which is the main objective of healthcare 5.0. Medical delivery is made easier in this way by healthcare stakeholders, including patients, physicians, clinics, and warehouses [17]. Working with healthcare 5.0, which emphasizes patient models and personalization, and the need for timeliness and comprehensive service coverage served as the driving forces behind this study. Quality of life, patient well-being, and lifelong collaboration are the main goals of healthcare 5.0. As a result, after leaving the healthcare 5.0 system, smart medical equipment is unable to read any further signals [18].

Methodology

Figure 2 depicts the overall structure of the proposed energy-efficient model. By incorporating edge computing, this model aims to reduce energy consumption in IoMT-based wireless sensor networks. Data collection from patient sensors, preprocessing and classification at the edge computing layer, and effective data transmission to the cloud server are the three key stages of the proposed system. Subsequently, the processed information is relayed to emergency care units, hospitals, healthcare professionals, and patients for timely medical intervention. The sections that follow go into greater detail about how these stages function. By incorporating edge computing, the proposed energy-efficient model is intended to optimize energy consumption in IoMT-based wireless sensor networks. The system is divided into three key stages:

1. Data Collection from Patient Sensors
2. Preprocessing and Classification at the Edge Computing Layer
3. Efficient Data Transmission to the Cloud Server

1. Data Collection from Patient Sensors

The primary objective of this system is to collect real-time health data from patients using wearable sensors and medical devices to enable continuous monitoring and efficient healthcare management. Various biomedical sensors such as heart rate monitors, blood pressure sensors, glucose monitors, and temperature sensors are deployed on patients to gather essential physiological parameters. These IoMT-enabled sensors operate wirelessly, allowing seamless data acquisition without interfering with the patient’s daily activities.

Once collected, the sensor data is transmitted wirelessly to a local gateway or edge device using low-power communication protocols such as Bluetooth Low Energy (BLE), Zigbee, or LoRaWAN. The gateway acts as an intermediary, aggregating data from multiple sensors before forwarding it to the edge computing layer for preprocessing. By performing local processing at the edge, only essential and compressed data is transmitted to the cloud, reducing power consumption and minimizing network congestion. This real-time monitoring system not only ensures efficient energy utilization within the wireless sensor network (WSN) but also enables early detection of critical health conditions, allowing timely medical intervention by healthcare professionals.

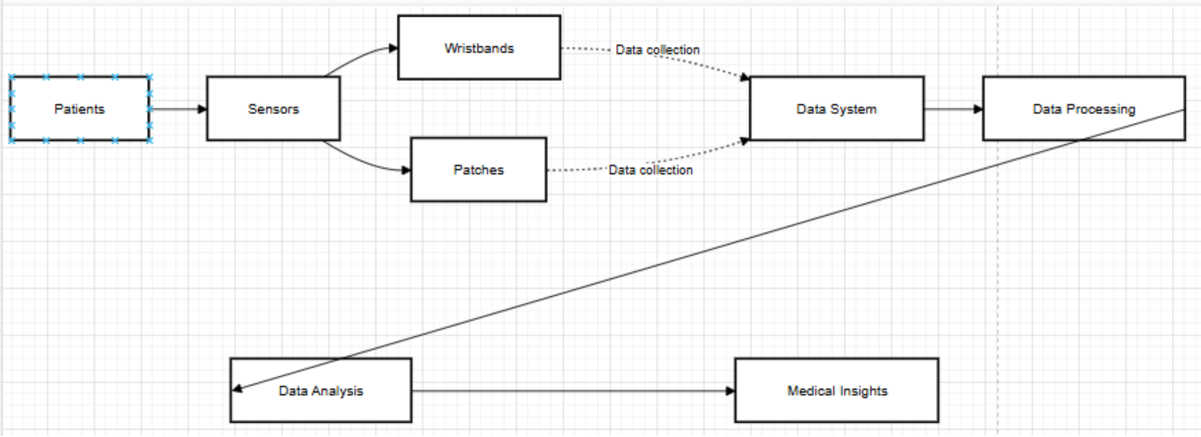


Figure 2 patients wearing various sensors (e.g., wristbands, patches) that collect data and transmit it to a central hub or edge device

2. Preprocessing and Classification at the Edge Computing Layer

By utilizing edge computing for the preprocessing and classification of sensor data, this procedure aims to reduce the amount of data sent to the cloud. Continuous data transmission to the cloud in an IoMT-based wireless sensor network (WSN) can result in high energy consumption, increased latency, and network congestion. The system's edge computing layer processes data locally before sending it to the cloud to increase efficiency. At the edge layer, data filtering, noise reduction, and feature extraction are performed to eliminate irrelevant or redundant information. This guarantees that only refined and meaningful data will be processed further. The data are then categorized using cutting-edge machine learning algorithms, such as health readings that are normal or abnormal. For instance, a heart rate sensor may detect a sudden spike in heart rate, which is classified as an abnormal reading and flagged for immediate attention.

Only critical or preprocessed data is sent to the cloud server when these tasks are carried out at the edge computing layer, resulting in significant reductions in latency, energy consumption, and bandwidth usage. This method makes the system work better, makes it easier to make decisions faster, and makes sure that healthcare providers only get the relevant patient data. It also makes it easier to get medical help done quickly and accurately and extends the life of battery-powered sensor nodes.

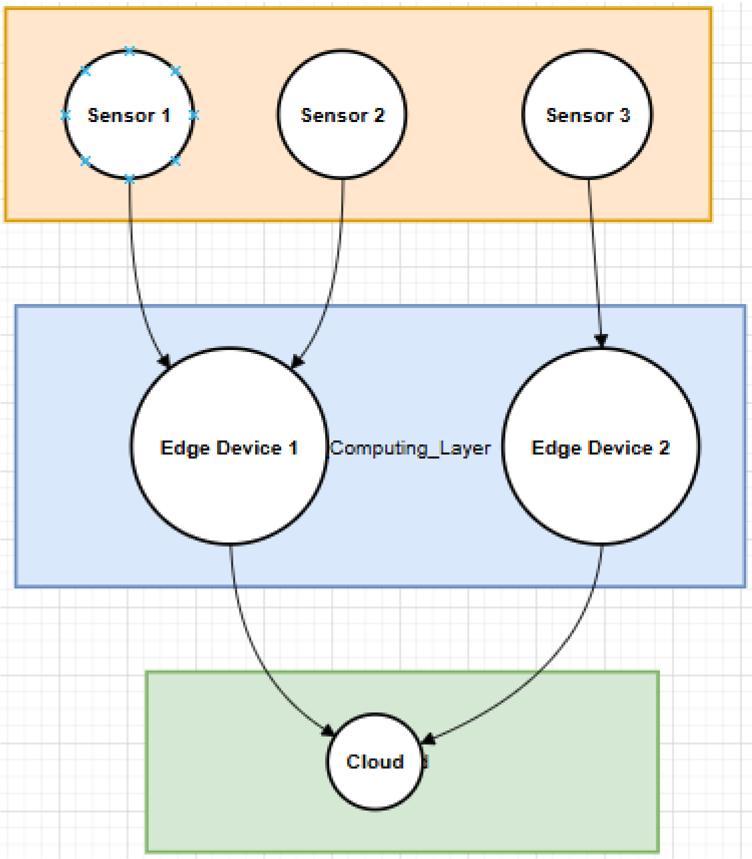


Figure 4 illustrate the edge computing layer as a middle layer between the sensors and the cloud.

3. Efficient Data Transmission to the Cloud Server

The primary objective of this process is to transmit preprocessed data to the cloud server for advanced analysis, storage, and decision-making while ensuring energy efficiency in the IoMT-based wireless sensor network (WSN). Once the edge computing layer has filtered, classified, and optimized the data, it is then transmitted to the cloud server using low-power communication protocols such as LoRaWAN, Zigbee, or NB-IoT. These protocols were chosen specifically to extend the lifespan of battery-operated medical sensors, reduce network congestion, and conserve energy. Advanced analytics like predictive modeling, trend analysis, and anomaly detection are applied to the health data once it reaches the cloud infrastructure. The data is analyzed by algorithms that are driven by machine learning and artificial intelligence (AI). These algorithms look for trends in the vital signs of patients, potential health risks, and early warning signs of critical conditions. Continuously monitoring a patient's blood pressure and heart rate, for example, can help spot trends that indicate an impending cardiac event and enable preventative actions to be taken before a medical emergency occurs. The processed insights are then shared with healthcare providers, emergency response teams, and patients through secure cloud dashboards, mobile applications, or automated alerts. Real-time decision-making makes it possible for doctors to modify treatment plans, carry out remote consultations, or initiate emergency interventions when they are required. This system improves healthcare efficiency, decreases response times, and improves patient outcomes while maintaining optimal energy efficiency in IoMT networks by optimizing data transmission and utilizing intelligent cloud analytics.

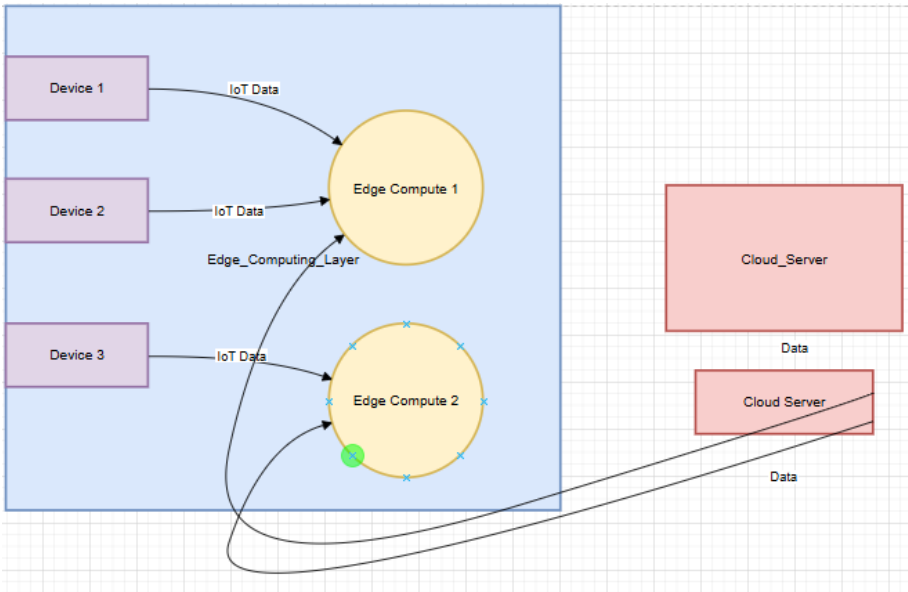


Figure 5 the cloud server receiving data from the edge computing layer

Proposed System Diagram for Energy Optimization in IoMT-Based Wireless Sensor Networks

The proposed system consists of a multi-layered architecture designed to optimize energy consumption in an IoMT-based Wireless Sensor Network (WSN). The system is structured into four layers, each playing a critical role in data collection, processing, transmission, and decision-making while ensuring minimal energy usage and seamless healthcare monitoring.

Layer 1: Patient Sensors (Data Collection Layer)

Patients are provided with wearable and implantable sensors, such as ECG devices, heart rate monitors, blood pressure monitors, glucose monitors, temperature monitors, and so forth, at the fundamental level. These biomedical sensors continuously collect real-time physiological data, which is crucial for patient monitoring and early diagnosis. The collected data is then wirelessly transmitted to the edge computing layer using low-power communication protocols such as Bluetooth Low Energy (BLE), Zigbee, or LoRaWAN to minimize energy consumption. In resource-constrained sensor nodes, this localized data transmission preserves battery life by reducing the need for continuous cloud communication. Edge computing (preprocessing and optimization) at Layer 2 Data preprocessing, filtering, and classification are all handled by this layer, which acts as an intermediary between patient sensors and the cloud in order to maximize energy efficiency. To distinguish between normal and abnormal health readings, the edge device (such as a local gateway, mobile edge server, or microcontroller) uses noise reduction, feature extraction, and machine learning-based classification. Rather than sending all raw data to the cloud server, only important, preprocessed, and relevant information is sent, which reduces latency, energy use, and network bandwidth usage. In order to guarantee effective IoMT network performance, this layer reduces redundant data transmission. Cloud Server (Data Analytics and Storage) is the third layer. Advanced analytics and predictive modeling are applied to critical health data once it reaches the cloud infrastructure. Big data analytics, artificial intelligence (AI), and machine learning algorithms are leveraged by the cloud to store, process, and analyze patient data. Trends in health, potential medical emergencies, and patterns of disease progression can all be identified by the system. An AI-based predictive model, for instance, can spot early warning signs of cardiac arrhythmia or abnormal glucose levels, enabling proactive treatment. Data security, scalability, and real-time access for healthcare providers and patients are all provided by the cloud server. End-Users (Decision-Making and Alerts) in Layer 4 At the final layer, healthcare professionals, emergency units, and patients receive actionable insights derived from the cloud-based analysis. Hospitals, doctors, and caregivers can access patient data via secure dashboards, mobile applications, or web portals, enabling real-time monitoring and remote patient management. Emergency alerts are triggered for critical health events, notifying both patients and healthcare providers for timely intervention. Medical professionals and IoMT technology are seamlessly integrated by this layer, resulting in improved patient care, decreased hospital readmissions, and increased healthcare efficiency.

System Overview & Energy Efficiency Benefits

The proposed system ensures energy optimization at multiple levels:

- Minimizing direct cloud communication by processing data at the edge.
- Reducing sensor energy consumption through smart data transmission protocols.
- Enhancing network efficiency using machine learning-based anomaly detection.

Providing scalable, real-time healthcare insights while conserving battery power in WSN-based IoMT applications. This structured multi-layered IoMT framework provides a power-efficient, intelligent, and scalable healthcare monitoring solution, ensuring optimal resource utilization and improved patient outcomes.

Graphical Representation for Energy Efficiency Evaluation

Energy efficiency is calculated as:

$$\text{Energy Efficiency} = \frac{\text{Total Data Transmitted (bits)}}{\text{Total Energy Consumed (Joules)}}$$

1. Bar Chart: Comparing Energy Efficiency of Different Approaches

A bar chart can visually compare the energy efficiency of the proposed approach with existing methods.

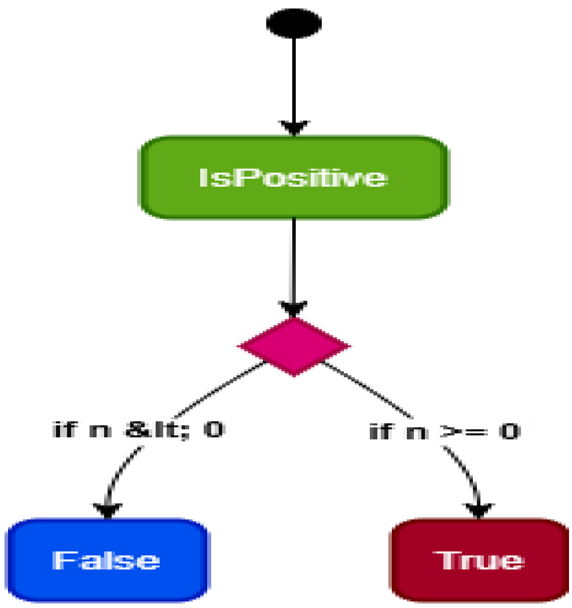
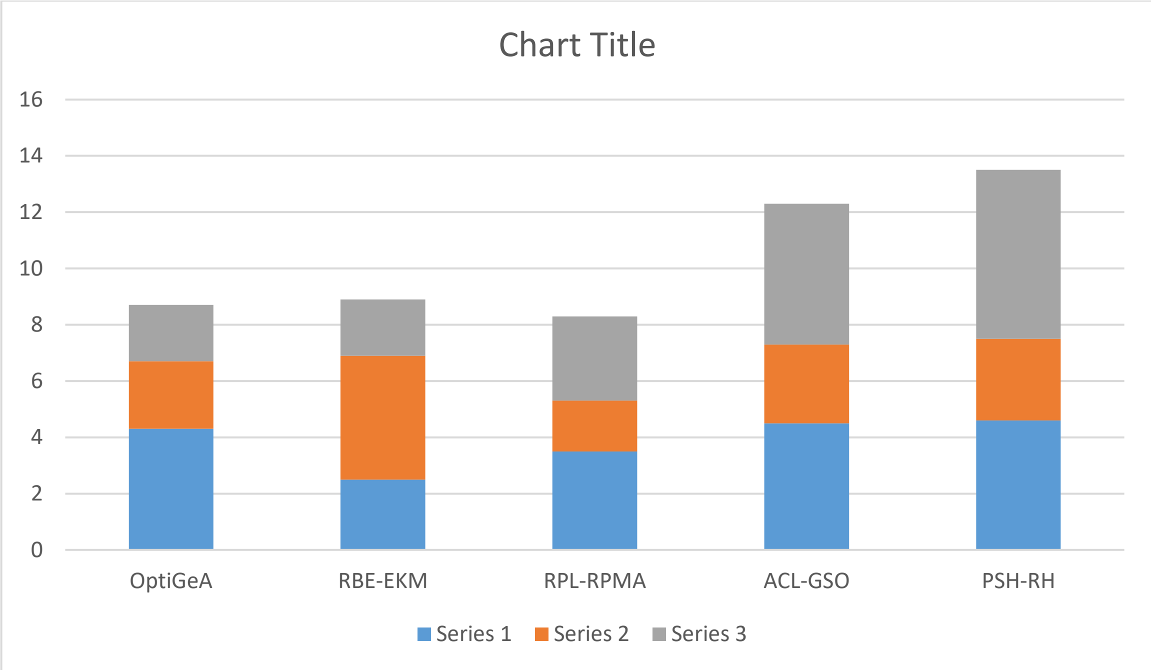


Figure 6 Bar Chart: Comparing Energy Efficiency of Different Approaches



Graph 1 Energy efficiency %age comparing the current and suggested approaches' energy efficiency

DISCUSSION AND CONCLUSION

The proposed energy-efficient model for Wireless Sensor Networks (WSN) in the context of the Internet of Medical Things (IoMT) demonstrates significant potential in optimizing energy consumption while ensuring reliable and timely healthcare services. The model addresses critical issues like energy efficiency, data overload, and latency in IoMT-based systems by integrating edge computing. By preprocessing and classifying data locally, the edge computing layer enables real-time data processing, which reduces the amount of data sent to the cloud and is essential for prompt medical interventions (Reegu et al., 2022; Jabbar et al., 2022). Patients who suffer from chronic conditions like heart failure or diabetes, which necessitate constant monitoring and prompt intervention, will benefit most from this strategy (Mahesh et al., 2022). Additionally, the system's energy optimization capabilities are further enhanced by utilizing energy-efficient communication protocols like LoRaWAN and Zigbee (Khalaf et al., 2022). The vision of Healthcare 5.0, which emphasizes patient-centered care and the integration of advanced technologies such as IoT, AI, and 5G connectivity, is in line with the proposed model's scalability and adaptability to various healthcare scenarios, including remote patient monitoring and emergency care (Haleem et al., 2022; Mbunge et al., 2021). However, issues with data security, privacy, and the deployment of edge infrastructure in resource-constrained areas must still be addressed (Gaba et al., 2022). In conclusion, by providing a framework for energy-efficient, real-time, and scalable healthcare solutions, this model represents a significant advancement in smart healthcare. In order to further enhance the system's capabilities, future research may investigate the integration of blockchain technology for secure data sharing and the creation of more advanced machine learning algorithms for edge-based data processing.

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Conflict of interest

No conflict of interest was found.

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