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A Cloud-Enabled Assistive Robotics System for Secure and Interoperable Internet of Medical Things Ubiquitous

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Abstract

The current landscape of assistive robotics in digital healthcare faces significant challenges, particularly in ubiquitous environments. Existing systems need the necessary infrastructure to monitor and process data, hindering their effectiveness. Moreover, the arrangement and management of IoMT (Internet of Medical Things) data across various nodes present a new challenge, further complicating the deployment of assistive digital healthcare solutions. We propose a novel Assistive Robotics-Based Digital Healthcare System within a Ubiquitous IoMT Cloud network to address these challenges. This system supports various medical care applications, including digital wheelchair location tracking, artificial limbs, and remote surgical operations across different hospitals. Our contributions are as follows: We introduce the ARDTS (Assistive Robot Digital Healthcare Task Scheduling) algorithm to efficiently process data across multiple nodes; ensuring secure data handling based on the systems security protocols. We implement a convolutional neural network for data standardization, converting non-linear data into a linear form to predict relevant features accurately. We develop a socket-enabled cross-platform system to enhance interoperability for seamless data sharing and processing.

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1. Introduction

A significant advancement in modern healthcare is marked by the convergence of Assistive Robotics and the ubiquitous Internet of Medical Things (IoMT) in an Edge Cloud Network [1]. Because they can enhance the quality of life and promote autonomy, assistive robots—designed to aid individuals with disabilities, the elderly, or those recovering from surgery—have become widely accepted. Combined with IoMT, these robots can access vast amounts of patient data, enabling them to provide customized care and make educated decisions [2].

The seamless network of medical devices, sensors, and systems that collect and transmit health data is called the ubiquitous Internet of Medical Things (IoMT). This data-centric paradigm allows patients to be continuously monitored, which allows medical concerns to be identified early, appropriate action taken, and individualized treatment plans developed. Using IoMT, assistive robots can provide context-sensitive and adaptive support by integrating real-time data from many sensors, including motion sensors, glucose meters, and heart rate monitors [3]–[6].

The capabilities of this system are further strengthened by Edge Cloud Networks, which analyze data closer to its source, reducing latency and improving the efficiency of real-time decision-making. The timely operation of assistive robots depends on the timely availability of critical patient data, which is ensured by our distributed data processing approach. Furthermore, since sensitive medical data may be handled locally without being transmitted to a centralized server, data privacy and security are increased [7]–[10].

Essentially, by providing patients with intelligent, flexible, and individualized treatment, the amalgamation of Assistive Robotics and Ubiquitous IoMT within Edge Cloud Networks holds the capacity to revolutionize the healthcare industry. In an ever-changing digital context, this approach improves patient outcomes and satisfies the growing need for effective, safe, and affordable healthcare solutions [11], [12]. However, the existing assistive robotics system for digital healthcare has many issues. Therefore, we consider the different research questions that are here. (i) Assistive robotics systems lack the infrastructure to monitor and process data in ubiquitous environments. (ii) The arrangement of IoMT data on different nodes is a new challenge in the assistive digital healthcare system. With this motivation, we present the novel Assistive Robotics-Based Digital Healthcare System in Ubiquitous IoMT Cloud network and make the following contributions.

- The devised Assistive Robotics-Based Digital Healthcare System supports many cases of medical care applications. For instance, the system supports digital wheelchair location searching, artificial legs, hands, and remote surgeries in different hospitals.
- We present the ARDTS algorithm scheme (assistive robot digital healthcare task scheduling scheme) to process the data on different nodes. It processes the data in a secure form based on the security scheme in the system.
- For the data standardization, we devise the convolutional neural network to convert the non-linear data into linear and predict the data features.
- For interoperability, we devise the socket-enabled cross platform system for data sharing and process.

The study is organized in the following way. Section 2 is about related work. Section 3 is about the proposed system and its components.

2. Related works

This work [1] Integrates System with IoMT and Edge Cloud for Enhanced Patient Care. The objective is to explore how assistive robotics can be integrated with the Internet of Medical Things (IoMT) and edge cloud computing to enhance patient care, focusing on improved efficiency, real-time data processing, and personalized treatment. These studies [2]–[4] investigate the security and privacy challenges in IoMT-based assistive robotics and propose edge cloud network solutions to mitigate risks, ensuring secure patient data handling and communication.

These studies [5]–[8] explore machine learning approaches in the context of assistive robotics integrated with IoMT and edge cloud computing, focusing on improving decision making, adaptability, and personalized care in medical applications. These studies design and analyze IoT and cloud based architectures tailored for assistive robotics in healthcare, emphasizing the benefits of cloud computing in supporting scalable and efficient robotic systems for patient care. These studies [9]–[14] provide a comprehensive review of the convergence between IoT and edge cloud computing in medical assistive robotics, highlighting current trends, challenges, and future research directions. These studies leverage blockchain and edge computing to ensure data integrity, privacy, and secure access in healthcare applications.

These studies [15]–[20] To explore the potential of next generation healthcare systems by integrating IoMT and robotics with edge cloud computing, aiming to revolutionize patient care through innovative technologies. These studies identify and address cybersecurity challenges in IoMT-based assistive robotics using edge-computing approaches, proposing solutions to ensure the secure and reliable operation of robotic systems in healthcare. These studies [21]–[27] suggested privacy-preserving mechanisms in IoMT-enabled assistive robotics using edge computing. The goal was to propose privacy-preserving mechanisms for IoMT-enabled assistive robotics, utilizing edge computing to protect patient data and ensure secure operation in medical applications. These studies suggested secure data management in IoMT-based assistive robotics using blockchain and edge computing. Objective: To develop secure data management solutions for IoMT-based assistive robotics, leveraging blockchain and edge computing to ensure data integrity, privacy, and secure access in healthcare environments.

However, the current studies suffered from many issues. Several challenges hinder the current assistive robotics systems in digital healthcare. One major issue is the lack of adequate infrastructure to monitor and process data in ubiquitous environments, limiting the systems' ability to provide consistent, real-time support across various healthcare settings. Additionally, the complex arrangement of IoMT (Internet of Medical Things) data across different nodes presents a significant challenge. This complexity can lead to inefficiencies in data management, potential security risks, and difficulties in maintaining seamless communication between devices. Addressing these challenges is crucial to improving assistive robotics' effectiveness, reliability, and overall impact in healthcare.

3. Methodology

As shown in Figure 1, the proposed system architecture defines the integration and application of Assistive Healthcare Robotics within a Distributed Digital Healthcare Environment. The study aims to illustrate the system's architecture, components, and functionalities contributing to enhanced patient care and operational efficiency in medical settings. Specifically, it focuses on the role of the Internet of Medical Things (IoMT) and Edge Cloud Networks in enabling real-time, responsive, and secure assistive robotics. The system has the following components. IoMT applications: The first application is IoMT Walking Assistive Devices. It integrates walking assistive devices with IoMT to support patients with mobility impairments. The focus is on real-time monitoring and assistance provided by robotics.

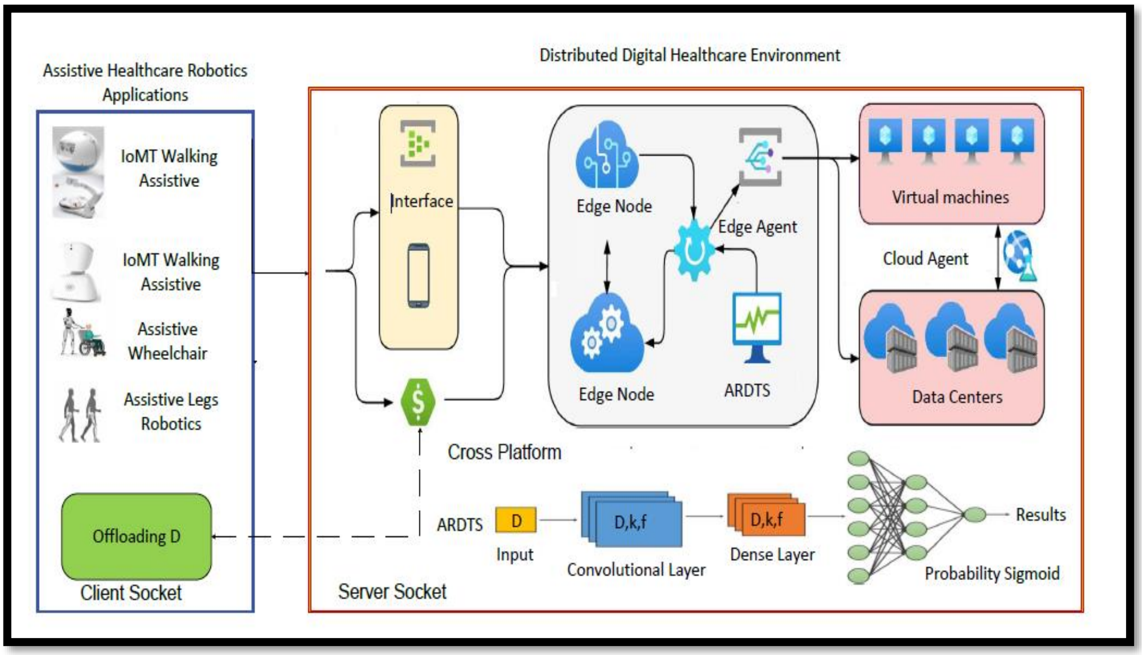

Figure 1. ASRDHS: Assistive Robotics Based Digital Healthcare System in Ubiquitous IoMT Cloud Network.

Assistive Wheelchairs: This paper explores the functionality and IoMT integration of assistive wheelchairs, which cater to the specific needs of individuals with varying degrees of mobility challenges. Assistive Legs Robotics: Examines the application of robotic legs within healthcare, emphasizing IoMT capabilities for patient-specific adjustments and monitoring. The system considers the different nodes, such as edge nodes in the healthcare robotics system, that process data locally to reduce latency and enhance decision-making for real-time applications. Edge Agents: Describes the functionality of edge agents in managing and executing tasks at the edge of the network, ensuring responsive support for assistive devices.

Cloud Agents: The integration of cloud agents, which assist in offloading complex tasks and maintaining synchronization across the distributed system. Each cloud node has virtual machines and data centres that analyze the infrastructure provided by virtual machines and data centres to support distributed digital healthcare environments, ensuring scalability and efficiency in data processing. The offloading data and tasks to appropriate nodes within the network, balancing workloads, and optimizing resource use. The system integrates an ARDTS algorithm scheme consisting of data and convolutional layers to process input data, with dense layers used for final decision-making tasks, particularly in assistive robotics. On the other hand, probability and sigmoid functions classify and predict patient needs based on real-time data inputs. We apply the data security method to transmitting and storing secure data within the IoMT and edge-cloud integrated system to ensure patient confidentiality and system integrity. We process the data based on socket programming between IoMT devices and edge and cloud nodes for interoperability and cross-platform among nodes. The socket has both a client socket and a server socket for processing and transferring data among nodes.

4. Results and Discussions

Figure 2 shows the structure of an Assistive Robotics- Based Digital Healthcare System integrated within a pervasive Internet of Medical Things (IoMT) Cloud Network. It serves as a visual overview of how different components function together within this advanced healthcare framework. The illustration emphasizes crucial elements such as sensors, IoMT devices, edge computing units, cloud servers, assistive robots, healthcare providers, and patients, highlighting the exchange of data and actions among them.

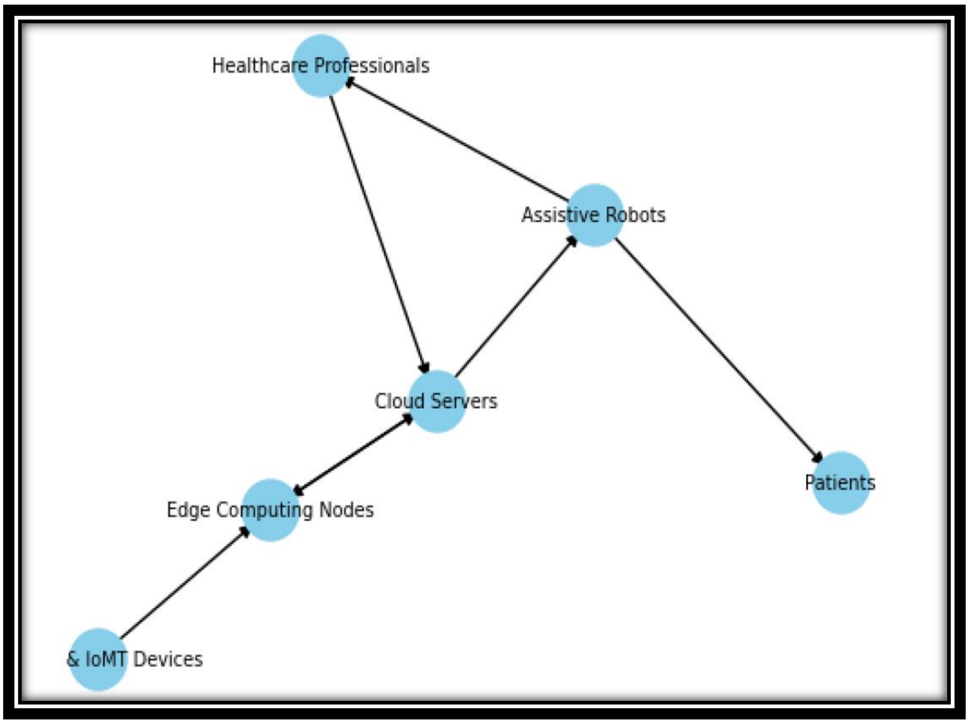

Figure 2. Application Workflow in Different Nodes for Assistive Data processing.

Beginning from the lower left corner of the illustration, the”Sensors & IoMT Devices “node symbolizes various medical sensors and IoMT gadgets that gather patient health information. These devices may include wearable’s like smart watches and fitness trackers, as well as more specialized medical instruments such as glucose meters, heart rate monitors, and blood pressure cuffs. Typically, these devices are situated in patients’ homes or worn on their bodies, continuously tracking different physiological metrics. The data collected by these devices is essential as it serves as the foundation for remote monitoring and diagnostics within the healthcare network.

The information generated by these IoMT devices is subsequently transferred to”Edge Computing Nodes.” Edge computing involves processing data closer to where it is created, rather than transmitting it all to a centralized cloud server. This method helps decrease latency and bandwidth consumption, which is especially vital in healthcare environments where prompt responses are often necessary. Edge nodes handle the initial processing of raw data from IoMT devices, removing any irrelevant information and conducting preliminary analysis. This initial processing stage helps lighten the burden on cloud servers and delivers faster responses for critical healthcare scenarios. After being processed by the edge nodes, the refined data is forwarded to ”Cloud Servers. “The cloud servers function as the core of the system, where more comprehensive data storage, analysis, and machine learning processes are carried out. These servers can consolidate data from various sources, facilitating extensive data analysis and generating insights that would not be achievable with isolated data alone.

Figure 3 features two distinct lines, each representing different healthcare system configurations. The blue line represents the Assistive Robotics-Based Digital Healthcare System (ASRDHS), while the red line represents the Edge-Device Healthcare System (EDHS). The x-axis indicates the Robotics Healthcare Data Size (in Megabytes, MB), ranging from 0 to 140 MB. The y-axis represents the Latency (in milliseconds, ms), ranging from 0 to 200 ms.

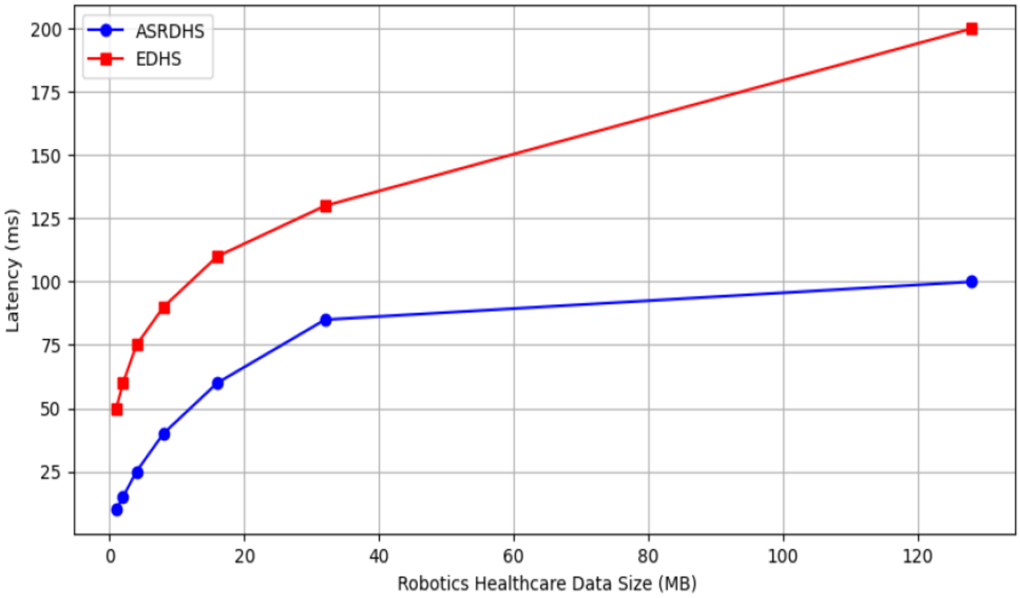

Figure 3. Assistive Robotics Data Analysis Computation Latency.

The blue line shows the latency performance of the Assistive Robotics-Based Digital Healthcare System (ASRDHS) as data size increases. Starting at 0 MB, the latency is near zero, reflecting an optimal response time when there is no data to process. As the data size increases, latency begins to rise, but at a relatively moderate rate compared to the EDHS.

At approximately 10 MB, the ASRDHS shows a latency of around 50 ms, indicating a quick processing time even as data size starts to grow. By 40 MB, latency increases to about 75 ms. Beyond this point, as data size grows to 120 MB, the latency reaches around 85 ms, displaying a nearly linear but gentle increase. This gradual rise in latency as data size increases suggests that the ASRDHS is designed to handle large data sizes more efficiently. It likely utilizes optimized algorithms or distributed processing techniques that prevent latency from escalating too rapidly as the data size grows.

In contrast, the red line represents the Edge-Device Healthcare System (EDHS), which exhibits a different performance profile. Initially, at 0 MB, the latency is again near zero. However, as the data size begins to increase, the latency of EDHS rises more sharply than that of the ASRDHS. At around 10 MB, the latency reaches approximately 90 ms, which is nearly twice as high as that of the ASRDHS at the same data size. As the data size continues to increase, the latency in the EDHS grows rapidly. By 40 MB, the latency has climbed to approximately 120 ms, indicating that the system is becoming less efficient as the data size grows. At the maximum data size of 120 MB, the latency in the EDHS reaches around 200 ms, significantly higher than the ASRDHS. This steeper increase in latency for the EDHS indicates that the system may not be as well optimized for handling larger data sizes. The rapid rise suggests that the EDHS might rely more heavily on centralized processing or less efficient data handling techniques, which cause a bottleneck as the amount of data to be processed increases.

The key takeaway from the graph is the stark contrast in how the two systems handle increasing data sizes in terms of latency. The ASRDHS demonstrates superior performance, maintaining lower latency across all data sizes, which is especially evident at higher data loads. This characteristic makes it a more suitable option for healthcare scenarios where timely responses are critical, such as in real-time patient monitoring or emergency interventions. On the other hand, the EDHS, while still capable of handling smaller data sizes with acceptable latency, quickly becomes inefficient as data sizes increase. This rapid rise in latency suggests that EDHS may be better suited for applications where data size remains small or where processing delays are less critical.

The results shown in the graph have important implications for the deployment of digital healthcare systems, especially in environments that rely on assistive robotics and IoMT devices. For healthcare applications requiring real-time data processing and quick response times, such as critical care monitoring, emergency response, or interactive assistive robotics, the ASRDHS is clearly the more suitable choice. Its ability to maintain low latency even as data sizes increase ensures that patient data can be processed and acted upon swiftly, potentially improving patient outcomes. Conversely, the EDHS might be more appropriate for noncritical applications where data sizes are smaller and delays are less impactful. Examples might include long-term data logging, where data is collected over extended periods without the need for immediate processing, or in environments where the cost of deploying more systems that are sophisticated is prohibitive.

Figure 4 presents a comparison of resource consumption among four different methods or systems, which are labeled as ASRDHS, EDHS, Assistive Cloud Robot, and Assistive Edge Robot. The y-axis represents the resource consumption of nodes, presumably in some quantifiable unit, while the x-axis lists the methods or systems being compared. Looking at the bars, we can immediately see that the Assistive Cloud Robot method has the highest resource consumption among the four. This suggests that it demands the most from the nodes it operates on, which could be due to higher computational requirements, data processing, or other resource-intensive operations typical of cloud-based systems. In contrast, the ASRDHS method shows the lowest resource consumption, which indicates a more efficient use of resources. This could mean that ASRDHS operates with more optimized algorithms; either has a lighter computational load, or effectively manages its resource utilization to keep consumption minimal.

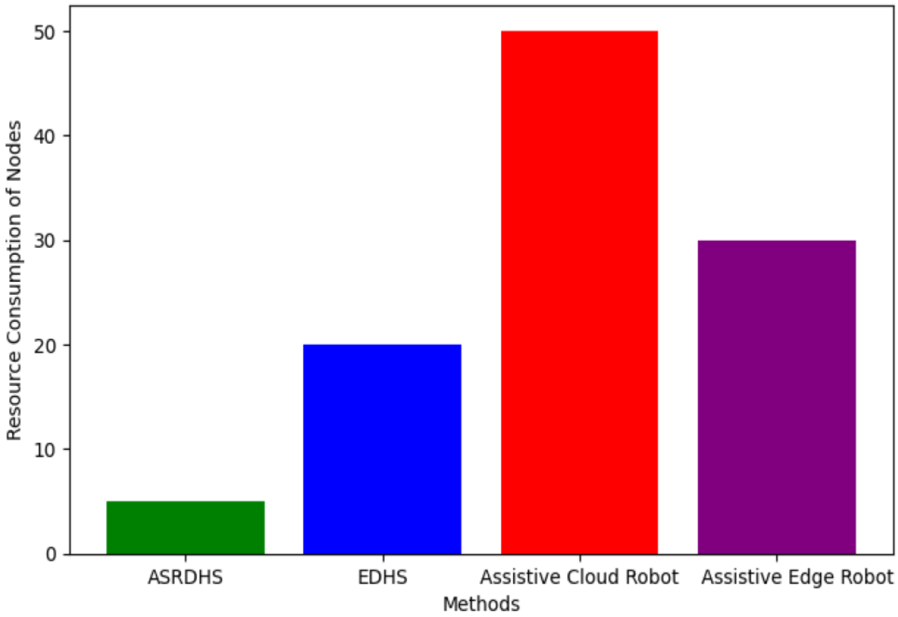

Figure 4. Scheduling Assistive Robotics Data Analysis Resource Consumption.

The EDHS method has a moderate level of resource consumption. It is not as low as ASRDHS but significantly lower than the Assistive Cloud Robot. This suggests that while EDHS is more resource-intensive than ASRDHS, it still maintains a relatively efficient consumption pattern. This could imply a balanced approach in its design, potentially optimizing certain operations while being more demanding in others. The Assistive Edge Robot also shows moderate resource consumption but is notably less than the Assistive Cloud Robot and more than EDHS and ASRDHS. This indicates that the Assistive Edge Robot operates with a fairly efficient use of resources, likely because edge computing typically involves processing data closer to where it is generated, reducing the need for extensive data transfer and potentially lowering resource use compared to cloud-based methods.

Comparing all methods, ASRDHS clearly stands out as the most resource-efficient, while the Assistive Cloud Robot is the most resource-intensive. The difference in consumption between these two suggests significant variations in their operational strategies or in the complexity of the tasks they are designed to handle. The lower resource consumption of ASRDHS could be particularly advantageous in environments where resource availability is limited, such as in remote or edge environments, or where cost-efficiency is a priority. On the other hand, the high resource consumption of the Assistive Cloud Robot might be justified in scenarios where its performance benefits outweigh the resource costs. For example, cloud-based systems often provide powerful computational capabilities and can handle large-scale data processing tasks more effectively than edge devices. If the tasks it is designed to perform require such capabilities, the resource consumption might be an acceptable trade-off.

The EDHS and Assistive Edge Robot methods, sitting between the two extremes, suggest a middle ground. The EDHS could represent a system that, while not as lightweight as ASRDHS, still maintains an efficient use of resources, perhaps by employing some cloud-based functionalities but in a more controlled or limited manner. The Assistive Edge Robot, while consuming more resources than EDHS, may be designed to leverage edge-computing capabilities, providing a balance of local processing power and resource use. In terms of practical implications, the choice between these methods would likely depend on the specific requirements of the use case. For applications where minimizing resource consumption is crucial, ASRDHS would be the ideal choice. In contrast, if maximum computational power and data handling are required, and resource consumption is less of a concern, the Assistive Cloud Robot might be more appropriate. For scenarios where a balance is needed between resource use and computational capabilities, EDHS or Assistive Edge Robot could be considered, depending on whether the focus is slightly more on efficiency or on computational power, respectively.

Overall, this graph provides a clear visual representation of the differences in resource consumption between these four methods. Each method has its strengths and trade-offs, and the best choice would depend on the specific needs and constraints of the situation in which they are being used. The clear distinctions in resource consumption also suggest that these methods are designed for different operational contexts, highlighting the importance of selecting the right tool for the right job to ensure optimal performance and efficiency.

5. Conclusion

In this work, we addressed assistive robotics s significant challenges in digital healthcare, particularly within ubiquitous environments. The existing systems were identified as lacking the necessary infrastructure to monitor and process data, which hindered their performance effectively. Additionally, the arrangement and management of IoMT data across various nodes posed a challenge, complicating the deployment of assistive digital healthcare solutions. We developed a novel Assistive Robotics-Based Digital Healthcare System within a Ubiquitous IoMT Cloud network to overcome these issues. The system supported various medical care applications, such as digital wheelchair location tracking, artificial limbs, and remote surgical operations across different hospitals. Our contributions included the introduction of the ARDTS algorithm for efficient and secure data processing, implementing a convolutional neural network for data standardization, and developing a socket-enabled cross platform system to enhance interoperability and seamless data sharing.

Future work will focus on extending the capabilities of the Assistive Robotics-Based Digital Healthcare System to include more complex medical scenarios and environments. Further research will be directed toward improving the scalability of the ARDTS algorithm to handle larger datasets and more networks that are extensive. Additionally, we will explore integrating advanced machine learning models to enhance the prediction accuracy and efficiency of data processing. We also plan to further investigate the potential of decentralized systems and blockchain technology to strengthen data security and privacy within the system. Finally, user studies and real-world trials will be conducted to assess the practical effectiveness and adaptability of the system in various healthcare settings.

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