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ORIGINAL STUDY

Federated Learning-Driven IoT and Edge Cloud Networks for Smart Wheelchair Systems in Assistive Robotics

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ABSTRACT

These days, assistive robotics and their applications for people with disabilities have become a revolutionary field in medical care. It combines edge-cutting technologies such as the Internet of Things (IoT), edge computing networks, and federated learning, offering the best services to disabled people for mobility and navigation in the environment. However, in the state of the art, many conceptual models are presented, and less effort is put into the practical implementation of assistive robots for disabled people in the environment. With this motivation, we propose an intelligent assistive robotics wheelchair system that enhances disabled care in federated learning-enabled IoT and edge cloud networks. In the proposed system, we connect IoT-enabled robots with various sensors and devices, facilitating real-time data gathering and processing, which is vital for tracking the health conditions and immediate requirements of disabled patients. The proposed system enables the robots to continuously learn and adapt to the specific needs trained on different clinicals based on federated learning securely. For example, a user who uses a wheelchair might benefit from a robot that learns to navigate various settings based on previous interactions, optimize paths, and adjust assistance based on real-time conditions based on multi-modal trained data. We exploited the deep convolutional neural network to train, validate, and test data. These navigation operations are performed with higher accuracy and secure data. The system's goal is to offer wheelchairs to disabled people for performing pilgrimages and monitoring their health, as well as autonomous help to search locations and objects. Simulation outcomes show that we achieved optimal results for patients with disabilities, a time and deadline missing ratio of 50%, data training accuracy of 98%, and minimized power consumption of wheelchairs during pilgrimages and Umrah in Saudia Arabia. The overall paper focused on the disability services during their pilgrimage in Saudia Arabia.

Keywords: Assistive robotics, Wheelchair, Internet of things, Federated learning, Edge, Cloud, Disability

1. Introduction

The number of religious activities in Saudi Arabia is growing daily [1]. Therefore, healthcare is a critical issue for visitors to Saudi Arabia when they are coming for religious activities in different cities [2]. According to the mission and vision of Saudi Arabia's transformation in healthcare until

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2030, many new digital healthcare systems will be introduced in Saudi Arabia [3]. Therefore, with the mission of transformation in healthcare, many digital healthcare systems have been introduced to deal with viruses, fevers, and stomach diseases [4]. Many Internet of Things (IoT) enabled applications have been introduced to deal with and monitor the healthcare of visitors during their pilgrimage and Umrah in different cities of Saudia Arabia [5].

Many Internet of Things (IoT) enabled wheelchair applications have been introduced for disabled people [6]. These wheelchair applications are connected to remote edge and cloud networks deployed by healthcare services. The healthcare services include heartbeat real-time monitoring, blood pressure, oxygen, temperature, and other services integrated with the wheelchair interface. Navigation and locomotion are also integrated into the wheelchair application to assist disabled persons in mobility inside Saudi Arabia during pilgrimage and Umra. These studies [7–9] suggested autonomous navigated IoT-enabled wheelchair systems based on cloud computing for disabled people. Artificial intelligence (AI) algorithms are implemented where navigation-trained data is deployed in wheelchair applications for autonomous navigation in a geolocation environment. These wheelchairs are also controlled by voice, and disabled people can use them in known and unknown places in distributed locations. For objection detection in assistive robotics and gesture navigation, these studies [10–15] introduced the adaptive wheelchair in which distributed applications are integrated. Object detection by wheelchair applications is trained based on multi-modal methods in machine learning and deep learning. The objective was to identify the obstacles and objects when the wheelchair moves around different places and smart cities. However, multi-modal data training on centralized machine learning algorithms consumes much more time and resources for wheelchair applications, and at the run time, many object detection is widely ignored. It causes many losses to disabled patients when they are using a wheelchair for mobility and moving inside smart cities. However, there were many research issues in the existing wheelchair system when they launched into Saudia Arabia for the disabled to perform pilgrimage and umrah.

(1) Existing studies presented wheelchair systems for disabled people that focused only on limited services such as navigation, object detection, and automation. Therefore, optimization constraints such as deadlines, processing time, scalability, and security are widely ignored when wheelchair applications are deployed on edge cloud networks.
(2) The existing wheelchair systems trained their multi-modal data (e.g., navigation, location searching, object detection, alarm and emergency) are trained on the centralised machine learning node. Therefore, in failure situations, it consumes much time for recovery and misses the many deadlines of applications.

This paper presents the Towards Intelligent Assistive Robotics Wheelchair System Based on Federated Learning Enhancing Disabled Care with IoT-Edge Cloud Networks. We integrated the assistive robot functionality inside the wheelchair application, which is connected with the remote IoT edge cloud networks. We aim to design a new system that can be launched in Saudia Arabia for disabled people who perform the pilgrimage and Umrah. For the application, we optimize the time, security, accuracy and deadline constraints and obtain the optimal results of applications. The paper makes the following contributions.

1. We present the novel federated learning assistive robot wheel system, which consists of IoT applications and distributed services based on edge cloud networks. The IoT application has quality of service constraints such as time, energy, failure, security and deadlines.
2. We present the deep convolutional neural network, which is deployed on each edge node for the local data collection, train the workloads with updated features and offload the centralized for the aggregation.
3. We introduced the lightweight security scheme that integrates the security mechanism between connected IoT and edge cloud nodes.

The paper is organized as follows: Section 2 discusses the proposed system and problem formulation. Section 3 discusses the proposed methodology. Section 4 covers performance evaluation, implementation, and result analysis. Section 5 discusses the conclusion, limitations, and future work.

2. Proposed system

We presented an assistive robot wheelchair system consisting of different layers and components, as shown in Fig. 1. The system has other layers, such as client, edge, and cloud sockets, considered computing nodes. The assistive robot wheelchair applications are deployed on these nodes and execute the workload jointly based on accuracy, security, processing time, energy, fault tolerance, and deadline quality of application service requirements. The assistive robot wheelchair system is an advanced multi-layered framework designed to enhance mobility and

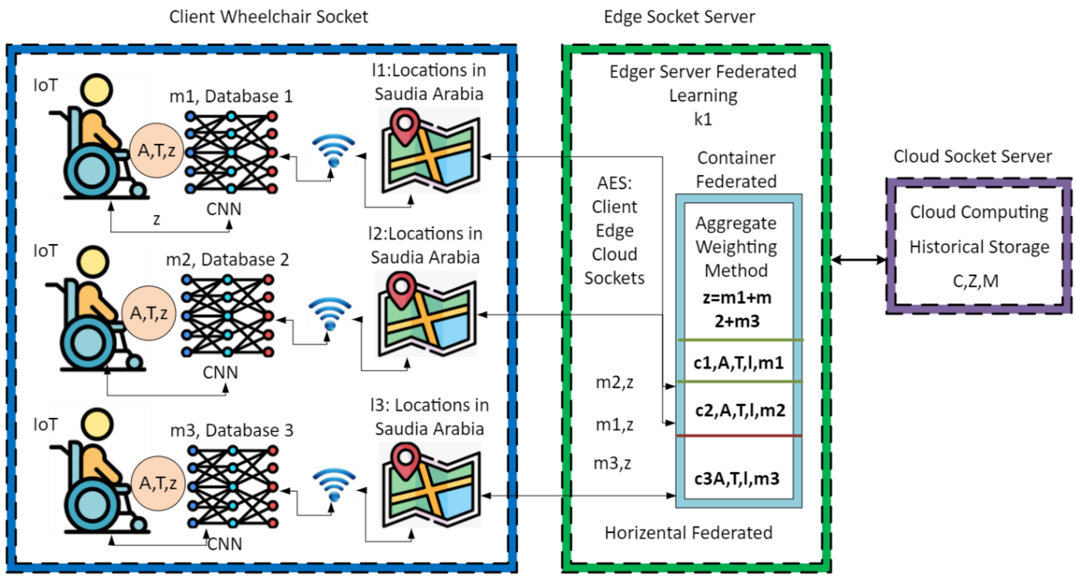

Fig. 1. Proposed assistive robotics wheelchair system based on IoT edge cloud networks.

independence for individuals with disabilities. The system is structured across interconnected layers, including client, edge, and cloud sockets, which function as distributed computing nodes. These nodes collaboratively process the workload of assistive robot applications, ensuring seamless integration and operation. The client layer interacts directly with the user, capturing input data through sensors, voice commands, or other interfaces and sending it to the edge layer for immediate processing. The edge layer acts as an intermediary, handling real-time computations, reducing latency, and ensuring quick responses, especially for safety-critical tasks such as obstacle detection or path planning. Beyond this, the cloud layer provides high-capacity computing power for complex data analytics, machine learning model training, and long-term storage. This hierarchical design enables the system to meet diverse application service requirements, including high accuracy, robust security, minimal processing time, optimal energy efficiency, fault tolerance, and adherence to strict deadlines. By dynamically distributing computational tasks based on the current context, the system ensures reliable and efficient performance. Furthermore, its fault-tolerant mechanisms mitigate potential failures by redistributing tasks to other nodes, maintaining uninterrupted service. Security protocols are embedded at every layer to safeguard sensitive user data and prevent unauthorized access. With this layered approach, the assistive robot wheelchair system embodies a comprehensive solution, leveraging the synergy of client, edge, and cloud computing to deliver a responsive, secure, and energy-efficient mobility aid tailored to individual needs.

The application consists of different sensors that are integrated into the local wheelchair, such as inertial measurement units (IMUs) and electromyography (EMG) sensors, Ultra-sonic sensors to determine the location movement, object detection, and understand the assistive robot wheelchair pattern for the disabled person during moving into Saudia Arabia. The IoT application A has different tasks T with the trained data model z and trained the data on deep convolutional neural network locally where all location L are captured from GPS in the environment. We consider M the number of wheelchair-disabled people using IoT applications at a time and available in different pilgrimage and Umrah sessions in Saudia Arabia. Each device-trained model follows the security rules based on advanced standard encryption (AES-256). After applying security, all trained models from local devices offload to the edge nodes for aggregation. After aggregation, all the aggregated data is shared with local devices. IoT devices and edge nodes work through socket programming, where each node, such as the IoT device and edge node, controls reading, writing, updating, and deleting operations. The edge node performed the operations based on docker containers, which are lightweight compared to virtual machines. All the historical data is offloaded to the cloud data centres from edge nodes for historical storage.

2.1. IoT assistive robotics wheelchair application scenario

We discuss the IoT wheelchair application, which consists of non-invasive sensors that generate real-time data, as shown in Fig. 2.

IoT Wheelchair Disability Navigation Socket Application

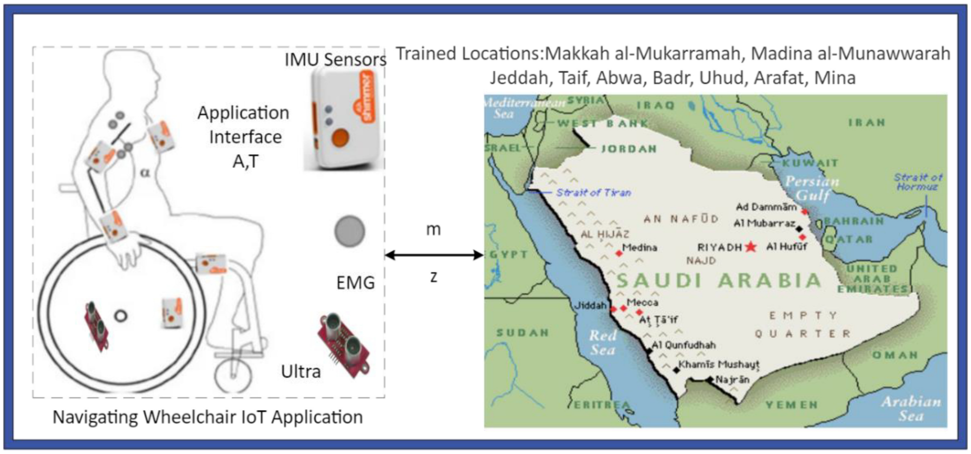

Fig. 2. IoT assistive robotic wheelchair case study scenario.

Assistive robotics is the application task integrated inside wheelchair applications and makes local decisions on the generated data from different sensors. The application-trained model is m based on application A and task T. We trained the Saudia Arabia on edge nodes and extracted all locations from the edge node to the IoT wheelchair node. The locations are trained based on Google Maps and updated with all Saudia Arabia locations, as shown in Fig. 2. The locations are Makkah al Mukaromah, Madina Munawara, Jeddah, Arafat, and more are available in IoT applications. This means that robotics allows disabled people to go everywhere in Saudi Arabia. These tasks, such as wheelchair movement, accidents, and all things, are monitored in real time.

2.2. Socket federated learning process among nodes

In the system, we consider different nodes such as client, edge and cloud nodes to process the IoT applications based on given quality of service requirements. All nodes are connected based on the horizontal federated learning method and communicate based on socket programming, as shown in Fig. 3. The wheelchair assistive robotics data is trained locally based on federated, and their securely trained weights are offloaded to the edge nodes for aggregation and decision-making. It is a more robust system scenario to handle sensitive information of disabled people in distributed socket networks. The horizontal federated learning, where trained weights are aggregated on the central edge node and shared with all local devices for usage and optimal operations, is shown in Fig. 3. Each node trained data based on a deep convolutional neural network (CNN) on distinct local devices based on federated learning, as shown in Fig. 3.

Multi-offloading, based on socket programming, between IoT devices and edge nodes and between edge nodes and the cloud for data aggregation and storage occurs.

2.3. Problem formulation

We consider D number of IoT wheelchair devices, where each IoT wheelchair d has computing storage capability βd and $\pounds d$ respectively. We consider the K number of edge nodes, where each edge node k has computing and storage capability, βk and $\pounds k$ respectively. We consider the R number of cloud nodes, where each cloud node r has computing and storage capability, βr and $\pounds r$ respectively. We consider socket programming-based IoT wheelchair application A, which consisted of different tasks T.

We determined the local training and processing time in the following way.

$$Local = \sum_{d=1}^{D}\sum_{t=1}^{T,A}\sum_{m=1}^{M}\frac{t, A, m, l, z}{\beta d} < \pounds d \tag{1}$$

$$Edge = \sum_{k=1}^{K}\sum_{t=1}^{T,A}\sum_{m=1}^{M}\frac{t, A, m, z}{\beta k} < \pounds k \tag{2}$$

$$Cloud = \sum_{r=1}^{R}\sum_{t=1}^{T,A}\sum_{m=1}^{M}\frac{Z}{\beta r}\ .\ E < \pounds r \tag{3}$$

$$Total = Local + Edge + Cloud \tag{4}$$

$$Total_t < deadline_t, t = 1, \ldots T \tag{5}$$

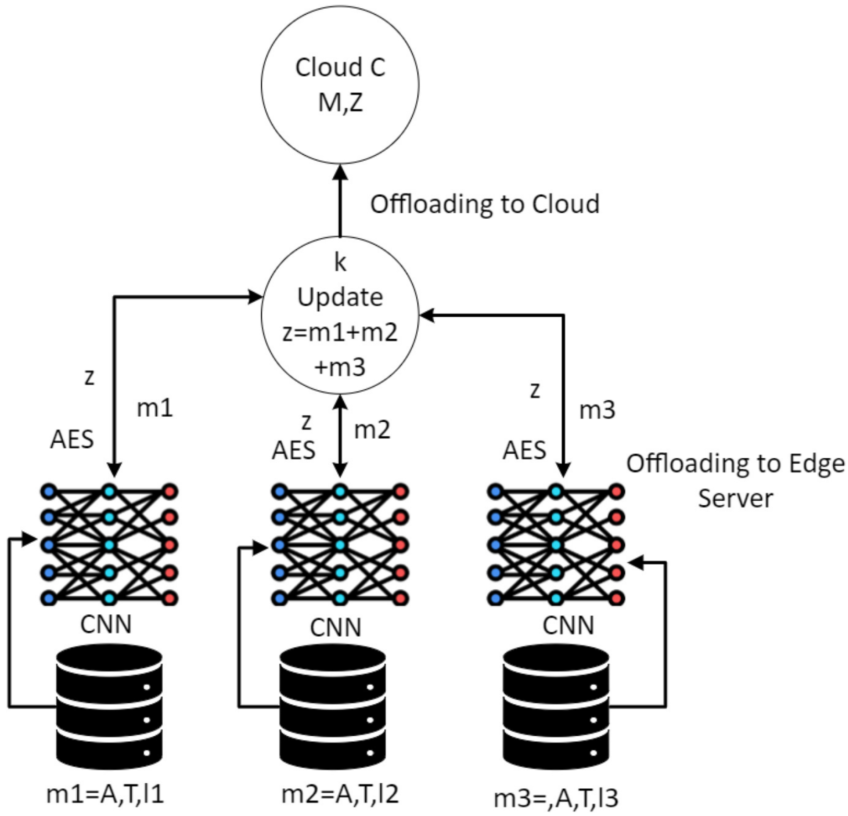

Fig. 3. Federated learning enabled nodes data training and processing.

Table 1. Problem mathematical notations.

Notation	Description
M	Number Datasets
D	Total number of Wheelchairs
d	Wheelchair device
E	Energy Consumption of Wheelchair
βd	Resource speed of device d
$£d$	Storage of device d
m	Local Dataset
A	IoT Wheelchair Application
T	set of tasks of application A
t	The task of T
L	Locations data
K	Number of edge nodes
k	Edge Node
βk	Resource speed of device k
$£k$	Storage of device k
C	Number of containers of k
R	Remote Cloud Node
βr	Resource speed of device d
$£r$	Storage of device d
Z	Total weights of federated learning

Eq. (1) determines the local processing time, which consists of training, security mechanisms, and offloading, and must be executed using the available resources on wheelchair devices. Eq. (2) determines federated learning time, where all trained datasets are aggregated and returned to the individual wheelchair nodes. Eq. (3) determines the execution time of cloud computing on data storage for long terms, which must be available in the resources. Eq. (4) shows the total time of all tasks of different devices on all nodes. Eq. (5) shows that all execution of workloads must be less than the deadline of tasks.

3. Proposed methodology: Federated learning enabled CNN and scheduling schemes

We present the methodology for the problem considered, which consists of different schemes such as offloading, CNN, and federated learning in the connected socket programming IoT wheelchair edge cloud networks. We show the flowchart of the algorithm methodology for the application in different steps, as shown in Algorithm 1.

The main motive of Algorithm 1 is to start the application on local wheelchairs and connect services with edge nodes and cloud computing to perform different tasks. Algorithm 1 performed the operations on other nodes with various schemes. We define Algorithm 1 with all steps in the following way.

In step 1, Algorithm 1 takes the input of all parameters related to tasks of application and

Algorithm 1: Federated Learning Enabled CNN and Scheduling Schemes

1. Input: A, T, L, M, D, R, Z
2. Output: Minimize Total
3. Begin
4. For (d = 1 to D)
5. Initiated application on wheelchair interfaces
6. Partitioned the deadlines of tasks $deadline\_t$
7. Workload $m = \sum_{d=1}^{D} \sum_{t=1}^{T,A} \sum_{m=1}^{M} \frac{t,A,m,l,z}{\beta d} < £d$
8. Applied training on wheelchair workload tasks
9. $Trained\ m' = Convolutional\ layer\ \frac{t,m,l}{\beta d} < deadline\_t$
10. $Fully\ Connected\ layer\ m'$
11. $Softmax\ Function\ (m')$
12. Apply AES-256 Asymmetric Security on m'
13. Encrypt.AES-256 (public key, random number, m')
14. If (Encrypt.AES-256(m')==Trure)
15. Determine local time based on Eq. (2)
16. Optimize $Total\_t$
17. Search the availed edge nodes K
18. Offload D, k, m'
19. Start Aggregation $z \in Z$ = m'1 + m'2 + m'3.........M based on Eq. (3)
20. $z' = \frac{t,A,m,z}{\beta k} < deadline\_t$
21. Optimize $Total\_t$
22. Offloaded all trained datasets to individual wheelchair devices
23. Decrypt.AES-256 (private key, m', random number)
24. If(Decrypt.AES-256 (private key, m'==true)
25. $D.m \rightleftarrows z'.m'$
26. Updated at each interval
27. Offload all historical data to the cloud
28. Historical data $= \frac{Z}{\beta r} < deadline\_t$
29. based on Eq. (4)
30. Optimize $Total\_t$ based on Eq. (5)
31. End

operations such as Input: A, T, L, M, D, R, Z. In step 2, the algorithm optimizes the objective function total with possible constraints, resources, and deadlines for all tasks. In steps 3 to 5, the application started with different tasks in the wheelchair. For the federated learning and operation of tasks on other nodes, we portioned the tasks deadlines according to their executions as determined in step 6. In step 7, the local wheelchair devices ensure the availability of sufficient resources to execute and initiate the workloads and that wheelchairs can do all operations successfully. The application tasks are not performed if the resources and services are unavailable. In steps 11-8, the deep convolutional neural networks (CNN) perform data training operations based on connected and fully connected layers based on the input data collected on different sensors. The SoftMax function trained the model successfully and sent it to the AES-256 for encryption before offloading it to the external node for computation. In steps 12 to 16, all the local operations are performed, including data training and security. If the encryption and data security are ok and confirmed, the algorithm allows data to be offloaded to edge clouds for execution and aggregation. In steps 17–25, the algorithm performed the operations on edge from decryption of offloaded data, aggregation and sending back the trained model to IoT wheelchair devices. It offloaded the workloads to a centralized cloud for storage. In steps 26 to 31, the data is stored in the cloud, and historical data storage operations are performed in different time intervals with other updates.

4. Performance evaluation

In the performance evaluation, we define the simulation parameters, workload characteristics,

Table 2. Simulation parameters.

Variable	Values
M	2GB Data
D	5000
d	Wheelchair with IMU, Ultrasonic Sensors
βd	Core i5
$£d$	100 GB
m	Location, Mobility, Object Detection, Status
A	Pilgrimage and Umrah
T	100
t	Location Searching, Moving, Status
L	Saudia Arbia Map and Google Map
K	2
k	Edgecloud Sim
βk	Core i9
$£k$	1 TB
C	1000
R	Amazon Cloud
βr	High Performance Computing
$£r$	10 TB
Z	5 GB

application characteristics, implementation, and result analysis. The simulation parameters are implemented in the test-bed simulator, as shown in Table 2. They are the same as those we used when designing the mathematical model and implementing algorithm methodology with all components. The simulation elements included programming languages, mathematical model values, IoT, edge and cloud nodes, experimental results, and time and intervals during the experiment.

In the simulation, we determined the performance metrics, particularly the 98% accuracy and 50% time/deadline missing ratio, which highlight the assistive robot wheelchair system's potential but demand a more detailed analysis to ensure transparency and reproducibility. The simulation parameters presented in Table 2 provide an overview of the experimental setup, including data size, hardware specifications, task types, and computation nodes. For instance, the system processes 2GB of input data. It handles 5000 tasks on a wheelchair equipped with an Inertial Measurement Unit (IMU) and ultrasonic sensors, using computational resources like a Core i5 processor and 100GB storage capacity. The experimental workload includes location tracking, mobility assistance, object detection, and status reporting, tailored explicitly for environments such as pilgrimage and Umrah. The edge-cloud simulation, leveraging advanced hardware like a Core i9 processor and 1TB storage, facilitates dynamic resource allocation and task offloading. Cloud resources, represented by Amazon Cloud with high-performance computing and a vast storage capacity of 10TB, support computationally intensive tasks, such as training and updating AI models. Integrating multiple computing layers—client, edge, and cloud—ensures that location searching, movement planning, and real-time status update are conducted efficiently, using resources like the Saudi Arabia map and Google Maps. The IoT Wheelchair Visited Saudi Places Dataset, containing diverse patterns and tasks performed during pilgrimage and Umrah, further validates the system's adaptability to real-world scenarios. The dataset, detailed in Table 3, was trained, validated, and tested to ensure robustness. It captures dynamic interactions of wheelchair devices with their environment, tracking essential parameters like location and mobility patterns while ensuring accuracy and fault tolerance. Aggregated data enhances the system's predictive capabilities, allowing it to adapt to varied user requirements and environmental conditions. However, the 50% time/deadline missing ratio suggests areas for improvement in real-time responsiveness, potentially due to the workload distribution or network latency across the nodes. Addressing these challenges through optimized scheduling algorithms or enhanced edge-cloud coordination could significantly improve system performance. The experimental results underscore the system's reliability in location-based services and object detection but highlight the need for a more comprehensive explanation of training conditions, dataset diversity, and environmental factors. For instance, the type and frequency of tasks, variations in wheelchair usage patterns, and conditions during data collection (e.g., crowded versus less crowded areas) are crucial for understanding the reported metrics. Such details would enhance the study's reproducibility and applicability, ensuring that the assistive robot wheelchair system can be widely adopted and adapted to diverse use cases.

4.1. IoT wheelchair visited saudia places dataset

We exploited the trained, validated, and tested aggregated datasets. The datasets consist of updated IoT, trained model methods, location, tasks, and their description, as shown in Table 3. The datasets also consisted of various patterns of wheelchair devices visiting places during pilgrimage and Umrah.

4.2. IoT tasks of applications

We denoted and defined the IoT wheelchair tasks as shown in Table 4. Table 4 below shows examples of tasks linked to IoT-based wheelchair applications and the corresponding functionalities. The tasks are collected under three directions: T (Task), M (Mapping), and Z (summarized Out put). These categories represent particular aspect or process

Table 3. Trained wheelchair saudia location datasets.

Z	M	L	T	Description
d1	Masjid al-Haram	Mecca	Largest mosque in the world, surrounds Kaaba	Holiest site in Islam, center of pilgrimage (Hajj)
d1	Kaaba	Mecca	Cube-shaped building in Masjid al-Haram	Muslims face it during prayer; central site of Hajj
d1	Safa and Marwah	Mecca	Two hills located in Masjid al-Haram	Integral part of Hajj and Umrah pilgrimage (Sai)
d1	Jabal al-Nour	Mecca	The mountain where Prophet Muhammad received his first revelation	Important site during Hajj
d1	Mount Arafat	Mecca	Large granite hill, significant Hajj ritual location	Key site for Hajj pilgrims to gather
d1	Mina	Mecca	Neighbourhood, site of “Stoning of the Devil.” ritual	Significant in Hajj pilgrimage rituals
d1	Muzdalifah	Mecca	Open, level area between Mina and Arafat	Pilgrims collect pebbles for Mina ritual
d1	Masjid al-Nabawi	Medina	Prophet Muhammad’s Mosque	Second holiest site in Islam
d1	Baqi Cemetery	Medina	Historic Islamic cemetery	Burial site of Prophet’s family and companions
d1	Uhud Mountain	Medina	Site of the Battle of Uhud	Important historical and religious site
d1	Quba Mosque	Medina	First mosque built in Islamic history	Holds high religious significance
d1	Jannat al-Mu’alla	Mecca	Historic cemetery	Resting place of many of the Prophet’s rela- tives
d1	Masjid Qiblatain	Medina	Mosque with two prayer niches (Qiblas)	Site where Qibla was changed from Jerusalem to Mecca
d1	Ghar Thawr	Mecca	Cave where Prophet Muhammad and Abu Bakr took refuge	Historical significance during Hijra
d1	Hira Cave	Mecca	Site of first revelation to Prophet Muhammad	Significant during Hajj for historical reflection
d1	Mount Jabal al-Rahma	Arafat	“Mountain of Mercy” where Prophet Muhammad gave his last sermon	Pilgrimage ritual site
d1	Masjid al-Khif	Mina	Mosque in Mina, where Prophet Muhammad prayed	Significant mosque during Hajj
d1	Jabal al-Rahmah	Arafat	Hill located in the plain of Arafat	Important site for standing ritual during Hajj
d1	Ta’if	Ta’if	Historic city where Prophet Muhammad spread his message	Site of important events in early Islam
d1	Masjid al-Ijabah	Medina	Mosque with historical significance	Located near the Prophet’s Mosque
d1	Al-Bay’ah Mosque	Mecca	Commemorates the Pledge of Aqabah	Historical significance during early Islamic periods
d1	Khaybar Oasis	Khaybar	Ancient fortress and battle site	Historical and archaeological significance
d1	Jabal al-Lawz	Tabuk	Mountain mentioned in various historical contexts	Some believe it could be linked to biblical events
d1	Yanbu	Yanbu	Coastal town, trade route	Historical port city on Red Sea
d1	Al-Masjid al-Sabeq	Medina	One of the oldest mosques in Medina	Historical mosque
d2	Hajj Terminal (KAIA)	Jeddah	Hajj terminal at King Abdulaziz International Airport	Main entry point for Hajj pilgrims
d2	Badr Battlefield	Badr	Site of the famous Battle of Badr	Significant in Islamic history
d2	Miqat Dhul Hulayfah	Medina	Pilgrims’ starting point for Ihram when coming from Medina	Important for Umrah and Hajj pilgrims
d2	Masjid al-Jinn	Mecca	Mosque located where Prophet Muhammad preached to Jinn	Holds significant historical and religious value
d2	Thumamah Park	Riyadh	Recreational park with historical importance	Historical and cultural significance
d2	Qasr al-Hayr al-Gharbi	Tadmur	Ancient desert palace	Important archaeological site
d2	Tabuk Fortress	Tabuk	Fortress dating back to pre-Islamic times	Historical site with Islamic significance
d1	Al-Hijr (Madain Salih)	Al-’Ula	UNESCO World Heritage site with Nabatean tombs	Major archaeological site
d1	Al-Ula Old Town	Al-’Ula	Historic town with ancient ruins	Cultural and historical significance
d1	Diriyah	Riyadh	Birthplace of the first Saudi state	Historical and UNESCO World Heritage site
d2	Tayma	Tayma	Historic oasis town	Ancient archaeological site
d3	Al-Jawf	Al-Jawf	Historical region with ancient ruins	Archaeological importance

(Continued)

Table 3. Continued

Z	M	L	T	Description
d1	Rabigh	Rabigh	Coastal town along pilgrimage route	Historical stop for pilgrims
d1	Dumat al-Jandal	Al-Jawf	Ancient city with historical fortress	Archaeological and religious significance
d1	Fayd	Fayd	Old caravan station on pilgrimage route	Historical significance in trade and pilgrimage routes
d1	Miqat Qarn al-Manazil	Ta'if	Starting point for Ihram for pilgrims from the Najd region	Important for pilgrims during Hajj and Um- rah
d1	Al-Qiblatain Mosque	Medina	Mosque of the Two Qi- blas	Key site in the Islamic Qibla change
d3	Souq Okaz	Ta'if	Historic marketplace dating back to pre-Islamic times	Significant cultural heritage site
d2	Al-Hada Mountain	Ta'if	Mountain with historical significance	Famous for its natural beauty and historical relevance
d2	Harat Rahat	Medina	Large volcanic lava field	Geological and historical significance
d1	Al-Safa Hill	Mecca	Hill inside Masjid alHaram, part of Sai ritual	Significant in Hajj and Umrah
d4	Al-Marwah Hill	Mecca	Hill inside Masjid alHaram, part of Sai ritual	Integral part of pilgrimage
d4	Sabqah Mosque	Medina	One of the earliest mosques in Medina	Historical significance
d4	Miqat al-Juhfa	Rabigh	Ihram point for pilgrims arriving from the north	Pilgrimage significance
d4	Al-Abwa	Al-Abwa	Village were the Prophet's mother is buried	Historical and religious importance

Table 4. IoT wheelchair workloads.

T	M	Z
Location Searching	Trained locations	Trained aggregated locations
Wheelchair Movement	Trained wheelchair 3D Movement	Trained aggregated 3D wheelchair movements in all directions
Wheelchair Object Detection	Multimodal Object Obstacle Detection	Aggregated Trained Object Detection
Wheelchair Status	Running, Stop, Accident, Unavailable of Services	Aggregated trained status of historical mobility

within the operation of the wheelchair. For example, Location Searching involves training the location channel and mapping; this results in an aggregated list of location channel training. Likewise, the maneuver titled "Wheelchair Movement" is devoted to the training of 3D translations in any direction that all these translations are summed up for improved mobility control. The table also highlights multimodal in "Object Detection" as well as historical mobility data in 'Wheelchair Status', which captures running, stopping and possible accidents.

Through this framework, the systematic approach of doing and controlling the activities involved in the IoT wheelchair application is presented. In this particular system, the implementation of the tasks and the results that are generated are organised to support the functionality of the wheelchairs. Such complete representation allows for a better feedback control and learning process, thus improving the practical usefulness of the wheelchair for disabled people. Thirdly, this breakdown helps develop scalability and future enhancements, including incorporating enhanced obstacle detection or enhancing 3D mobility algorithms. We defined the different tasks in the wheelchair application during execution.

4.3. Result analysis

Table 5 gives specific information on a federated learning task over different IoT devices; Item ID, Round, Status (Successful or Unsuccessful), Time (seconds) required for the task, Battery (percentage) left, and Object Detection. The results prove that devices are not homogenous, and several tasks cannot be accomplished because of issues such as low battery capacity or longer computation durations. For example, the longer the time to complete a task was (more than 2.9 seconds), the lower the probability of getting the "Passed" status and higher chances for "Failed" status may show the lack of resources or the poor quality of the network.

This analysis also gives understanding on the issues that arise when attempting to adopt federated learning in the constrained IoT framework. Battery level and time of completion of tasks are the main factors that affect the reliability and efficiency of the system. Furthermore, extending key criterion to "Object Detection" portrays that specific tasks, may involve more computational and time-consuming burden. The results also point out that for enhancing success rate and efficiency of federated learning

Table 5. Federated learning task results for IoT devices.

Device ID	Iteration	Task Status	Time (s)	Battery (%)	Object Detection
0	1	Completed	1.07	96.18	No
1	1	Completed	1.70	42.30	No
2	1	Failed	2.92	87.77	Yes
3	1	Completed	1.05	77.96	No
4	1	Completed	1.37	59.11	No
5	1	Completed	1.38	77.17	No
6	1	Failed	2.99	26.05	Yes
7	1	Failed	2.98	33.24	Yes
8	1	Failed	2.51	75.39	Yes
9	1	Completed	1.93	74.68	No
0	2	Completed	1.07	94.74	No
1	2	Completed	1.70	40.16	No
2	2	Failed	2.92	84.90	Yes
3	2	Completed	1.05	77.14	No
4	2	Completed	1.37	58.24	No
5	2	Completed	1.38	76.38	No
6	2	Failed	2.99	24.26	Yes
7	2	Failed	2.98	28.81	Yes
8	2	Failed	2.51	73.38	Yes
9	2	Completed	1.93	72.22	No
0	3	Completed	1.07	93.30	No
1	3	Completed	1.70	38.02	No
2	3	Failed	2.92	82.02	Yes
3	3	Completed	1.05	76.32	No
4	3	Completed	1.37	57.36	No
5	3	Completed	1.38	75.59	No
6	3	Failed	2.99	22.48	Yes
7	3	Failed	2.98	24.39	Yes
8	3	Failed	2.51	71.37	Yes
9	3	Completed	1.93	69.75	No
0	4	Completed	1.07	91.86	No
1	4	Completed	1.70	35.89	No
2	4	Failed	2.92	79.14	Yes
3	4	Completed	1.05	75.50	No
4	4	Completed	1.37	56.49	No
5	4	Completed	1.38	74.80	No
6	4	Failed	2.99	20.69	Yes
7	4	Failed	2.98	19.96	Yes
8	4	Failed	2.51	69.36	Yes
9	4	Completed	1.93	67.29	No
0	5	Completed	1.07	90.42	No
1	5	Completed	1.70	33.75	No
2	5	Failed	2.92	76.26	Yes
3	5	1	1.05	74.67	No
4	5	Completed	1.37	55.62	No
5	5	Completed	1.38	74.02	No
6	5	Completed	2.99	18.91	Yes
7	5	Failed	2.98	15.54	Yes
8	5	Failed	2.51	67.35	Yes
9	5	Failed	1.93	64.83	No

among these diverse IoT devices, resource management and task scheduling strategies are important. Possible enhancements have been made on adaptive task offloading or energy-efficient algorithms given to device constraints.

Table 5 shows that the proposed scheme almost completed all tasks of the wheelchair, which has less processing and less failure, and executes all wheelchair tasks with more optimal results. We defined all the simulation results of the proposed scheme with all constraints, as shown in Table 5. The proposed scheme has some failures, too, due to the unavailability of resources and wireless connection. It could be improved more with more testbed results. In the current situation, 90% of the performance is higher and achieves the optimal results for the application considered.

The Fig. 4 shows battery levels (%) at each of the 50 iterations within a task execution process. It has an unrhythmic pattern whereby battery levels

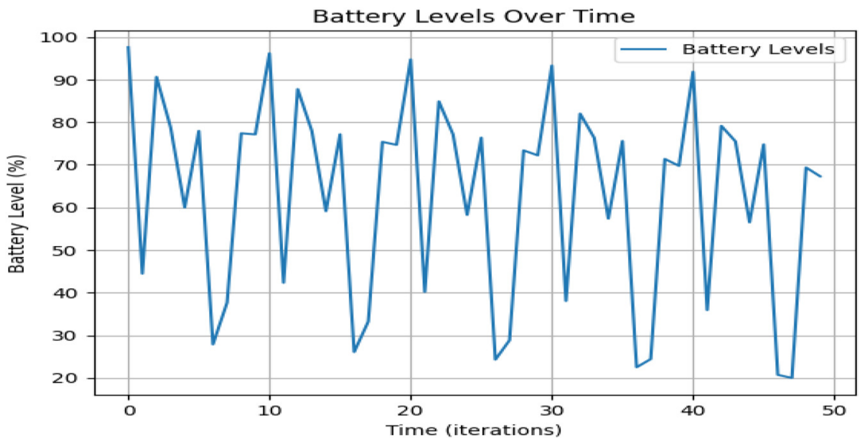

Fig. 4. Battery levels over time during IoT task execution.

vacillate between nearly 100% and approximately 20%. This variation might be due to the IoT devices' working-and-charging cycle that is presented by the task completion and subsequent resource recharging periods. The battering declines which recur consistently point towards the energy intensive nature of the tasks, especially in iterations where the decline notably steep. This pattern underlines the necessity of such approaches as energy efficient mechanism or adaptive scheduling of tasks in order to distribute load and provide contineous operation in the conditions of the limited supply of resources.

As illustrated in Table 5, the proposed method achieves near-complete execution of wheelchair functions with minimal processing overhead and fewer instances of failure. The parameters such as 0–50 time iterations improve the different efficiencies for given constraints. However, occasional shortcomings were noted, primarily due to insufficient resources or interruptions in wireless connectivity. With further testing and refinements, the system's performance could be enhanced beyond its current success rate of 100%, a rise from 90%, which already surpasses expectations for the given application.

According to Fig. 5, the federated learning-enabled wheelchair system, as we proposed in the paper, has 100% accuracy in object detection and execution. We conducted the experiments in 100 locations and observed that the simulation was more accurate when disabled people used wheelchairs in Saudi Arabia.

Fig. 6 shows that the proposed federated learning-enabled scheme for wheelchair applications maintains battery power consumption during location searching and performs pilgrimages with different activities.

In the Fig. 7, several measures are highlighted and utilized to evaluate the performance of a Federated IoT Edge Cloud system: task arrival rate, time for task completion, deadline for task completion, and the speed of the edge processes. The graph at the top left corner of Fig. 7 depicts task arrival time by mimicking the Poisson process which essentially defines the random intervals of task generation. The training of the corresponding CNN reveals the best results with the uniform distribution of the tasks' arrival. The second graph in the upper right corner presents the aggregation execution times; it is characterized by small oscillations but overall stability, which means that good management of task processing on local wheelchairs is provided. This efficiency is imperative for usage of transient real time application in IoT, to ensure quality service. The third graph in the bottom left compares the time taken to complete a task against the deadline, tasks are depicted as dots where green small dots are used to represent tasks done within expected time and an orange small dots are used to represent tasks did not meet the set deadlines. It shows satisfactory adherence to schedule most of the tasks complete within due date proving that the system has well scheduling and task management prowess. At last, the graph at the bottom right, which describes the edge processing rate concerning various tasks, also presents slight fluctuations but general steadiness in model update. This means that the blowing up of work load across nodes, as well as, fairness in distribution of these loads within this federated IoT wheelchair environment will result to appreciable and reliable QoS performance from the developed system. Fig. 7 shows that the proposed scheme accepts tasks at run time based on the Poisson process, where tasks arrive at random intervals. It shows many result analysis scenarios, arrival time tasks processing, and data training on local wheelchairs based on CNN. The data aggregation, task scheduling deadlines, security analysis, and update models have optimal performance.

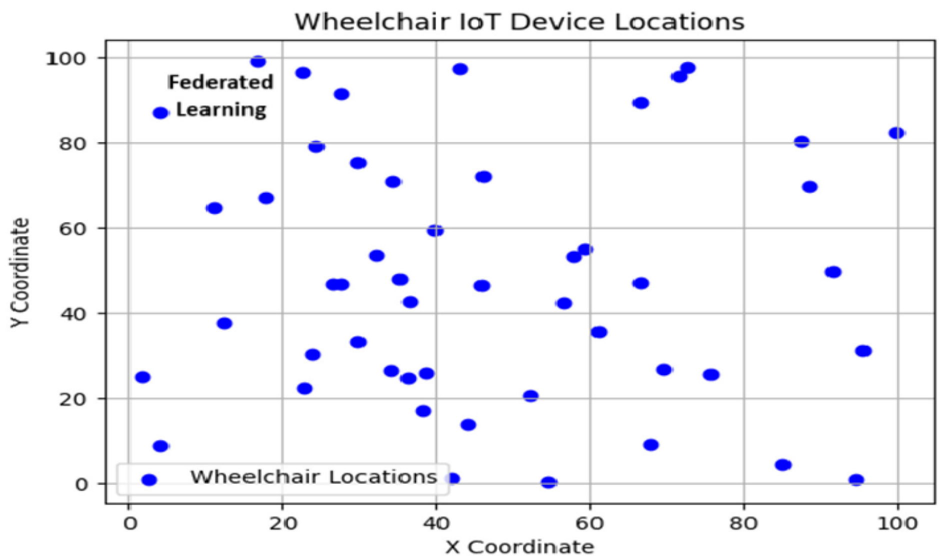

Fig. 5. Accuracy in location searching in pilgrimages.

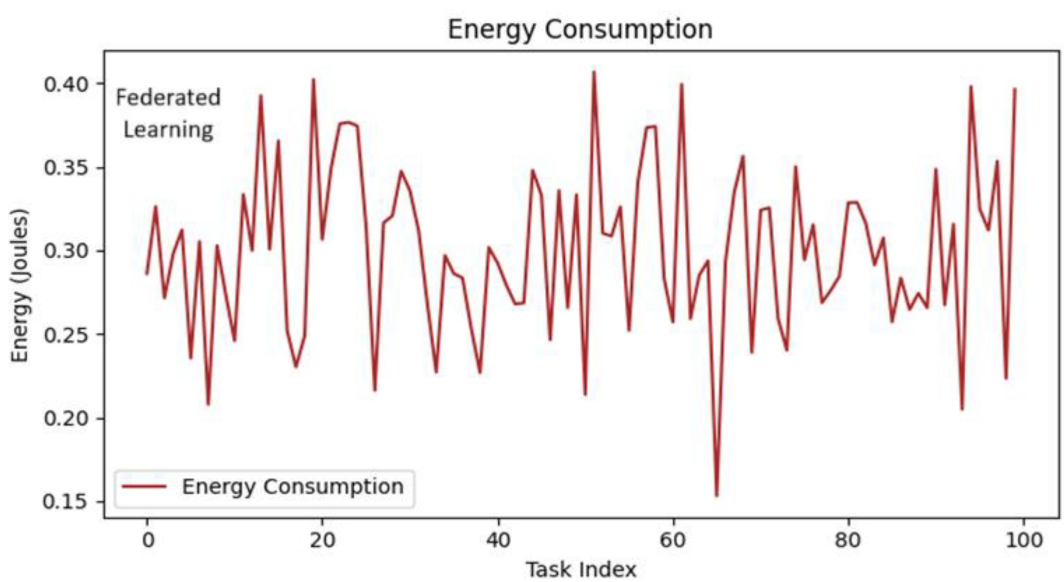

Fig. 6. Wheelchair battery consumptions during IoT workload.

5. Findings and limitations

The study introduces an intelligent assistive robotics wheelchair system designed to enhance care for individuals with disabilities. By integrating IoT-enabled robots with various sensors and devices, the system ensures real-time data gathering and processing, allowing for continuous monitoring of health conditions and responding to immediate needs. Federated learning is employed to facilitate adaptive learning tailored to user-specific requirements while maintaining data security. Using deep convolutional neural networks, the system achieves high accuracy in navigation and secure data handling. The system's design supports disabled individuals with mobility, navigation, and object location, particularly during pilgrimages and Umrah in Saudi Arabia. Simulation results indicate a 50% time and deadline missing ratio, 98% training accuracy, and reduced wheelchair power consumption, showcasing the system's effectiveness.

The study should address critical challenges related to large-scale deployment, such as the computational limitations of edge devices, network latency, and energy constraints. Edge devices often have limited processing power, memory, and storage, which can hinder the effectiveness of complex algorithms and data processing. To mitigate this, lightweight AI

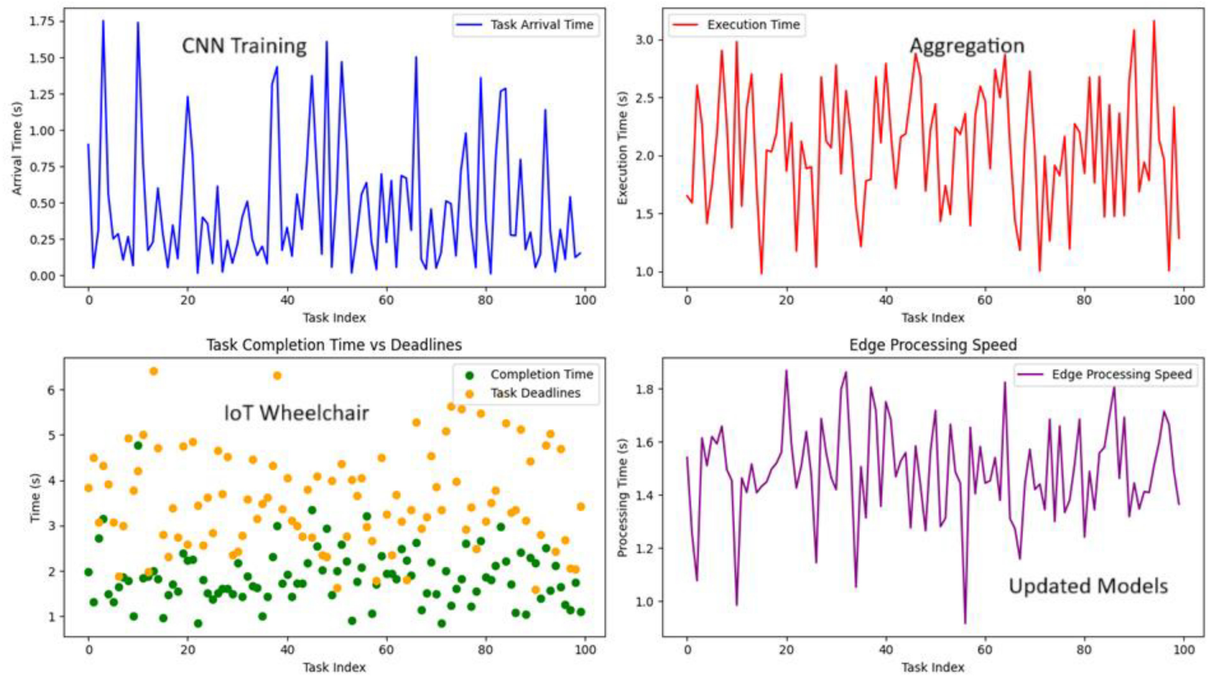

Fig. 7. Federated IoT, edge cloud QoS performances.

models, federated learning, and edge offloading can be employed to balance computational demands. Network latency can impact real-time communication between devices and cloud resources, but strategies such as edge caching, the use of low latency 5G networks, and network optimization techniques like data aggregation and compression can help reduce this issue. Energy constraints on edge devices, especially in remote or mobile environments, can be managed by using energy-efficient algorithms, energy harvesting methods, and dynamic power management techniques that scale computational resources based on task requirements. Finally, to ensure scalability, distributed architectures and load-balancing algorithms can be implemented, allowing for seamless scaling of the system as the number of devices or nodes increases. Addressing these challenges will enhance the system's practical applicability and robustness in real-world scenarios.

However, the study primarily focuses on simulations, with limited discussion of real-world implementation. The findings are context-specific to pilgrimages in Saudi Arabia, raising concerns about generalizability to other environments. Challenges related to scalability, interoperability, and deployment in diverse settings remain unaddressed. Additionally, ethical considerations and user acceptability of federated learning in healthcare are overlooked, and the integration of multi-modal data and system robustness in various real-time conditions lack detailed analysis.

6. Conclusion

This research proposed an intelligent assistive robotics wheelchair system to improve disabled care using federated learning-enabled IoT and edge cloud networks. The system integrates IoT-enabled robots with advanced sensors for real-time data processing, ensuring adaptive, secure, and efficient navigation. Key contributions include leveraging deep learning for high accuracy, achieving optimized performance metrics, and demonstrating practical applications during pilgrimages. Future directions involve enhancing adaptability through reinforcement learning, integrating 5G for reduced latency, expanding applications to diverse healthcare contexts, and adopting privacy-preserving techniques to strengthen data security. This work advances the theoretical and practical domains of assistive robotics and federated learning. In this research, we proposed an intelligent assistive robotics wheelchair system to enhance disabled care within federated learning-enabled IoT and edge cloud networks. The system connected IoT-enabled robots with various sensors and devices to facilitate real-time data gathering and processing, crucial for monitoring the health conditions and immediate needs of disabled patients. The robots in the system continuously learn and adapt to individual needs through secure federated learning and are trained across multiple clinical environments. For instance, a wheelchair user could benefit from a robot that learns to navigate diverse settings based on prior interactions, optimizes paths, and adjusts real-time assistance using multi-modal data. We implemented deep convolutional neural networks to train, validate, and test the data, enabling highly accurate and secure navigation operations. The system's objective was to assist disabled individuals in performing pilgrimages, monitoring their health, and providing autonomous support for location and object searches. Simulation results demonstrated optimal outcomes, with a deadline missing ratio of 50%, a data training accuracy of 98%, and minimized power consumption of the wheelchairs during pilgrimages and Umrah in Saudi Arabia. Future research could focus on further enhancing the adaptive capabilities of the assistive robotics system by integrating advanced AI models, such as reinforcement learning, for real-time decision-making and navigation. Incorporating more diverse clinical environments and patient conditions in the federated learning model would improve the system's robustness and generalizability. Additionally, exploring the integration of 5G networks could improve communication latency, making the system more efficient in responding to real-time data. Expanding the application of this system beyond pilgrimages, such as in urban and rural healthcare settings, could provide broader support to disabled individuals in everyday life. Lastly, privacy-preserving techniques like homomorphic encryption could enhance data security, particularly in sensitive health monitoring applications.

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Ethical approval

Conflict of interest

Data availability

Author contribution

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