Alexandria Engineering Journal 125 (2025) 441–448

Contents lists available at ScienceDirect

Alexandria Engineering Journal

journal homepage: www.elsevier.com/locate/aej

Original article

An improved and decentralized/distributed healthcare framework for disabled people through AI models

Geetanjali Rathee [a], Sahil Garg [b,c,*], Georges Kaddoum [b], Samah M. Alzanin [d], Mohammad Mehedi Hassan [e,f]

[a] Department of Computer Science and Engineering, Netaji Subhas University of Technology, Dwarka Sector-3, New Delhi 110078, India
[b] Electrical Engineering Department, École de technologie supérieure, Montréal, QC H3C 1K3, Canada
[c] Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, 140401, Punjab, India
[d] Department of Computer Science, College of Computer Engineering and Sciences, Prince Sattam bin Abdulaziz University, Al-Kharj 11942, Saudi Arabia
[e] Department of Information Systems, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia
[f] King Salman Center for Disability Research, Riyadh 11614, Saudi Arabia

ARTICLE INFO

Keywords:
Decentralized healthcare system
AI models for disabled people
e-health in Saudi Arabia
AI in healthcare
Saudi vision 2030
Disabled accessibility

ABSTRACT

Access to adequate healthcare is critical for everyone, but people with disabilities often face considerable challenges in receiving reliable and timely medical treatment. The Vision 2030 plan in Saudi Arabia intends to change the healthcare system by incorporating new technologies that increase accessibility, efficiency, and service delivery. However, current healthcare systems continue to suffer from delays, inefficient data processing, and accessibility concerns, especially for the visually impaired. This study proposes a more decentralized healthcare system that uses artificial intelligence (AI) and machine learning (ML) models to improve healthcare services for individuals with disabilities. The system achieves real-time data processing, reduces latency, and enhances decision-making accuracy by combining federated learning and zero-shot architectures. Furthermore, smart technologies such as the Internet of Things (IoT) and natural language processing (NLP) provide seamless data collection and analysis, allowing healthcare practitioners to provide prompt and personalized treatment. The suggested solution solves crucial issues such as inefficiencies in data processing, delays in obtaining medical information, and limits in current healthcare processes. This platform improves impaired people's freedom and mobility by delivering remote healthcare solutions using AI-powered diagnostics and real-time monitoring. This study contributes to a more inclusive and efficient healthcare system in Saudi Arabia by bridging the gap between technology and accessibility, which aligns with the Vision 2030 objective of providing fair healthcare services to everyone.

1. Introduction

Healthcare is one of the most significant sectors for a nation and plays a crucial role in shaping its future and growth opportunities. In a country where people can access online and offline health services, there is a greater potential to improve e-health systems. This is particularly beneficial for individuals with disabilities, as it allows them to acquire medical services more consistently and efficiently [1]. When developing healthcare frameworks or services, it is essential to consider all types of patients, ensuring that the benefits and functionalities of these systems are accessible to everyone. Today, Saudi Arabia is undergoing rapid transformations in multiple sectors, positioning itself as one of the fastest-growing developing nations [2]. The Vision 2030 initiative has driven major policy reforms within the healthcare sector, focusing on privatization, public–private partnerships, and increased foreign investment in medical infrastructure and services. As a central component of this strategic plan, the healthcare sector is being improved through the integration of advanced technologies, innovative methodologies, and strategic initiatives. These efforts not only aim to improve service delivery but also to ensure the availability of skilled healthcare professionals, including nurses and physicians, to meet the growing demand for high-quality medical care. A crucial aspect of improving healthcare services involves addressing the needs of all patients, particularly people with severe health conditions and disabilities [3,4]. Although individuals without disabilities can generally access diagnostic and treatment services with relative ease, people with disabilities often face significant barriers to obtaining routine medical

* Corresponding author at: Electrical Engineering Department, École de technologie supérieure, Montréal, QC H3C 1K3, Canada.
E-mail addresses: geetanjali.rathee123@gmail.com (G. Rathee), sahil.garg@ieee.org (S. Garg), georges.kaddoum@etsmtl.ca (G. Kaddoum), s.alzanin@psau.edu.sa (S.M. Alzanin), mmhassan@ksu.edu.sa (M.M. Hassan).

https://doi.org/10.1016/j.aej.2025.03.010
Received 4 December 2024; Received in revised form 23 February 2025; Accepted 4 March 2025
Available online 22 April 2025

care [5]. Mobility challenges, logistical difficulties, and the need for frequent medical interventions exacerbate these barriers, making real-time access to healthcare services particularly critical for this population. To successfully implement the objectives outlined in Vision 2030, it is essential to incorporate advanced technological tools and mechanisms that facilitate accessible and efficient healthcare services for both disabled and non-disabled individuals. In 2017, Saudi Arabia had an estimated population of 33 million and a Human Development Index (HDI) of 0.84, ranking 39th globally [6]. These indicators highlight the ongoing need for strategic healthcare care management and continuous development efforts to further enhance accessibility and quality of medical services.

1.1. Healthcare facilities for disabled people

Disability is the human condition that an individual faces daily along with limited opportunities for physical activity. According to WHO, approximately 1.3 billion people live with major impairment. People with disabilities have lower health, which requires more care and attention compared to other people. In Saudi Arabia, around 66 000 people have disabilities, including children and young people, which require accurate medical facilities and services. In recent times, the expansion of healthcare services has accelerated in several areas, especially in the health sector [7]. Many studies have shown that the use of new technologies has a great impact on the mental and physical health of people with disabilities. In addition, contemporary technologies can help patient treatment, diagnosis, in a more excited and happier way. despite the advancements and improvement in healthcare, people with disabilities in Saudi Arabia still facing the issues of accessibility, delay and services in acquiring the medical facilities. Emerging technologies such as AI and machine learning can further improve accessibility to medical services with more accuracy and diagnosis on a regular basis.

1.2. Role of AI and ML for disable people in Saudi Arabia

AI-powered technologies, such as medical imaging, information generation, and data analysis, play a crucial role in the early detection and management of severe health conditions. Furthermore, integrating traditional healthcare solutions with AI or ML-assisted schemes, such as prosthetics, aims to improve independence, mobility, and accessibility to medical care from an early stage [8]. Furthermore, real-time monitoring and expert-guided management of critical cases in remote locations can significantly improve the delivery of healthcare services. Although numerous AI/ML-based schemes [9–12] have been proposed by researchers and engineers, real-time processing and access to medical records for efficient data analysis remain insufficient in current studies [13]. In addition, efficient data management and the timely transformation of medical records with minimal delay remain a problem in Saudi Arabia's healthcare sector. The integration of AI/ML models with existing techniques may further improve diagnostic accuracy and enhance the decision-making process, particularly for individuals with disabilities.

However, current studies suffer from several shortcomings, which can be summarized in the following research gaps:

RG1: Lack of efficient data processing — Integration of smart technologies, such as IoT and smart devices, generates vast amounts of medical data. However, existing healthcare data processing solutions often do not adequately address delays in data collection and processing. In addition, the information collected can be susceptible to overloading and communication delays within network infrastructures.

RG2: Need for minimal delay processing schemes — Information generated by smart devices must be processed efficiently to support timely decision making. In real-time scenarios, current mechanisms lack the ability to process data from intelligent devices with minimal delay while maintaining high accuracy.

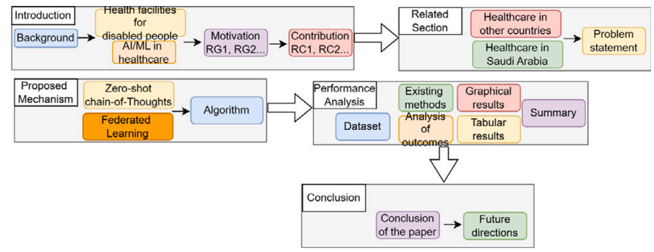

Fig. 1. Complete organization of the paper.

RG3: Improving data accessibility for disabled people — Existing healthcare systems require further improvements to better serve people with disabilities by providing more accurate and accessible health services. Traditional healthcare systems are prone to delays and slow service delivery, highlighting the need to adopt new ML/AI-based approaches to offer greater benefits to disabled individuals.

To address these challenges, this article proposes an efficient communication mechanism with reduced latency and improved accuracy using federated learning schemes. The contributions of this study are further detailed in Fig. 1.

1.3. Contribution

In response to the identified research gaps, this paper makes the following contributions:

RC1: The first contribution of this paper is the implementation of a federated learning model to reduce latency and mitigate network overload while efficiently distributing and communicating information.

RC2: In addition, a zero-shot architecture is introduced to enhance the computational process by minimizing delays. Complex problems and issues are addressed using differential equations, improving overall efficiency and precision in computation within the network.

The remainder of the structure of the paper is discussed as follows. Section 2 presents the existing healthcare systems and mechanisms in Saudi Arabia for the normal and impaired population of the country. Section 3 detailed the proposed framework or mechanism including an AI-assisted technique such as a federated learning scheme to process the information with minimum delay and more accuracy. In addition, Section 4 validates the proposed mechanism in terms of various measuring parameters in comparison with existing techniques and methods. Finally, Section 5 concludes the paper and determines the future directions of the work.

2. Related works

This section explores various AI- and ML-based healthcare systems and frameworks proposed by researchers to improve reliable and efficient communication. The existing literature review is divided into two parts. The first part examines healthcare system improvements in other countries, highlighting various solutions adopted worldwide to improve the growth of the healthcare system. The second part focuses on improving healthcare services in Saudi Arabia, emphasizing the role of AI and ML-assisted techniques in achieving the objectives of Saudi Vision 2030. The advancement of healthcare in the country depends on the adoption of these innovative technologies to optimize medical services and the overall efficiency of the system. Table 1 provides a comprehensive literature survey that highlights the proposed mechanisms, performance analyzes, and limitations of existing research in this domain.

Table 1
Literature survey on healthcare systems targeting other countries and Saudi Arabia.

Authors name	Country	Proposed scheme	Proposed metrics	Application	Survey/research contribution	Limitation
Aldolaim et al. [14]	Saudi Arabia	AI and metaverse	inaccurate measurements and ongoing feeling and pain of fear	Healthcare	Research contribution	Long computation delay
Pandey et al. [15]	other country	enhanced healthcare systems by determining the role of technologies	explored the role of technologies	healthcare	survey	Complex communication analysis
Hafidh et al. [16]	other country	proposed an innovative genetic smart knowledge	adopted the ontology methodology for translating the unstructured information	healthcare	Research contribution	Large verification time
Rafid [17]	other country	brain sense device for acquiring the brain activities	accuracy among translated and intended execution	healthcare	research contribution	Communication and communication delay
Alkhateeb et al. [18]	Saudi Arabia	analysis report of BMD by showing the 45% availability of staff, and 7% availability of overstaffing status	provided and addressed a creditable solution	healthcare	survey paper	no comparison
Ai-Anezi et al. [19]	Saudi Arabia	analyzing and identifying the current status of healthcare systems	analyzing the challenges faced by Saudi Arabia including implementation, insurances, accessibility and workspace	healthcare	research contribution	Large encryption time
Aladaili and Mottershead [20]	Saudi Arabia	new digital health frontiers by visioning and ingenuity	included the support, progress, by accelerating the military contributions	healthcare	research contribution	Large processing delay
Alsaleh [21]	Saudi Arabia	quantitative research on collecting the information	figured the medical services in an area of mHealth	healthcare	research contribution	Lack in computation and communication process
Albejaidi and Alharbi [22]	Saudi Arabia	technological systems and frameworks in e-health	valuable insights in order to measure the current trend and fostering the society	healthcare	research contribution	reduced accuracy
Aljohani et al. [23]	Saudi Arabia	developed a health clinic system using android technology	front-end and back-end software using several tools such as PHP, CSS, HTML and MySQL	healthcare	research contribution	communication overhead

2.1. Improving healthcare around other countries

Aldolaim et al. [14] proposed a novel mechanism for physical therapy clinics in Saudi Arabia that incorporates modern technologies such as IoT, AI and metaverse to overcome treatment barriers faced by patients. Their approach addresses challenges in treatment and diagnosis, including long-term rehabilitation, inaccurate measurements, and persistent discomfort and fear of pain. The authors designed an architecture for a smart physical clinic tailored for individuals with mobility disabilities using IoT and AI techniques in Saudi Arabia. Pandey et al. [15] discussed the enhancement of healthcare systems by examining the role of emerging technologies. They emphasized the need to monitor individuals with disabilities, who require sensitive attention and care, especially when handling emergencies. In addition, the authors explored how technological interventions can protect the rights and privileges of disabled people while providing better support. Hafidh et al. [16] developed and proposed an innovative genetic smart knowledge base built on a six-layer data management model. They adopted an ontology-based methodology to convert unstructured information into a structured, knowledgeable representation that can be applied in education, social services, and healthcare. In addition, the authors developed an infrastructure to bridge the gap between schools and the processes of education, health, and care services. Rafid et al. [17] employed a brain-sensing device to capture brain activities and classify them into several categories. They implemented a brain–computer interface to allow disabled individuals to operate a wheelchair without manual intervention. The authors evaluated the proposed mechanism in terms of the accuracy of translating brain signals into intended actions. Their system has improved the healthcare industry by improving the quality of life for disabled people in Bangladesh.

2.2. Improving healthcare in Saudi Arabia

Alkhateeb et al. [18] conducted a survey on healthcare facilities, including reports from the Biomedical Engineering Department (BMD), revealing a 45% staff availability and a 7% overstaffing rate. To address staffing challenges, the authors proposed a heuristic formula to improve the readability and applicability of healthcare processes. Ai-Anezi et al. [19] analyzed the Saudi Arabian healthcare system in three key areas. The first part assessed the current status of healthcare infrastructure, budget allocation, and resource distribution. The second section identified key challenges such as implementation barriers, insurance policies, accessibility issues, and workforce management. The third section proposed strategic improvements in healthcare access, workforce efficiency, and expenditure management to align with Vision 2030. Aladaili and Mottershead [20] examined digital health advances in Saudi Arabia, particularly within the Center for National Military Command and Health Control. Their research emphasized the role of military contributions in accelerating digital health adoption to achieve Vision 2030, highlighting support, progress, and technological advancements in healthcare. Alsaleh [21] conducted a quantitative study using patient questionnaires to explore the impact of mobile health (mHealth) technologies in Saudi Arabia. The study examined aspects such as risk assessment, patient referrals, appointment scheduling, and medical record management, providing information on administrative improvements and professional healthcare practices that are applicable both locally and internationally. Albejaidi and Alharbi [22] investigated technological advancements in Saudi Arabia's e-health sector, evaluating strategies for enhancing healthcare accessibility and sustainability through new digital health technologies. Their findings underscored the role of e-health in promoting social and economic development by establishing a strong and sustainable healthcare system. Aljohani et al. [23] developed a health clinic system using Android technology at a university in Saudi Arabia. Their system was built using Java for both front-end and back-end development, incorporating PHP, CSS, HTML, and MySQL. Their research introduced an automated healthcare system designed to improve patient care, improve healthcare infrastructure, and optimize medical data collection.

Despite these technological advances, very few studies have focused on the challenges people with disabilities face in accessing healthcare services. AI-assisted frameworks offer the potential to significantly improve healthcare access for disabled people by providing real-time assistance, minimal delay, and highly accurate diagnostics. However, existing systems require further improvements in terms of reducing delays, increasing accuracy, and streamlining data processing. The proposed framework aims to minimize latency while ensuring high-accuracy, real-time access to medical information, whether for in-person consultations or remote healthcare services. Federated learning is used to efficiently manage heterogeneous medical records from multiple intelligent devices, enabling precise data processing, minimal delay, and seamless access to patient records. Furthermore, optimizing secure and efficient data routing within smart healthcare networks can further improve healthcare access for individuals with disabilities in Saudi Arabia, aligning with the wider goals of Vision 2030.

3. Proposed approach

ML and AI mechanisms are among the most significant approaches to improving healthcare systems, especially for disabled individuals. To date, numerous scientists and researchers have proposed ML- and AI-based schemes to address complex tasks related to data gathering and processing. However, existing ML models often lack accuracy and suffer from real-time delays when accessing or processing the communicated information. Therefore, to improve the healthcare system in Saudi Arabia, it is necessary to enhance the accuracy and real-time assessment and processing of information by incorporating reasoning capabilities and more realistic learning models that also benefit disabled individuals. In this paper, we propose a hybrid approach that combines chain-of-thoughts with federated learning. The zero-shot algorithm is used to divide the complex task into sub-problems; once these sub-problems are clearly defined, they can be more accurately learned and analyzed using a federated learning algorithm at local edges, resulting in reduced complexity as well as lower computational and storage overhead.

3.1. Chain-of-thoughts

To enhance the reasoning ability of language models, chain-of-thought (CoT) techniques are considered advanced methods for handling complex tasks such as physical and mathematical problems. To further improve reasoning and logical deductions, in-context learning can be employed by injecting prompts and updating parameters, thereby improving the accuracy of the network. Chain-of-thoughts, also known as zero-shot CoT, are generated without prior knowledge of training samples. To operate in a more real-time and natural manner, zero-shot learning models can take advantage of LLM to improve system accuracy and readability.

Least-to-most CoT: Least-to-most CoT involves breaking down complex issues into simpler subproblems that can be solved sequentially. This approach is implemented by training and prompting the chain of thought. It serves to illustrate teaching techniques by progressively sequencing prompts and generalizing complex problems for effective problem solving. The least-to-most CoT mechanism is further illustrated in Fig. 2, which shows problem reduction and sequential sub-problem solving.

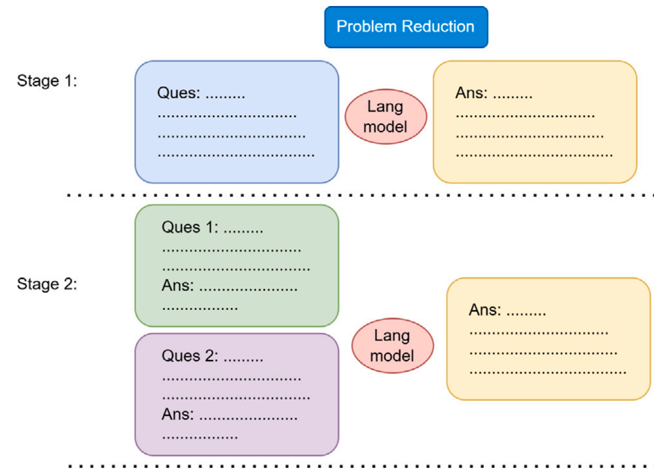

Fig. 2. Extended healthcare for data processing using CPS.

It is used to prompt the solving of math problems in two stages: problem reduction and problem solving. In the first stage, complex issues are decomposed into a series of similar sub-problems, demonstrating the reduction process, which is then followed by specific questions. In the second stage of least-to-most prompting, these sub-problems are solved sequentially. The zero-shot phase consists of three parts: demonstrating sub-problems through consistent examples, an empty list of answered sub-questions, and the remaining questions to be answered. The model then solves the sub-problems in sequence while applying the reduction process.

3.2. Federated learning

Once the problem has been subdivided into sub-problems, the federated learning framework distributes the system into smaller localized units capable of performing computational tasks. Fig. 3 presents the high-level design of a general federated learning system, including a zero-shot architecture in which information is aggregated on edge devices, with each local model processing data solely on its respective device. Once the information is generated in response to a user query in real time, the final results are stored on a cloud server and in online storage.

Furthermore, Fig. 4 presents the proposed block diagram of the federated and zero-to-shot architecture model applied to build an application in the domain of healthcare diagnostics. The proposed system, targeting healthcare applications, provides access to an interface that connects with a baseline model specific to the data set.

The availability of open-access datasets for similar problems improves accuracy and optimizes the federated learning process. Using this application, healthcare professionals can perform inference on new datasets using a local version of the model and train the local data model on their respective machines. The aggregation algorithm, which minimizes weights, is then used to update the global model, with the final information stored on online storage devices. The steps involved in training a new model on a dataset are illustrated in Fig. 5.

An algorithm of the proposed mechanism is presented in the Algorithm 1.

4. Performance analysis

4.1. Existing methods

When comparing the proposed mechanism with traditional AI/ML-based approaches, such as decision trees, regression trees, and support

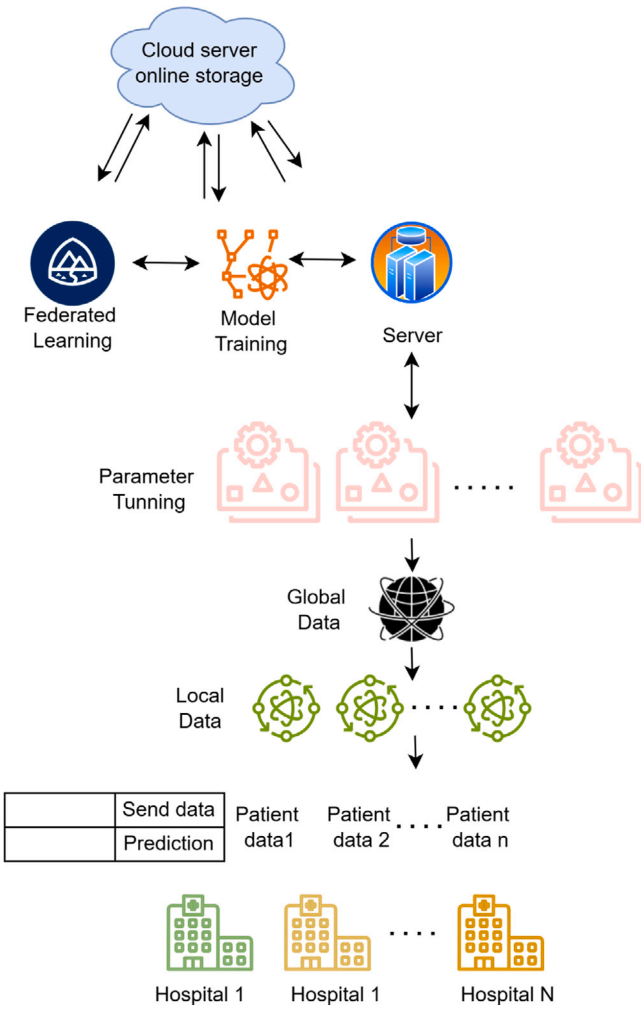

Fig. 3. High level designing of general federated learning include zero-to-shot architecture.

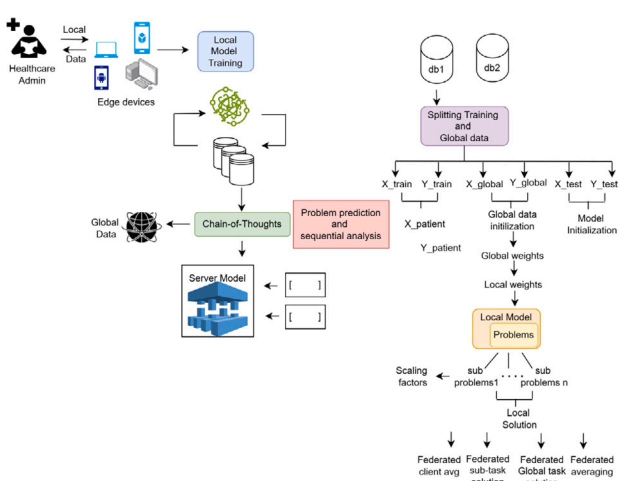

Fig. 4. Proposed block diagram of federated and zero-to-shot architecture model.

vector machines (SVM), it becomes evident that the proposed model outperforms these methods in multiple aspects, demonstrating its superiority. The effectiveness of the proposed mechanism is evaluated against several AI techniques, as well as two recently developed healthcare frameworks specifically designed for Saudi Arabia. Albejaidi and

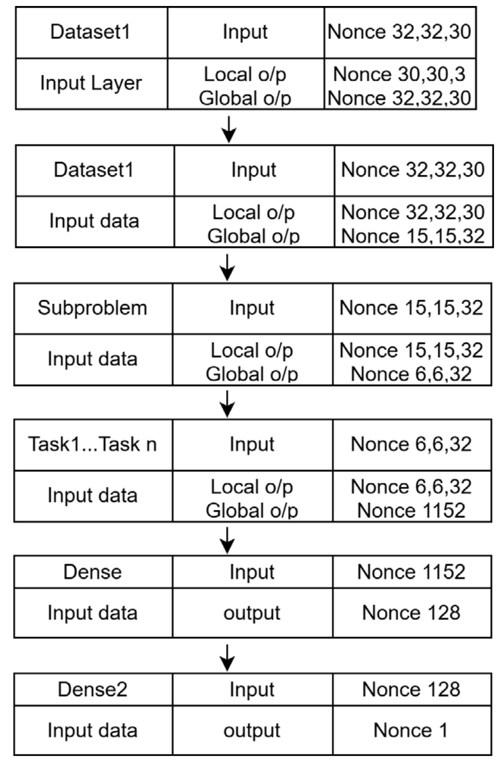

Fig. 5. Steps involved in federated learning.

Algorithm 1 Proposed Mechanism

Input Value: patient query, problem statement
Output: fast access of record and problem using CoT and federated learning
$P \leftarrow (p_1, p_2, \dots, p_n)$
$Sub_{problem} \leftarrow$ Complete problem
Matrix $\leftarrow$ sub-problems {stored at local edges}
Weights $\leftarrow$ (local weights, $list_{scaling}$)
$L \leftarrow$ list()
$N \leftarrow LW(local\_weight\_list)$
for $i = 0$ to $n - 1$ **do**
  Divide the problem into subtask or sub-problems and adjust weights accordingly
end for
for each $local\_weight$ in LW **do**
  $Layer_{sum} \leftarrow \min(local\_weights, \text{axis} = 0)$
  Weights.append($Layer_{sum}$)
end for
$Global_{weights} \leftarrow$ Weights
$New_{server\_weight} \leftarrow$ Global weights
Return New_{server_weight}

Alharbi [22] explored technological systems and frameworks in Saudi Arabia's e-health sector, evaluating strategies to improve healthcare services. They proposed an improved healthcare framework based on new services and emerging technologies, providing valuable information on current trends, societal benefits, and economic advancements. Their research aimed to establish a strong and sustainable health system in Saudi Arabia. Furthermore, Alsaleh [21] conducted quantitative research by distributing questionnaires to patients and collecting data on various aspects of mobile health services (mHealth) in the Kingdom of Saudi Arabia. The study examined risk assessment, patient referrals, appointment scheduling, medical record management, and other key

Table 2
Existing healthcare services comparison in terms of recall, precision, accuracy and delay.

SVM	89	0.73	0.02	1.2
Decision tree	91	0.35	0.03	0.96
Naive Bayes	92	0.52	0.10	0.93
Regression algorithm	93	0.84	0.16	0.83
Federated Learning	96	0.98	0.23	0.75

areas. The findings contributed to a greater understanding of the applications of mHealth and their potential improvements. The results of this analysis provide valuable insights into healthcare management and professional practices in other countries. A comparison of traditional ML/AI techniques in terms of precision, delay, and recall is presented in Table 2, while the graphical representation of each evaluation measure, including a comparison of recent healthcare frameworks with the proposed mechanism, is detailed in the following graphs and subsections.

4.2. Analysis of outcome

The entire data set is divided into 70:30 training and testing ratios for each of the mechanisms or algorithms used for classification and measuring other metrics. The goodness of the classification is based on precision, recall, accuracy, and delay. The parameters used for computing precision, accuracy, recall and delay are further detailed as in Table 3

The confusion matrix represents the classifier's performance when testing structured and unstructured data. The number of false positive, false negative, true positive, and true negative results is obtained after classifying the confusion matrix. We have calculated the following parameters to determine the performance of the classifier.

Accuracy: It is defined as the accuracy in identifying the current classifier of the dataset mentioned by the proposed framework.

$$Accuracy = \frac{TN + TP}{TP + TN + FN + FP} \tag{1}$$

Precision: It is defined as the portion of information identified as positive and is actually correct in the environment.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall: It is defined as the portion of information identified as negative, but is actually correct in the environment.

$$Recall = \frac{FP}{FP + TN} \tag{3}$$

Delay: It is defined as the amount of time required by the proposed mechanism to respond to the user's query.

Communication and computation overhead: This refers to the resources required to compute and analyze the information using the proposed mechanism while improving the accessibility of resources to the network.

Table 4 presents the comparison of existing methodologies with the proposed mechanism in terms of tools and limitations. The data distribution along with the confusion matrix and the decision tree classifier that includes all characteristics of the data set is further identified in Tables 5, 6, and 7.

4.3. Graphical results discussion

This section discusses the graphical results obtained from executing the proposed mechanism and recent existing ML/AI-based schemes. The proposed mechanism is further validated on the basis of accuracy, precision, minimal delay, and recall, comparing its performance against existing techniques. Fig. 6 illustrates the precision of the proposed framework compared to traditional methods. The proposed framework demonstrates improved record generation and efficient record

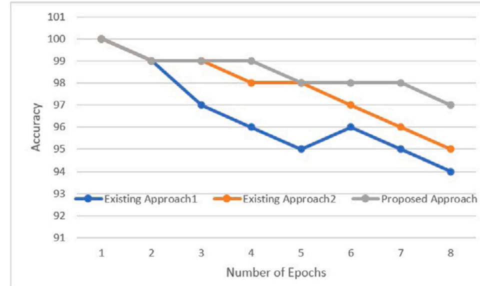

Fig. 6. Accuracy.

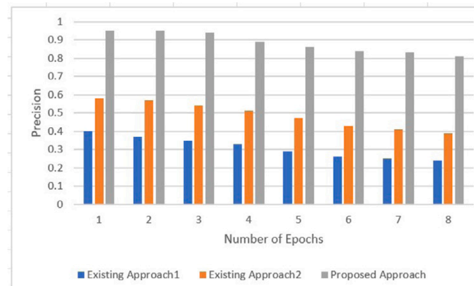

Fig. 7. Precision.

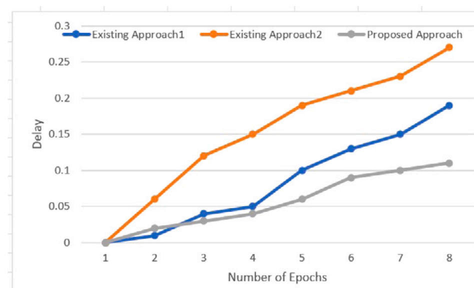

Fig. 8. Delay.

access for patients, outperforming conventional approaches. This improvement is primarily attributed to the reduced processing delay and increased accuracy achieved through the federated learning scheme.

Furthermore, Fig. 7 presents the precision rate of the existing and proposed mechanism where the proposed framework outperforms because of the federated learning scheme, which computes the information in the local machine before directly passing it to the online storage. The local machine computation involves more accuracy along with minimum delay to ensure the identification of correct information in comparison of existing methods.

Fig. 8 presents the minimum delay required to access and process the patient's query using a federated learning scheme. The reason is the same as that of the previous, where existing schemes gather the information and process it and analyze it on base stations. However, federated learning reduces the delay by processing and analyzing the information on local machines. The proposed mechanism improve the computation process with minimum delay by determining the impact of federated learning due to the integration of the zero-shot algorithm, which divides the problem into sub-tasks. In addition, each sub-task can be efficiently analyzed with more precision in the federated learning process.

Moreover, Fig. 9 deliberately recalls the results. The proposed mechanism reduces the amount of incorrect identification of information or

Table 3
Confusion Matrix.

Terms	Values
FP: The system has identified the ideal system incorrectly	FN: the incorrect information is identified wrongly as benign by the classifier
TP: the incorrect files are correctly identified as false by the classifier	TN: benign files are correctly identified as false by the classifiers.

Table 4
Comparison of different AI/ML techniques studied during literature survey.

S. No.	Technique name	Dataset	Federated Learning (Y/N)	Security aspect	Limitation
1	SVM	Large	N	N	Latency
2	Decision tree	small	N	Y	Communication overhead
3	Naive Bayes	Large	N	N	Delay
4	Regression algorithm	small	N	N	communication overhead and accuracy
5	Federated Learning	large	Y	Y	None

Table 5
Data distribution.

Class label	Number	Volume
Structured data from homogeneous devices	3,658,045	73,221
Structured data from heterogeneous devices	356,789	5,351
Unstructured data from heterogeneous devices	1,278,451	2,056
Unstructured data from heterogeneous devices	4,56,871	5,345

Table 6
Confusion matrix.

	Structured	Unstructured
Structured	TP	FN
Unstructured	FP	TN

Table 7
Proposed classifier on all features.

Data type	Precision	Recall	Accuracy
Structured data (small size)	0.23	0.33	97.56
Structured data (large size)	0.56	0.83	96.23
Unstructured data (small size)	0.31	0.45	93.25
Unstructured data (large size)	0.65	0.71	89.63

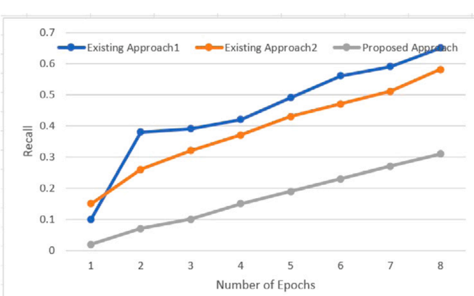

Fig. 9. Recall.

Table 8
Computation and communication overhead rate.

Approach	Overhead	EA1	EA2	PA
Structured record (small dataset)	Communication (%)	82	79	56
	Computation (0–1)	0.13	0.25	0.15
Unstructured record (small dataset)	Communication	89	85	63
	Computation	0.39	0.57	0.23
Structured record (large dataset)	Communication	80	93	31
	Computation	0.33	0.49	0.30
Unstructured record (large dataset)	Communication	75	66	65
	Computation	0.35	0.47	0.12

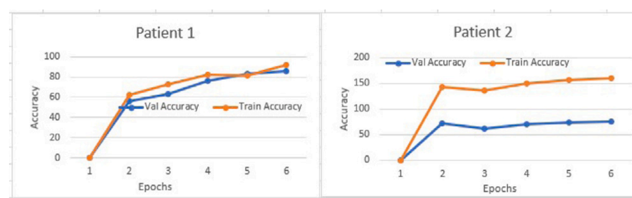

Fig. 10. accuracy of patient 1 and patient 2 over 5 epochs of round 1.

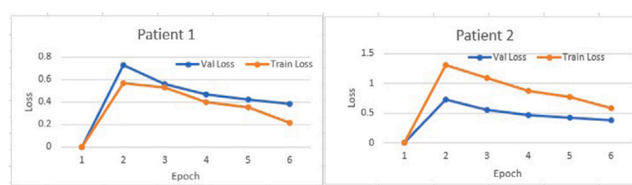

Fig. 11. loss of patient 1 and patient 2 while accessing the records over 5 epochs of round 1.

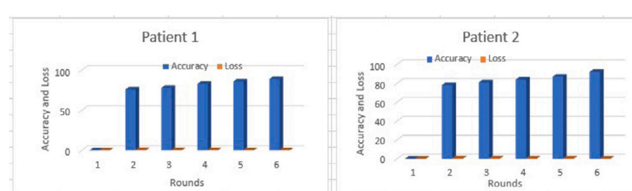

Fig. 12. accuracy and loss of model over 5 rounds of proposed model.

query in comparison with existing schemes. The reason is the involvement of the local machine for processing and analyzing the information rather than forwarding and recording it at the base stations.

The computation and communication overhead chart are further analyzed in comparison of proposed and existing schemes in terms of measuring the delay. Table 8 presents the communication and computation overhead rate.

4.4. Summary

Furthermore, Figs. 10, 11, and 12 present the centralized accuracy and loss results obtained for the centralized server over five rounds of completion using the federated learning algorithm. The validation data set used by the server contains 1500+ image samples. From the figures presented, it is evident that after five rounds of federated learning, the proposed model delivers impressive results due to the integration of chain-of-thought reasoning, which accelerates the analysis and result generation process, and federated learning, which enhances overall accuracy while reducing delay and latency in the communication process.+

The proposed framework is applied to healthcare data, where record access and analysis significantly improve when integrated with the latest technologies. In the context of Saudi Arabia, with a particular focus on disabled individuals, the proposed model improves real-time access and record generation for patients, achieving reduced delay and greater precision. These improvements address a critical concern for users accessing real-time healthcare applications. Furthermore, the computational complexity of the proposed mechanism is O(n), whereas the computational complexity of existing approaches is O(n × n). This improvement is attributed to the integration of the zero-shot mechanism with federated learning, which ensures that only legitimate devices participate in the communication process, thus reducing the complexity of verifying the legitimacy of the device.

In addition, the proposed approach is designed for specific healthcare use cases, particularly in disease detection. For example, in the case of pneumonia detection, the problem is divided into sub-tasks, where each symptom of pneumonia is identified and analyzed. The zero-shot method is used to detail each symptom, while federated learning processes these symptoms on edge devices, enabling faster and more accurate diagnoses. This approach minimizes delays, computational complexity, and storage overhead, thereby improving network efficiency.

5. Conclusion

Healthcare is one of the most critical sectors for a nation and plays a key role in shaping its future growth and development opportunities. Ensuring access to both online and offline healthcare services can significantly enhance e-health, particularly benefiting individuals with disabilities by providing continuous and faster access to medical facilities. The proposed framework aims to minimize delays while ensuring highly accurate real-time access to medical information, whether for in-person diagnoses and treatments or remote consultations. Federated learning is used to manage heterogeneous medical records from various intelligent devices, allowing precise data processing with minimal delay while allowing patients to access their records efficiently. The proposed mechanism is designed to improve diagnostic accuracy and reduce delays, with performance validation performed in terms of precision, accuracy, latency, and response time metrics. Furthermore, the proposed mechanism can be extended to enhance the security of data transmission by optimizing information routing within smart healthcare networks. Implementing a shortest and most secure routing approach could further improve the efficiency of processing and accessing medical records, ultimately benefiting individuals with disabilities in Saudi Arabia. These potential advances represent key future directions for this research.

CRediT authorship contribution statement

Geetanjali Rathee: Writing – original draft, Investigation, Formal analysis, Conceptualization. **Sahil Garg:** Writing – review & editing, Project administration, Data curation. **Georges Kaddoum:** Writing – review & editing, Resources, Funding acquisition. **Samah M. Alzanin:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Mohammad Mehedi Hassan:** Writing – review & editing, Validation, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors extend their appreciation to the King Salman Center for Disability Research, India for funding this work through Research Group number KSRG-2024-020.

References

[1] G. Wang, A. Badal, X. Jia, J.S. Maltz, K. Mueller, K.J. Myers, C. Niu, M. Vannier, P. Yan, Z. Yu, et al., Development of metaverse for intelligent healthcare, Nat. Mach. Intell. 4 (11) (2022) 922–929.
[2] A.A. Alasiri, V. Mohammed, Healthcare transformation in Saudi Arabia: an overview since the launch of vision 2030, Heal. Serv. Insights 15 (2022) 11786329221121214.
[3] H. Alharthi, Healthcare predictive analytics: An overview with a focus on Saudi Arabia, J. Infect. Public Heal. 11 (6) (2018) 749–756.
[4] M.K. Al-Hanawi, S.A. Khan, H.M. Al-Borie, Healthcare human resource development in Saudi Arabia: emerging challenges and opportunities—a critical review, Public Health Rev. 40 (2019) 1–16.
[5] A.Y. Alqassim, A.M. Makeen, M.S. Mahfouz, A.E. Ahmed, O.B. Albasheer, M.R. Zaino, M.H. Abutaleb, M.A. El-Setouhy, A.A. Alharbi, M.A. Muaddi, Assessing healthcare access among physical and hearing disabled persons in jazan region, Saudi Arabia, J. Dev. Phys. Disabil. 34 (6) (2022) 1071–1088.
[6] A. Woodman, N. Jaoua, L.H. Al-Jamea, J. Balilla, E.M. Al Zahrani, R.Y. Al-Ansari, S.H. Qahtani, Attitudes of health care providers in relation to disability, Saudi Arabia, Ibnosina J. Med. Biomed. Sci. (2024).
[7] A. Kavanagh, H. Dickinson, G. Carey, G. Llewellyn, E. Emerson, G. Disney, C. Hatton, Improving health care for disabled people in COVID-19 and beyond: lessons from Australia and England, Disabil. Heal. J. 14 (2) (2021) 101050.
[8] G.S. Nadella, S. Satish, K. Meduri, S.S. Meduri, A systematic literature review of advancements, challenges and future directions of AI and ML in healthcare, Int. J. Mach. Learn. Sustain. Dev. 5 (3) (2023) 115–130.
[9] A. Ali, I. Ullah, M. Shabaz, A. Sharafian, M.A. Khan, X. Bai, L. Qiu, A resource-aware multi-graph neural network for urban traffic flow prediction in multi-access edge computing systems, IEEE Trans. Consum. Electron. (2024).
[10] T. Alsarhan, O. Harfoushi, A.Y. Shdefat, N. Mostafa, M. Alshinwan, A. Ali, Improved graph convolutional network with enriched graph topology representation for skeleton-based action recognition, Electronics 12 (4) (2023) 879.
[11] M. Zakarya, A.A. Khan, M.R.C. Qazani, H. Ali, M. Al-Bahri, A.U.R. Khan, A. Ali, R. Khan, Sustainable computing across datacenters: A review of enabling models and techniques, Comput. Sci. Rev. 52 (2024) 100620.
[12] A. Sharafian, I. Ullah, S.K. Singh, A. Ali, H. Khan, X. Bai, Adaptive fuzzy backstepping secure control for incommensurate fractional order cyber–physical power systems under intermittent denial of service attacks, Chaos Solitons Fractals 186 (2024) 115288.
[13] X. Chen, AI in healthcare: Revolutionizing diagnosis and treatment through machine learning, MZ J. Artif. Intell. 1 (2) (2024).
[14] R.J. Aldolaim, H. Gull, S.Z. Iqbal, Boxly: Design and architecture of a smart physical therapy clinic for people having mobility disability using metaverse, AI, and IoT technologies in Saudi Arabia, in: 2024 IEEE International Conference on Information Technology, Electronics and Intelligent Communication Systems, ICITEICS, IEEE, 2024, pp. 1–5.
[15] S. Pandey, A.K. Dixit, R. Bahuguna, S.V. Akram, V. Pandey, S. Kathuria, AI and IoT enabled technologies for monitoring the right to health of disabled people, in: 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), IEEE, 2022, pp. 2227–2231.
[16] R. Hafidh, M.S. Sharif, M. Alsallal, Smart holistic model for children and youth with special educational needs and disabilities, in: 2019 International Conference on Computing, Electronics & Communications Engineering, ICCECE, IEEE, 2019, pp. 130–135.
[17] S.T.S. Rafid, R.A. Miazee, M.K. Byzid, A.A. Anika, S.S. Hossain, A.A.M. Azad, Development of a brain-computer interface (BCI) for person with disabilities to control their wheelchair using brain waves, in: 2023 IEEE 11th Region 10 Humanitarian Technology Conference (R10-HTC), IEEE, 2023, pp. 715–720.
[18] A.F. Alkhateeb, J.M. AlAmri, M.A. Hussain, Healthcare facility variables important to biomedical staffing in line with 2030 saudi vision, in: 2019 Industrial & Systems Engineering Conference, ISEC, IEEE, 2019, pp. 1–6.
[19] F.M. Al-Anezi, S. Alrajhi, N.M. Al-Anezi, D.M. Alabbadi, R. Almana, A review of healthcare system in Saudi Arabia, in: 2020 19th International Symposium on Distributed Computing and Applications for Business Engineering and Science, DCABES, IEEE, 2020, pp. 318–322.
[20] M.A. Aladaili, R. Mottershead, Exploring new digital health-care frontiers: Ingenuity and vision from Saudi Arabia in establishing a national military health control and command centre, in: 2024 IEEE 48th Annual Computers, Software, and Applications Conference, COMPSAC, IEEE, 2024, pp. 1880–1882.
[21] S. Alsaleh, Toward improving mobile health services in the Kingdom of Saudi Arabia based on the saudi 2030 vision, in: 2021 3rd International Conference on Electrical, Control and Instrumentation Engineering, ICECIE, IEEE, 2021, pp. 1–5.
[22] F.M. Albejaidi, A. Alharbi, Analyzing the technological framework for E-health in the Kingdom of Saudi Arabia, in: 2024 11th International Conference on Computing for Sustainable Global Development (INDIACom), IEEE, 2024, pp. 1822–1827.
[23] F.A. Aljohani, A.A. Alfaidi, M.S.M. Zahid, Health clinic system with e-health and android technology for university in Saudi Arabia, in: 2021 International Conference on Computer & Information Sciences, ICCOINS, IEEE, 2021, pp. 47–52.