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Enhanced healthcare using generative AI for disabled people in Saudi Arabia

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ABSTRACT

Saudi Arabia's Vision 2030 prioritizes advances in healthcare to improve accessibility, improve medical services, and support people with disabilities. Despite the adoption of telemedicine and AI-driven healthcare solutions, disabled and elderly people continue to face challenges in accessing real-time medical services, receiving accurate diagnoses and independently navigate healthcare facilities. Current healthcare systems often struggle with delays, lack of personalization, and inefficiencies in medical data processing, limiting their effectiveness in providing inclusive and responsive healthcare. To address these challenges, this paper proposes an AI-powered healthcare framework that integrates Generative Artificial Intelligence (GAI), Reinforcement Learning from Human Feedback (RLHF), and the Analytic Network Process (ANP). RLHF enables AI models to learn and adapt based on real-time user feedback, ensuring a personalized and interactive healthcare experience. Meanwhile, ANP optimizes decision-making processes, allowing for faster, more accurate medical service delivery by considering multiple healthcare factors. This combined approach improves remote consultations, intelligent diagnostics, and seamless real-time interactions, significantly improving accessibility to healthcare for disabled individuals. The proposed framework is evaluated against existing AI-driven healthcare models. Results demonstrate that the system outperforms traditional methods, providing a faster, more reliable, and patient-centered healthcare experience. By combining GAI, RLHF, and ANP, this research offers a practical solution to improve healthcare accessibility for disabled individuals, aligning with the goals of Saudi Arabia's Vision 2030.

1. Introduction

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have transformed many fields, including healthcare. These technologies can help improve medical services, making them more accessible and efficient. However, people with disabilities, especially in Saudi Arabia, still face serious challenges when trying to access healthcare. Tasks like booking a doctor's appointment, navigating a hospital, or understanding a medical prescription can be difficult without assistance. According to the World Health Organization (WHO), people with disabilities struggle with mobility, digital healthcare access, and overall interaction with their environment [1]. To address these challenges, there is a growing need for AI-powered assistive technologies that provide real-time, adaptive, and personalized healthcare support.

Saudi Arabia's Vision 2030 aims to improve the lives of people with disabilities by increasing employment opportunities and enhancing healthcare services. One of its key goals is to raise the employment rate of disabled individuals from 5% to 12% by 2030. This requires better healthcare accessibility, which can be achieved by using smart assistive technologies such as AI-driven decision-making models [2,3]. Telemedicine, AI-assisted diagnosis, and real-time healthcare monitoring are some of the advanced solutions that can help people with disabilities receive equal and inclusive medical services [4]. However, current AI-based healthcare systems still struggle with delays, security concerns, and lack of real-time adaptation, making them less effective for practical use [5,6].

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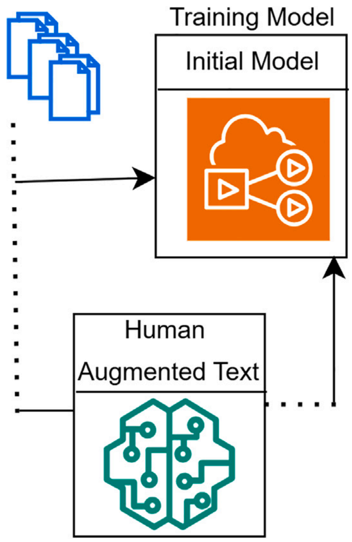

Fig. 1. Systematic presentation of proposed mechanism.

To overcome these challenges, this research proposes an AI-powered healthcare framework that combines Reinforcement Learning from Human Feedback (RLHF) and Analytic Network Process (ANP). RLHF is an advanced Generative AI (GAI) method that helps AI models learn from human interactions, improving their ability to make accurate and context-aware medical decisions. On the other hand, ANP is a multi-criteria decision-making tool that ensures better accuracy, optimized selection of medical services, and improved healthcare accessibility.

For example, imagine a person with visual impairment trying to visit a hospital in Saudi Arabia. This individual may face difficulties in booking an appointment, finding their way inside the hospital, or understanding their prescription. The proposed AI-powered framework can provide voice-guided appointment booking, real-time navigation assistance, and AI-generated medical instructions in an accessible format. Additionally, the system secures medical records and processes data quickly, thanks to ANP's structured decision-making approach.

Although AI, ML, and DL-based models have made healthcare more accessible, they still have limitations in real-time interaction, accuracy, and security [7,8]. Many current models do not adapt well to changing healthcare environments, leading to longer response times and reduced accuracy [9,10]. The proposed system bridges this gap by integrating human feedback into AI learning (RLHF) and using ANP for structured decision-making, making healthcare services more efficient and responsive. Fig. 1 presents the overall structure of the proposed AI-driven healthcare system, highlighting the key issues it addresses.

In general, this paper introduces an AI-powered framework that improves healthcare access for disabled individuals in Saudi Arabia. The main contributions are:

- Developing a Generative Artificial Intelligence (GAI) model for real-time healthcare services considering human feedback.
- Integration of the Generative Artificial Intelligence (GAI) model with the Analytical Network Process (AHP) to reduce computation delay and provide more accuracy while processing the information.
- Focus on addressing the specific challenges and needs faced by disabled people in the kingdom of Saudi Arabia.

The remainder of this paper is structured as follows. Section 2 presents a comprehensive review of the literature on advances in healthcare services for people with disabilities in Saudi Arabia. Section 3 details the proposed framework, including the methodology, flowchart, and algorithms. Section 4 discusses the data set used for training and testing, along with performance analysis and validation of the proposed scheme. Finally, Section 5 concludes the paper and provides future research directions.

2. Related work

The number of approaches has been proposed by existing researchers and scientists. This section details existing approaches and techniques to improve the quality of healthcare care using artificial intelligence for Saudi Arabian people. Table 1 presents a brief analysis of the existing schemes and mechanism along with the limitation of each approach.

2.1. Improved healthcare systems in other countries

Albaroudi et al. [11] have demonstrated the significance of using AGI in enhancing the healthcare while dealing with injuries and errors to train the quality and patient data. The authors have allowed the providers, researchers and stakeholders to implement the AGI while mitigating the possible crucial implications. Kuzlu et al. [12] have examined the current status of GAI in healthcare by discussing the challenges and benefits. Further, the authors have addressed the power of GAI in enhancing the healthcare system and outcome. Chen et al. [13] have surveyed the implementation of GAI in IoT healthcare system. the authors have introduced the potential benefits of GAI in health digital twin by defining the overall framework. They have explored the GAI details by enabling the communication, data acquisition, digital modeling and analysis. The authors have discussed and revolutionized the health monitoring and diagnosis process. Najim et al. [14] have reviewed the medical information including monitoring and real time diagnosis of patients using IoT to help disabled and elderly patients by comparing among them in order to analyze and judge the patient health. Alzahrani et al. [15] have explored the framework by discussing critical factors while sharing the data securely using blockchain in healthcare system. the authors have proposed 3 factor framework including data sharing, system factors and blockchain mechanism by expertizing the review and questionnaire. The authors have conducted the framework along with detailing the comprehensive review on practitioners.

2.2. Improved healthcare system in Saudi Arabia

Elkhalifa et al. [16] have investigated the factors that are affecting healthcare improvement in Saudi Arabia by presenting a novel E-Health model. The authors have influenced the positive actions of cues by representing the results. They have analyzed negative and positive influencers by presenting the coefficient paths along with determining the factors using E-Health applications in Kingdom of Saudi Arabia. Abaoud et al. [17] have conducted a comprehensive evaluation and simulation on concentrating the accuracy, privacy, and efficiency of in healthcare applications. The authors have proposed a novel federated learning mechanism for providing the privacy preservation mechanism. The authors have underscored the effectiveness and practicality of proposed approach by maintain the collective intelligence and privacy preservation in healthcare informatics. Pandey et al. [19] have conducted a systematic study on analyzing the sensitivity and assessment for finding the difficulties and implications in healthcare solutions. The authors have also discussed the data integrity and prioritized techniques and mechanisms using blockchain network. Amin et al. [18] have determined the patient state using speech, facial expression, gestures and movements of the patient. The authors have classified the condition of the patients as normal and pathological by monitoring the EEG in conjunction with providing emergency help in critical conditions to the patient. The proposed mechanism has achieved the accuracy and state of the art system in order to validate the mechanism.

Table 1
Literature survey on comparing existing mechanisms.

S. No.	Author name	Proposed scheme	Dataset	Performance metrics	Saudi Arabia	Limitation
1	Albaroudi et al. [11]	GAI algorithm	✓	Patient data storage	×	Long delay in processing the information
2	Kuzlu et al. [12]	GAI algorithm	✓	Healthcare	×	overhead in storing the records
3	Chen et al. [13]	Artificial Intelligence	✓	Digital modeling	×	delay in communication process
4	Najim et al. [14]	IoT devices	✓	Healthcare	×	complexity
5	Alzahrani et al. [15]	Blockchain	✓	Healthcare	×	Computation delay
6	Elkhalifa et al. [16]	Healthcare	✓	Blockchain	✓	Storage overhead
7	Abaoud et al. [17]	Survey	✓	Electroencephalogram (EEG)	✓	Complexity in processing the record
8	Amin et al. [18]	Patient speech	✓	E-health	✓	Overhead delay

2.3. Practical implementations in healthcare sector for disabled and elderly people in Saudi Arabia

Alharbi et al. [20] have provided a review in the context of improving the quality of life of disabled children in Saudi Arabia Vision 2030. The authors have provided semantic web by suggesting and promoting the decision-making in healthcare. The authors have also studied the determining the accessibility by gaining the services and target information of Saudi Arabia. Alghadier et al. [21] have showed the increasing number of publications by presenting scientific research on children's ability in Saudi Arabia. The authors have identified and provided a comprehensive overview on highlighting the research and efforts in children health. The authors have emphasized on conducting the research by developing the ideas on children's ability using support systems and interventions. Attar et al. [22] have explored the impact of smart cities in enhancing the quality of life for disabled people in Saudi Arabia. The authors have promoted the sustainability and equitability. Mohammed et al. [1] have predicted the health-related concerns for improving the quality of life for caregivers' children in Saudi Arabia. The authors have predicted the social activities and anxiety by predicting the fatigue, depression, and sleep disturbance.

2.4. Problem statement

Despite the advancements in AI-driven healthcare solutions in various countries, research in Saudi Arabia remains in its early stages, particularly in the integration of AI for improving healthcare services tailored to the needs of disabled individuals. Current approaches lack an efficient and secure mechanism to process and analyze real-time healthcare data while ensuring accuracy and responsiveness. The need for a robust system that can handle multi-criteria decision-making, optimize real-time interaction, and enhance accessibility is evident. This research aims to address these challenges by integrating Reinforcement Learning from Human Feedback (RLHF) with the Analytic Network Process (ANP) to develop an advanced AI-driven decision-making framework. RLHF is employed to refine decision-making by incorporating human preferences into AI models, while ANP ensures structured multi-criteria analysis for optimizing service efficiency. The proposed mechanism seeks to minimize computational delays, enhance accuracy, and provide real-time, secure, and adaptive healthcare services.

3. Proposed approach

This section details the proposed mechanism by integrating analytical process along with generative AI mechanism. The generative AI techniques are the one that uses neural networks to search the patterns in formation and create new content to provide accurate decision. There exist numerous GAI techniques such as Generative adversarial network, foundation models, reinforcement learning and so on. Among number of GAI schemes, this paper use Reinforcement Learning from Human Feedback (RLHF) by considering multiple model training process and various stages of deployment. Further, Analytic Network Process (ANP) is used considering multi-criteria decision-making process to provide accurate decisions. The RLHF involves multiple training process including several stages of deployment considering three core steps:

Table 2
List of abbreviations.

Terms	Definition
GAI	Generative AI
RLHF	Reinforcement Learning Human Feedback
ANP	Analytic Network Process
W_p, w_n1, w_n2, w_{pn}, w_{nn}	Weights assigned to network
C_1, C_2,..C_n	criteria s
W	overall weight
I	Unit matrix

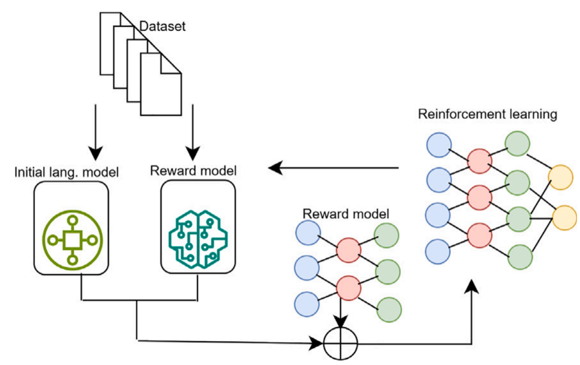

Fig. 2. Pretraining model.

- Pre-training language model
- Gathering information from environment and training reward model
- Fine tuning reinforcement learning

Table 2 presents the list of abbreviations used in the entire manuscript.

3.1. Pretraining language model

The model is pretrained using classical pretraining objectives in order to generate the information. The model responds to the diverse instructions for designing the language model. Further, the language model is used to train the reward model to determine the human preferences that are integrated to the existing systems. Fig. 2 presents the pretraining model consisting of text dataset ad human augmented text.

3.2. Reward model

The goal of reward model is to get the system which accepts the text in a sequence by returning reward information. The output of the scalar reward is the prompt generation pairs to generate new text. Further, the ranking is used to compare the multiple models for creating an efficient and much better regularized dataset. The ranked dataset is now transferred to the next phase of model.

Fig. 3. Reinforcement learning.

3.3. Reinforcement learning

The considering the initial model and preference model generated by reward model, the reinforcement learning model is used to optimize the language model to further maximize the reward metrics by updating the rules. The reinforcement learning is used to determine how to make decisions to achieve best outcome by receiving the rewards for correct incentives and penalty for the incorrect one's. it is further used to accurate the decisions by deploying the value-based, policy-based and actor-critic methods. Fig. 3 presents the complete RHLF model consisting of dataset, initial language model, reward model and reinforcement learning.

Further, in order to accurate the decision process considering multiple criteria and parameters of the dataset. The pseudo code of RHLF is presented in Algorithm 1.

Algorithm 1 RHLF Mechanism

Input Value: Raw Data
Output: Trained data
Step 1: Initialize dataset list
Step 2: Pre-train the language model
Step 3: Gather the information
Step 4:Train the reward model
Step 5: Apply reinforcement learning

3.4. Analytical Network Process (ANP)

The ANP considers network-structure format in order to process the generated records as presented in Fig. 4. The ANP method consist of four steps:

- Structuring the problem: here, the model is constructed by structuring the model in order to state the decision.
- Pairwise comparison and policy vectors: the pairwise comparison and policy vectors are used to compare each element in a cluster. The ANP method is used to identify the decision-makers by determining the relative significance and related criteria.
- Formation of matrix: Markov chain process is used to include interdependent influences and prioritized matrix. The local priority vectors are grouped based upon their influence flow according to different situations. The matrix of local priority vector is defined as:

$$\mathbf{W} = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{vmatrix} W_p & 1 & \dots & \dots & W_{pn} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ W_{n1} & W_{n2} & \dots & \dots & W_{n,n}, \end{vmatrix} \tag{1}$$

Where, c_p presents clusters

$(p = 1, 2, \dots, n)$

and each cluster (p) possess m_p elements having no influence and zero entry. Considering the three-level structure, the matrix is further defined as:

$$\mathbf{W} = \begin{vmatrix} 0 & 0 & 0 \\ W_{21} & W_{22} & 0 \\ 0 & W_{32} & I, \end{vmatrix} \tag{2}$$

Where, I is the unit matrix.

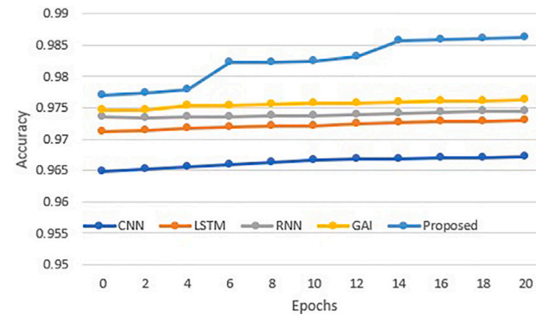

Fig. 4. Three level ANP structure.

- Selecting best alternative: the final matrix is further used to define the priority weights for compromising the interrelated clusters and computing the overall priorities according to best option selected.

Further, the pseudo-code of ANP mechanism is presented in Algorithm 2.

Algorithm 2 ANP Mechanism

Input Value: Structured and trained problem
Output: Accurate diagnosis
Step 1: Policy vectors and pair-wise comparison
Step 2: Formation of matrix
Step 3: Form the information in clusters
Step 4:Apply weights to each information
Step 5: Select best alternative

3.5. Existing work and comparison

Existing work in order to ensure an efficient and improved quality of life in healthcare sector for elderly and disabled people is presented in a tabular format. The researchers have implemented the proposed and enhanced schemes using several AI, Blockchain-based and cryptographic schemes. The below Table 3 presents a comparative analysis of existing approaches while implementing the proposed schemes such as CNN, LSTM, RNN, GAI and proposed mechanism.

3.6. Research gap

While several technological solutions have been proposed and developed to aid the disabled people, existing literature revels that traditional service devices, and techniques have limited usability and effectiveness. Recent advances in ML/DL-based techniques have further shown critical promise for addressing challenges. Several studies have explored the use of CNN, RNN, and decision-making scenarios for real-time interaction and services to the individual. Despite the potential demonstrated by these methods, limitations still exist in terms of usability, accuracy, real-time delay, and overhead. The proposed GAI and AHP method able to address this research gap by offering efficient and comprehensive solutions by leveraging the wearable and online applications. The proposed system seeks to improve the quality of life for disabled people by promoting more accuracy, less delay and overhead in real-time interaction, ultimately improving the mobility and independence in various environments.

3.7. Data collection

The data collection phase integrates five steps as presented in an Algorithm 3. (1) defining the list of objects, (2) use a smartphone to capture the images of objects from various conditions, angles, (3)

Table 3
Implementation and simulation concerns in improving the healthcare sector in Saudi Arabia.

Existing approach	Dataset	Imp. tool	Metrics	Limitation
Talaat et al. [23]	MNIST	Python	Accuracy, loss	Computation overhead
Alghadier et al. [21]	Analytical paper	Review	Accuracy	Large delay
Attar et al. [22]	Surveys	Python	Normality assessment	More delay and accuracy
Said et al. [5]	IWPD	Python	Prevalence, repair	overhead
Proposed mechanism	MNIST	Python	Accuracy, precision, recall	computation overhead

Table 4
Normal and disabled people dataset.

Category	Disability type	Gender	Age	Mobility assistive devices	Disability %
Normal	nil	M	37	mobile	0
Disabled	speech	M	58	Watch	10

organize the images into different folders (4) repeat the steps until the images are collected from dataset. (5) ensure that the information or images are of higher resolution.

Algorithm 3 Data collection process

Input Value: Raw Data
Output: Structured and cleaned data
Step 1: Initialize dataset list
Step 2: Define list of objects
Step 3: Capture text and images
Step 4: Organize all the information
Step 5: Ensure the higher resolution of images

The complete process of reinforcement learning along with ANP is presented in Algorithm 4.

Algorithm 4 Workflow of complete process

Input Value: Disabled people dataset
Output: Efficient and trained model
Step 1: Dataset is accessed by the devices
Step 2: Trust of each device is computed
Step 3: Pre-process the data
Step 4: Apply RLHF model;
Step 5: Get trained data
Step 6: Apply ANP mechanism by forming the matrix
Step 7: Select the best alternative for making decisions

4. Performance analysis

This section introduces the considered dataset and evaluation of proposed mechanism performance.

4.1. Dataset

The proposed mechanism is analyzed and compared by considering MNIST dataset as a benchmark in machine learning community [https://www.kaggle.com/datasets/thepbordin/indoor-object-detection,https://www.kaggle.com/code/ngbolin/mnistdataset-digit-recognizer/input.] . The proposed mechanism is useful for exploring the analytical performance of machine learning while recognizing the images and tasks. Further, we have considered Kaggle dataset for considering the several metrics and behavior of information. Table 4 presents some of the entries of disabled people dataset for disabled people in healthcare system. According to year 2022 housing and population census, approximate 5% people are disabled. The dataset of Saudi Arabia is categorized in terms of several factors such as disability type, gender, age, mobility assistive device, disability type, demographic factor etc.

4.2. Implementation

The proposed mechanism is analyzed using python considering NumPy, Matplotlib, and pandas' libraries. NumPy is used for numerical computations and handling metrics and arrays efficiently.

NumPy: it is used for numerical computations and handling matrices and arrays efficiently.

Pandas: the pandas are used for manipulating, handling and analysis of structured data.

Matplotlib: it is used for plotting graphs and data visualization.

TensorFlow: it is used for building the GAI learning models and building the training data.

SciKit Learn: the SciKit is used for model selection and evaluation process of machine learning algorithms.

In our proposed mechanism, we have used one of GAI algorithm i.e. RLHF that is basically used for categorizing and speedup the processing and analysis part of diagnosis. Further, ANP mechanism is used for analytical comparison and computation in order to further reduce the delay while ensuring real-time interaction for the disabled people on time.

4.3. Code structure

The code structure is divided into several parts such as data preprocessing, model architecture, training and testing the proposed mechanism. The pre-processing module provides the routine loading and cleaning of the dataset by removing the null entries. The basic GAI architecture was setup with TensorFlow with fully lined layers. Further, the RLHF model is used in the training module together with learning rate in model architecture. Further, ANP method is used to further prevent from reduced delay and speed up the process by selecting the significant parameters while processing and analyzing the model. Furthermore, the code modules are combined on several tests for validating and cross-validating the functionality of proposed framework.

4.4. Performance metrics

The following performance metrics are used to validate the proposed model such as delay, accuracy, recall, precision and F1 score. The delay presents the amount of time the module required to respond the individual query at a remote discuss in real-time interaction. Accuracy presents the correct prediction percentage while recall presents the proportion of true positive predictions overall actual positives. Precision quantifies the proportion of true positive predictions overall all positive predictions. Further, F1 score integrates the recall and precision providing a balanced measure. The metrics assess the system performance and effectiveness in different aspects of classification and prediction of the proposed system. Table 5 presents the evaluated metrics for validating the proposed scenario:

Table 5
Evaluation metrics.

Terms		Terms	
$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	(3)	$Precision = \frac{TP}{TP + FP}$	(4)
$Recall = \frac{TP}{TP + FN}$	(5)	$F1Score = \frac{2 \times precision \times recall}{precision + recall}$	(6)
$Delay = \frac{recall}{precision}$	(7)		

Table 6
Analytical comparison.

Metrics	Run cycle	Proposed mechanism
Computation overhead (ms)	1	0.23
	2	0.20
	3	0.17
	4	0.14
	5	0.12
Communication overhead (ms)	1	0.45
	2	0.43
	3	0.40
	4	0.37
	5	0.36
Delay (ms)	1	0.12
	2	0.10
	3	0.08
	4	0.07
	5	0.05
Accuracy (%)	1	98.7
	2	98.7
	3	98.8
	4	98.8
	5	98.8

4.5. Analytical comparison

This section presents the analytical comparison of proposed scheme in terms of communication, computation, delay and accuracy while compiling the proposed mechanism at least 5 runs. The computation, communication and delay are significantly less while increasing the run time of the process as the information is already stored and pre-processed by the system and provide accurate and real-time responses to the individuals. Further accuracy of proposed scheme further increases along with increasing run time cycles. Table 6 presents the brief chart of analytical comparison.

4.6. Results

This section discusses how the proposed mechanism worked in the ANP and RLHF models using the MNIST dataset: (1) CNN, (2) LSTM (3) RNN (4) GAI (5) RLHF. Fig. 5 exhibits the accuracy of all five existing and proposed approaches in order to analyze the performance validation. Based upon the provided results, it can be seen that all the existing learning algorithms such as CNN, RNN, LSTM and GAI have less accuracy as compare to proposed mechanism. The reason is because of involvement of ANP that further generates the accurate system before passing it to GAI for improving the overall accuracy of the proposed mechanism.

Additionally, Figs. 6 and 7 presents the delay and F1 score of the existing and proposed mechanisms. All the approaches demonstrate the comparable performance in terms of delay and F1 score approximately 0.97 of all the models.

Further, Figs. 8 and 9 exhibits the precision and recall of proposed mechanism in comparison of all the existing models. The precision and recall of proposed mechanism out-performs existing approaches achieving values from the range of 0.97–0.98. The presented results indicate the outperformed results of all the existing models achieving higher accuracy, precision, recall, F1 score with reduced delay.

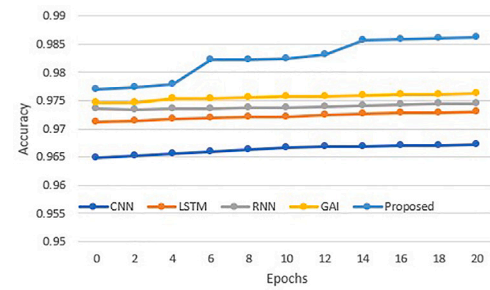

Fig. 5. Accuracy.

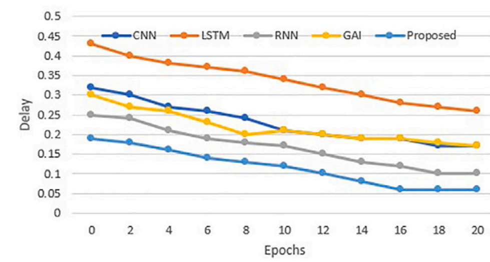

Fig. 6. Delay.

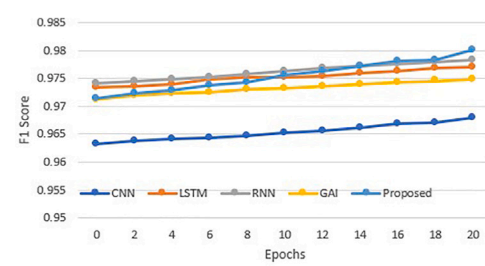

Fig. 7. F1 Score.

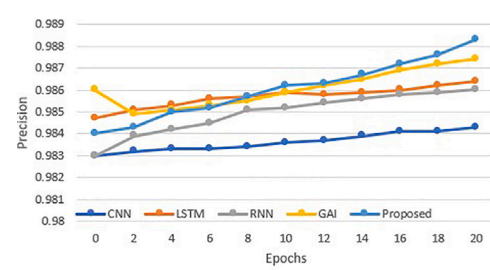

Fig. 8. Precision.

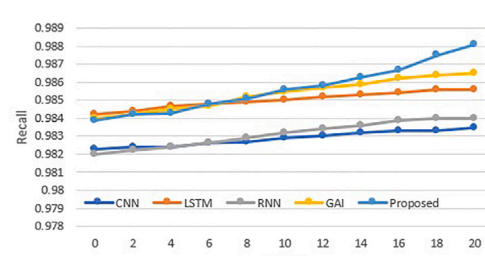

Fig. 9. Recall.

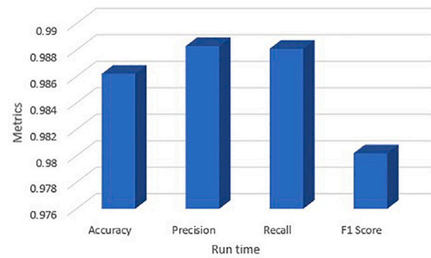

Fig. 10. Results of all different algorithms.

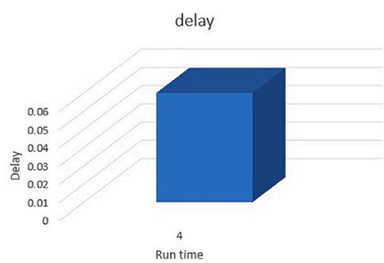

Fig. 11. Delay of proposed mechanism.

Finally, Figs. 10 and 11 presents the results of different learning algorithms in a bar chart on a scale of 0–1. The accuracy, recall, precision, and F1-score are measured in terms of percentage while delay is analyzed over milliseconds. The proposed mechanism outperforms all the computed metrics because of integration of two mechanisms such as RLHF and ANP for analyzing and computing the results against several metrics.

4.7. Discussion

The above experimental results demonstrated that our proposed framework significantly improves accuracy, reduces response time, and enhances decision-making efficiency when compared to traditional healthcare models. By incorporating RLHF, the proposed system continuously learns from user interactions, making it smarter and more accurate in providing personalized medical recommendations. The experiment demonstrated that our system achieved 98.8% precision, which greatly reduced errors in diagnoses, prescriptions, and medical advice. At the same time, ANP optimizes decision-making by efficiently managing healthcare resources, which helps to reduce delays, speed up processing times, and prioritize patient care. The experiment results also showed that response latency decreased from 0.12 ms to 0.05 ms, allowing for faster medical consultations, improved tele-medicine services, and real-time healthcare solutions that benefit both disabled and non-disabled individuals.

Our proposed system also showed notable performance in key healthcare metrics, such as precision, recall, and F1-score, ensuring that critical medical cases are identified and handled accurately with minimal false positives or negatives. The integration of ANP enabled smarter decision making, ensuring that patients received the most appropriate healthcare services with minimal delays. Additionally, RLHF helped the system continuously adapt to patient needs, making it more user-friendly and responsive over time.

In comparison to existing AI-based healthcare models, the proposed system outperformed traditional methods in accuracy, efficiency, and response time. The experiment confirmed that this framework is a more reliable and effective solution for providing healthcare services to individuals with disabilities. By integrating advanced AI and reinforcement learning techniques, this research successfully eliminates accessibility barriers, making healthcare more inclusive, efficient, and patient-centered. These findings align with Saudi Arabia's Vision 2030, contributing to smart, technology-driven healthcare solutions that improve the quality of life for disabled individuals and enhance the overall delivery of medical services.

5. Conclusions

In this paper, we proposed an innovative approach for improving healthcare services by integrating Generative Artificial Intelligence (GAI) techniques with advanced decision-making models. Specifically, we used reinforcement learning from human feedback (RLHF) and the analytical network process (ANP) to optimize service accessibility, reduce computational delays, and improve accuracy in real-time healthcare applications. The RLHF model was used to refine decision-making through iterative learning, while ANP facilitated multi-criteria decision-making to enhance service efficiency. Our experimental results demonstrate the effectiveness of the proposed mechanism compared to existing approaches such as CNN, LSTM, RNN, and conventional GAI models. The integration of RLHF and ANP significantly improved key performance metrics, including accuracy, precision, recall, F1-score, and response time. Furthermore, the analytical comparison highlighted the advantages of our framework in reducing computational overhead, improving security, and ensuring real-time accessibility for disabled and elderly individuals. The findings of this study emphasize the potential of AI-driven solutions in transforming healthcare access, particularly in Saudi Arabia, where research in this area is still in its early stages. Future research can further extend this work by integrating security and data integrity measures to protect patient records and by validating the proposed mechanism in real-world datasets. The implementation of such a robust AI-driven framework can contribute to improving the quality of life of people who need healthcare assistance, ultimately fostering a more inclusive and efficient healthcare ecosystem.

CRediT authorship contribution statement

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

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.

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