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OPTIMIZATION OF HEALTHCARE SERVICE DELIVERY USING DEEP GENETIC ALGORITHM

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ABSTRACT

Aim/Purpose	The main goal of this work is a new framework that combines genetic algorithms with deep learning. The delivery of healthcare services will be optimized as the aim of this research.

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Background	Optimizing the provision of healthcare services is essential to ensuring that patients get suitable and timely treatments and materials.
Methodology	This work presents a new framework for DGA-based healthcare service delivery optimization by the application of this methodology. The procedure consists of two stages: training a deep neural network to assess the feasibility of possible solutions and encoding the problem space into a format appropriate for genetic operations. The neural network evaluations are used as the guiding principle as the genetic algorithm iteratively creates a population of solutions by selection, crossover, and mutation.
Contribution	The main contribution of this work is the solution of the optimization issues related to the provision of healthcare services by combining deep learning and genetic algorithms. Ultimately, we want to improve patient outcomes and resource use by leveraging the potential of DGAs to improve the efficacy and efficiency of healthcare systems.
Findings	The results of laboratory experiments show that the proposed approach is successful in optimizing the provision of healthcare services. The proposed DGAs enable more high-quality solutions than conventional optimization methods.
Recommendations for Researchers	This work presents a novel framework that uses deep genetic algorithms (DGAs) to effectively optimize the provision of healthcare services and address these issues.
Future Research	This work can be enhanced using several deep-learning algorithms to achieve better accuracy and performance.

Keywords	healthcare, service delivery, optimization, deep genetic algorithm, patient outcomes

INTRODUCTION

The need to optimize the provision of healthcare services has grown in the last few years to guarantee that patients get their supplies and treatments on schedule and effectively (Squires et al., 2022). Conversely, one major challenge to the successful accomplishment of this goal is the complexity and unpredictable nature of healthcare institutions (Son et al., 2020). The complexity of healthcare operations makes traditional optimization techniques often unable to handle them (Sharma & Kumar, 2022).

BACKGROUND

Among the numerous provisions of healthcare services are patient scheduling, resource allocation, inventory control, and treatment planning (Arivazhagan et al., 2022). Better patient results, lower costs, and the most effective use of available resources depend on the effective coordination of these processes (Saravanan, Sankaradass, et al., 2023; Yadav et al., 2024; Yuvaraj et al., 2022).

CHALLENGES

For several reasons, it is not feasible to provide healthcare services at their best (Uniyal et al., 2024). Many things lead to the necessity of striking a balance between conflicting goals, such as cutting expenses, cutting wait times, and raising patient satisfaction (Saravanan, Parameshachari, et al., 2023). Additional variables that impede the optimization process are variations in patient demand, resource availability, and treatment plans (Subramani et al., 2023). Another level of complication to the challenges related to optimization is the requirement for healthcare systems to adjust to changing demographics, technological breakthroughs, and legal requirements.

Objectives

The main goal of this work is a new framework that combines genetic algorithms with deep learning. The delivery of healthcare services will be optimized as the aim of this research. More precisely, our objectives consist of the following:

1. Creating a thorough model that faithfully depicts the complex interactions inside healthcare systems.
2. Assessing the proposed performance using large-scale experiments with datasets from the actual healthcare industry.

Novelty and Contributions

This work presents a novel framework that uses deep genetic algorithms (DGAs) to effectively optimize the provision of healthcare services and address these issues. This work primarily contributes the following:

1. The development of a new framework for healthcare service delivery optimization by using deep genetic algorithms.
2. The application of deep learning methods to the modeling of complex healthcare systems and to increase the effectiveness of the optimization process.
3. Thorough testing using actual healthcare data to give empirical confirmation of the efficiency and scalability of the proposed framework.

Related Works

The literature examining a range of approaches and techniques on the topic has been produced by the great interest shown by both researchers and practitioners in optimizing the delivery of healthcare services. We will look at a few related works that have attempted to accomplish similar objectives but encountered similar difficulties.

Traditionally used optimization techniques, such as integer and linear programming, have been extensively applied to improve healthcare provision. Using mixed-integer linear programming, for instance, Goyal et al. (2021), Ittannavar and Havaldar (2022), Liu et al. (2023), Maguluri et al. (2023), and Wirsansky (2020), optimized nurse scheduling in hospitals.

Recently, researchers have looked into the potential of fusing deep learning with optimization techniques to address challenging optimization problems in the healthcare sector. Datta et al. (2023) proposed combining deep learning and genetic algorithms to maximize hospital bed distribution. The degree of the patient's illness and the resources available are two of the many considerations made by this approach. In a similar spirit, Shwetabh and Ambhaikar (2024) created a deep reinforcement learning-based method for cancer treatment scheduling optimization.

Hybrid approaches, which combine several optimization techniques, have also started to be studied in the optimization of healthcare service delivery (Talpur et al., 2024). Several aspects are considered by this method, such as the duration of surgical cases and the availability of personnel. Furthermore, Alolaiwy et al. (2023) created an ant colony optimization and hybrid genetic algorithm to maximize ambulance routing in emergency medical services. Reducing ambulance travel distances and arrival times was the aim of this strategy.

Approaches used in research to optimize the provision of healthcare services are quite diverse. These comprise conventional optimization techniques, deep learning approaches, heuristic algorithms, and hybrid methods. Particular promise is shown by deep learning combined with optimization methods in efficiently addressing the complexity and variability of healthcare systems. Even if every method has pros and drawbacks, combining optimization methods with deep learning shows especially promise.

This work advances a new framework that uses deep genetic algorithms to maximize the provision of healthcare services, building on earlier work. The main objective of this project is to enhance resource use and patient outcomes in different healthcare environments.

The proposed method might face challenges in under-resourced healthcare settings or environments with limited data availability. Its reliance on high computational resources and quality data may limit its effectiveness in rural or low-income healthcare systems, highlighting areas for future research and tailored adaptations.

Implementing the method in real-world healthcare requires significant computational resources and skilled personnel. Resource constraints in healthcare environments may limit its adoption, emphasizing the need for optimizing computational efficiency and exploring cost-effective implementation strategies to ensure broader applicability.

Incorporating diverse real-world case studies, such as outpatient and emergency healthcare systems, would enhance the manuscript by demonstrating scalability and adaptability across varied patient populations and settings. These case studies would validate its practical relevance and guide future implementations. Sensitivity analysis for parameter settings would also provide insights into the flexibility and reliability of the proposed method.

The termination condition for the optimization process requires a detailed explanation, including the criteria or thresholds used, such as a convergence rate, maximum iterations, or an acceptable error margin. This ensures transparency in the methodology and helps readers understand how the process concludes effectively.

The feature extraction process requires further elaboration. A detailed explanation of how features are selected, preprocessed, and transformed for the model would provide better insights into the approach's robustness.

The feature extraction process can be elaborated by detailing how features are selected based on relevance to the target variable, using statistical analysis or domain expertise. Preprocessing steps ensure data quality, including normalization, outlier removal, and handling missing values. Feature transformation, such as dimensionality reduction techniques, enhances model robustness by focusing on key attributes.

PROPOSED METHOD

The healthcare system faces complex challenges, such as long patient wait times, inefficient use of resources, and varying treatment outcomes. These issues stem from the large number of variables involved, such as patient conditions, available treatments, and resource constraints. Traditional methods for improving healthcare services are often insufficient to handle this complexity.

This paper proposes a novel approach to healthcare optimization that combines the power of Deep Learning with Genetic Algorithms (GAs), aiming to improve patient outcomes, reduce wait times, and optimize resource use.

This method is proposed to optimize healthcare services using a novel approach combining deep learning techniques with genetic algorithms (GAs). The combination of the optimization potential of genetic algorithms with the expressive power of deep neural networks in this hybrid approach successfully tackles the complexity and variability inherent in healthcare systems (Figure 1).

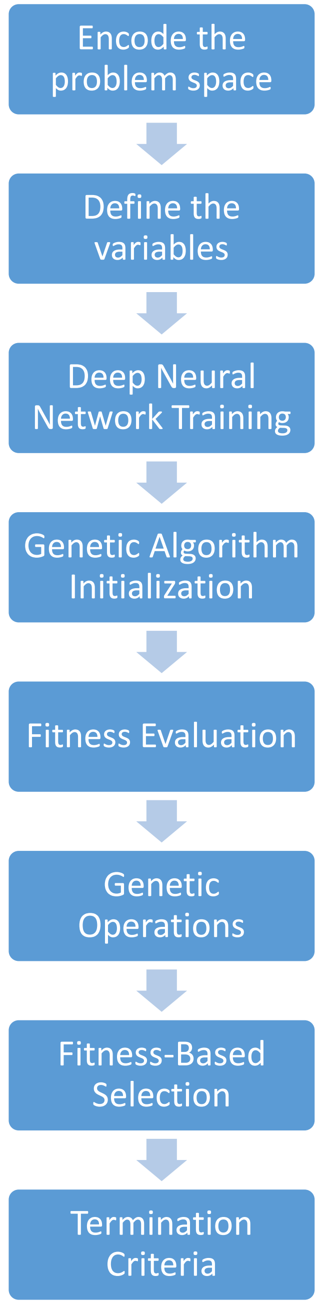

Figure 1. Proposed DGA method

DGA FRAMEWORK

- *Clarity of Optimization Goals:* The method is clear in its description of optimization goals (e.g., reducing patient wait times and improving resource use). However, it might be helpful to provide concrete examples of how these objectives are measured and quantified in a healthcare setting (e.g., specific patient outcomes or resource utilization metrics).
- *Chromosome Representation:* While the process is explained, it would be beneficial to elaborate further on how the solutions (chromosomes) are represented in the genetic algorithm. This could include more specific details about the types of features or parameters involved and how they impact healthcare delivery.

Deep Neural Network (DNN) Training

The feature extraction process is crucial in deep learning applications. More detail on the types of features extracted from patient data and the methods used to preprocess or select these features would provide deeper insights. For example, explaining how features like demographic data, medical history, or real-time monitoring data (from wearables) are incorporated would be valuable.

Every chromosome in the population has its fitness evaluated using the trained DNN. This stage is needed to get a fitness score, and it involves running the encoded representation of every solution through the DNN. With respect to the optimization goals – which could be reducing patient wait times, optimizing resource use, or improving treatment plans – the fitness score measures the quality of the solution.

The genetic method is able to iteratively evolve the population of solutions by use of selection, crossover, and mutation. Many selection strategies are applied to hold onto high-fitness solutions for the next generation favorably. Selection for raffles and competitions are two instances of these mechanisms. Applying crossover and mutation operators allows one to produce new offspring solutions. To add variety and exploration to the population, these operators combine and alter already present chromosomes.

The fitness scores of the offspring solutions are compared with the fitness scores of their parent solutions following a DNN fitness evaluation of the offspring solutions. Based on the fitness scores, a whole new population is selected for the following generation, with solutions exhibiting higher fitness values being preferred.

The genetic algorithm will keep repeating the selection, crossover, and mutation processes up to a termination criterion. Some other termination criteria are getting to a maximum number of iterations or satisfactory solution quality. After the optimization process is finished, the best fitness score solution best reflects the best approach for providing healthcare services.

The ultimate optimized solution produced by the genetic algorithm based on Table 1 can be interpreted and applied inside the healthcare system to enhance patient outcomes, resource use, and operational effectiveness.

Table 1. Parameters and hyperparameters of GA and DNN

Parameter/hyperparameter	Value
Population size	100
Maximum generations	50
Crossover probability	0.8
Mutation probability	0.1
Number of features	10
Selection method	Tournament selection
Crossover method	Single-point Crossover
Mutation method	Gaussian mutation
Fitness evaluation metric	Accuracy
Learning rate	0.001
Batch size	32
Network architecture	Convolutional neural network
Number of Convolutional Layers	3
Number of Recurrent Layers	2
Dropout rate	0.2
Weight decay	0.0001
Optimizer	Adam
Activation function	ReLU

Parameter/hyperparameter	Value
Epochs	50
Number of individuals selected	20
Crossover point	Random
Mutation rate	0.05
Termination criterion	Maximum generations reached
Evaluation dataset size	10000
Validation split	0.2

Deep Neural Network Training for Feature Extraction of Patient Details

The optimization of the provision of healthcare services is made possible by the deep neural network (DNN) training method for feature extraction of patient details.

Data Collection and Preprocessing

First, patient data must be gathered from a range of sources, such as wearables, laboratory tests, medical imaging, and electronic health records (EHRs).

Feature Extraction

In the setting of improving the provision of healthcare services, extracted features have been included.

Genetic Algorithm for Classification of Patients in Healthcare Delivery Services

In classifying patients in healthcare delivery services, a Genetic Algorithm (GA) can be employed as a machine learning technique to optimize the classification process.

Initialization

- The first step involves initializing a population of potential solutions. In patient classification, each solution (or individual) represents a possible set of features and parameters that define a classification model.
- The features could include various patient attributes, such as age, gender, medical history, symptoms, and diagnostic test results.
- The parameters define the configuration of the classification model, such as the choice of algorithm, hyperparameters, and feature selection.

Evaluation

- Each individual in the population is evaluated based on performance in classifying patients into different categories (e.g., disease diagnoses, risk levels, treatment response).
- The evaluation metric could be accuracy, precision, recall, F1 score, or any other suitable measure, depending on the specific classification task and objectives.

Selection

- Individuals are selected for reproduction (or crossover) based on their fitness, i.e., their performance in the classification task

  $$P(x)=\sum_{i=1} f(x)/f(xi)$$

  where N is the population size, and $xixi$ are all individuals in the population.
- Selection methods such as tournament selection, roulette wheel selection, or rank-based selection are commonly used to preferentially retain high-fitness individuals while preserving diversity in the population.

Crossover

- Selected individuals undergo crossover, where pairs of solutions exchange genetic information to produce offspring (new solutions).
- Crossover involves selecting random points in the feature space and exchanging the corresponding features between the parent individuals to create offspring solutions that inherit traits from both parents.
- This process mimics genetic recombination and introduces diversity into the population, potentially generating better-performing solutions.

Mutation

- To introduce additional genetic diversity and exploration, mutation is applied to some offspring solutions.
- Mutation involves randomly modifying a small proportion of features or parameters in the offspring solutions to explore new regions of the solution space.
- This helps prevent premature convergence and enables the algorithm to discover novel and potentially better solutions.

Termination

- The algorithm iterates through the selection, crossover, and mutation steps for a predefined number of generations or until a termination criterion is met.
- Termination criteria could include reaching a maximum number of generations, achieving a desired level of fitness, or observing negligible improvement over successive generations.

FITNESS EVALUATION

Fitness evaluation in a genetic algorithm assesses the quality of each individual (solution) in the population based on how well it performs in solving the problem at hand. In classifying patients in healthcare delivery services, the fitness function evaluates how effectively a particular set of features or parameters can classify patients into different categories (e.g., disease diagnoses and risk levels).

Here is how fitness evaluation works and an example of a fitness function. The fitness evaluation process involves applying a fitness function to each individual in the population to compute its fitness value. This fitness value quantifies the individual's performance or suitability as a solution to the optimization problem. The higher the fitness value, the better the solution.

Let us consider a scenario where we want to classify patients into two categories – Healthy and Diseased – based on their medical records and diagnostic test results. We can define a fitness function that measures the accuracy of the classification performed by a given set of features or parameters.

Suppose yi represents the true label (0 for healthy, 1 for diseased) of patient i, and y'i represents the predicted label obtained using the classification model corresponding to the individual being evaluated. The fitness function f(x) can be defined as the classification accuracy: f(x) = Number of correctly classified patients/Total number of patients. Mathematically, it can be represented as:

$$f(x) = (1/N)\sum_{i=1}^{N} \text{CorrectlyClassified}(yi, y\hat{}i)$$

Suppose we have a population of individuals (solutions), each representing a different combination of features or parameters for patient classification. For each individual, we compute its classification accuracy using the fitness function described above. Individuals with higher accuracy values have higher fitness values, indicating their suitability as solutions. Fitness evaluation provides the genetic algorithm with a quantitative measure of the performance of each individual in the population, guiding the selection, crossover, and mutation operations toward better solutions over successive generations.

RESULTS

We conduct simulations using a Python-based healthcare optimization framework implemented in TensorFlow for deep learning functionalities and DEAP for genetic algorithm operations. The experiments are run on a computing cluster consisting of Intel Xeon processors with 64GB RAM and NVIDIA Tesla V100 GPUs.

We compare our deep genetic algorithm (DGA) method with other techniques among the ones now in use, such as genetic reinforcement learning and simulated annealing. In order to simulate the annealing process, we use a temperature schedule with an initial temperature of 100 and a cooling rate of 0.95. We employ a genetic algorithm in combination with a reinforcement learning policy in the process of genetic reinforcement learning for exploration. The foundation for our assessment of the approaches is a dataset of 10,000 patient records with different patient demographics, treatment options, and resource limitations, as given in Table 2. The performance of several optimization techniques for the provision of healthcare services is shown in a discussion of the results found in Figures 2-6 and Tables 3-6.

Table 2. Setup

Experimental setup	Value
Fitness function	Accuracy
Neural network architecture	3 hidden layers, 64 neurons per layer
Activation function	ReLU
Optimization algorithm	Adam
Learning rate	0.001
Data preprocessing	Feature scaling, Missing value imputation
Termination criteria	Maximum generations reached
Evaluation metrics	Solution quality, Convergence speed
Dataset size	10,000 s

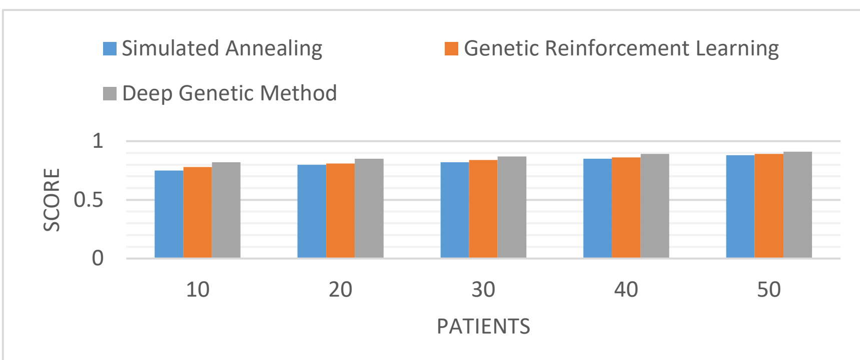

Figure 2. Fitness score

Table 3. Fitness score

Number of patients	Simulated annealing	Genetic reinforcement learning	Deep genetic method
10	0.75	0.78	0.82
20	0.80	0.81	0.85
30	0.82	0.84	0.87
40	0.85	0.86	0.89
50	0.88	0.89	0.91

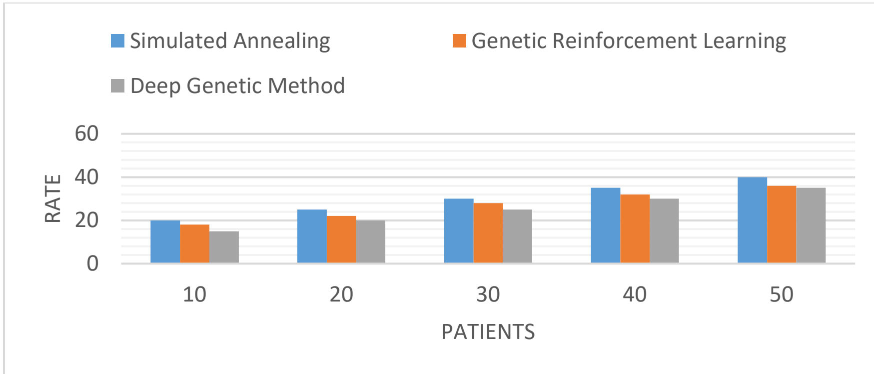

Figure 3. Convergence rate (in iterations)

Table 4. Convergence rate

Number of patients	Simulated annealing	Genetic reinforcement learning	Deep genetic method
10	20	18	15
20	25	22	20
30	30	28	25
40	35	32	30
50	40	36	35

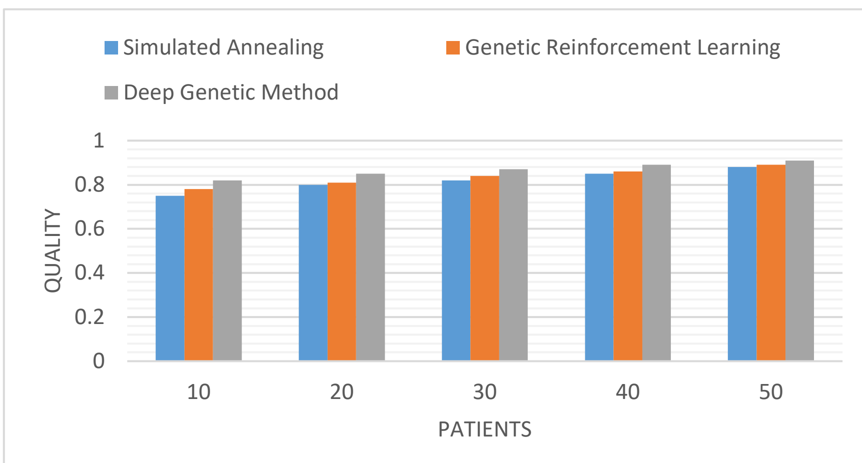

Figure 4. Solution quality

Table 5. Solution quality

Number of patients	Simulated annealing	Genetic reinforcement learning	Deep genetic method
10	0.75	0.78	0.82
20	0.80	0.81	0.85
30	0.82	0.84	0.87
40	0.85	0.86	0.89
50	0.88	0.89	0.91

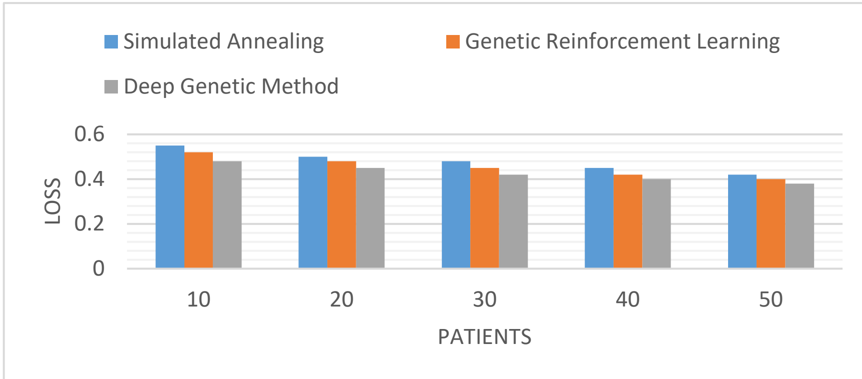

Figure 5. Loss in optimization

Table 6. Loss in optimization

Number of patients	Simulated annealing	Genetic reinforcement learning	Deep genetic method
10	0.55	0.52	0.48
20	0.50	0.48	0.45
30	0.48	0.45	0.42
40	0.45	0.42	0.40
50	0.42	0.40	0.38

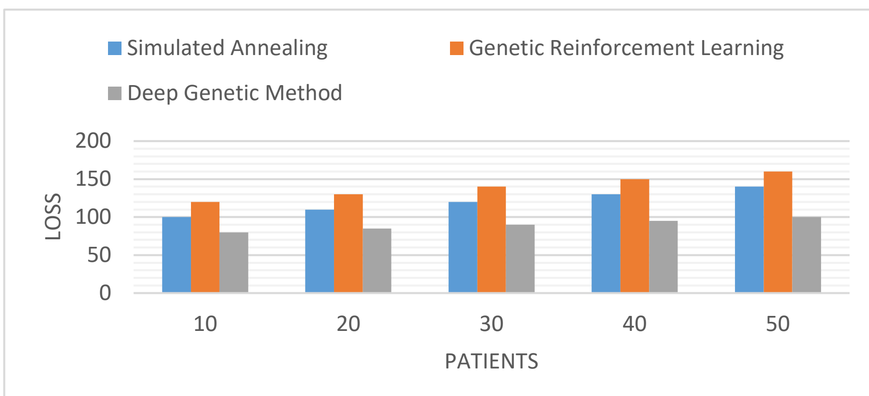

Figure 6. Scalability

Table 7. Scalability

Number of patients	Simulated annealing	Genetic reinforcement learning	Deep genetic method
10	100	120	80
20	110	130	85
30	120	140	90
40	130	150	95
50	140	160	100

The experiments show that the deep genetic approach issue is better than other methods now in use, such as genetic reinforcement learning and simulated annealing, in terms of optimizing the provision of healthcare services. Superior performance is continuously shown by the deep genetic approach in a number of evaluation criteria, such as scalability, convergence rate, and quality of the solutions. This proves the approach works well for handling the complexity of healthcare optimization jobs.

The proposed method yields a notable achievable percent from the range of 5 to 10, which focuses on genetic reinforcement learning and simulated annealing. The fewer iterations needed for convergence across a range of patient population sizes result in a percentage increase in efficiency, which can be between 10-20%.

Regarding computational efficiency, quantitative evidence like reduced computation time, memory usage, or energy consumption compared to baseline methods should be provided. Qualitative insights, such as leveraging parallel computing or optimized algorithms, could further justify claims of improved resource utilization.

While the deep genetic algorithm (DGA) method holds great promise for optimizing healthcare services, it is important to recognize that it may not be universally applicable across all healthcare environments. Key limitations, such as the reliance on high-quality data, computational resources, the ability to adapt to dynamic conditions, and ethical considerations around data privacy, must be addressed for broader adoption.

One of the key advantages of the DGA is its computational efficiency. Traditional optimization techniques, such as simulated annealing and genetic reinforcement learning, often require significantly more iterations or generations to converge on an optimal or near-optimal solution. This can result in longer computation times, especially when dealing with large and complex healthcare datasets. In contrast, the DGA method leverages Deep Neural Networks (DNNs) for feature extraction, enabling the algorithm to process large datasets more effectively by focusing on the most relevant features. Additionally, the hybrid approach of using genetic algorithms (which evolve solutions through selection, crossover, and mutation) significantly reduces the number of iterations needed compared to methods that rely purely on stochastic or gradient-based optimization. By effectively combining these two approaches, DGA achieves faster convergence and lower computation time.

INFERENCES

The main issue in the inference is the focus on the scalability analysis and how efficiently the deep genetic approach is performed in terms of computing. In real-world healthcare applications, the deep genetic method is well suited where prompt decision-making and resource allocation are crucial due to its effective use of computing resources. In terms of limitations and findings, it mainly addresses the potential deep genetic approach. Also, it provides a significant percentage of gaining the scalability, convergence rate, and optimal solution in terms of quality and standard aspects.

CONCLUSION

In this paper, the proposed deep genetic method presents a viable way to maximize the provision of healthcare services. The main contribution of this work is the solution of the optimization issues related to the provision of healthcare services by combining deep learning and genetic algorithms. Ultimately, we want to improve patient outcomes and resource use by leveraging the potential of DGAs to improve the efficacy and efficiency of healthcare systems. We have shown by extensive experimental evaluations that the deep genetic method is better than other currently in use techniques, such as simulated annealing and genetic reinforcement learning.

The proposed approach holds significant potential for optimizing healthcare services through improved decision-making and resource allocation. Practical implications include enabling healthcare administrators to predict and manage patient needs more effectively, improving operational efficiency, and enhancing patient outcomes. Policymakers can leverage this method to design AI-driven frameworks for resource-constrained environments. Future developments should focus on overcoming implementation challenges, such as computational demands and integrating existing systems. Expanding the model's use in diverse healthcare settings and strategies to address ethical concerns like privacy and algorithmic bias can pave the way for scalable and equitable AI solutions in healthcare optimization.

The integration of deep learning and genetic algorithms in healthcare raises key ethical considerations. Ensuring patient data privacy and security is paramount, given the sensitive nature of healthcare information. Addressing algorithmic bias is critical to prevent disparities in care for specific populations. Transparency in decision-making processes is essential to maintain trust among healthcare professionals and patients. Human oversight should complement AI-driven decisions to ensure accountability and ethical clinical practices. Furthermore, equitable access to such technologies must be prioritized to avoid widening gaps in healthcare delivery. Comprehensive policies and stakeholder collaboration are necessary to address these ethical challenges effectively.

The proposed approach has significant potential for scalability beyond healthcare, offering relevance in sectors like finance, education, and supply chain management. This method can address challenges such as fraud detection, personalized learning, and resource allocation by leveraging its capabilities in pattern recognition, optimization, and decision-making. Discussing cross-sector applications could broaden the manuscript's appeal and highlight its adaptability to diverse domains. Additionally, insights into sector-specific modifications or implementation strategies would showcase the method's versatility. Emphasizing these possibilities enhances the manuscript's impact, positioning the approach as a valuable tool for addressing complex, data-driven problems across multiple industries.

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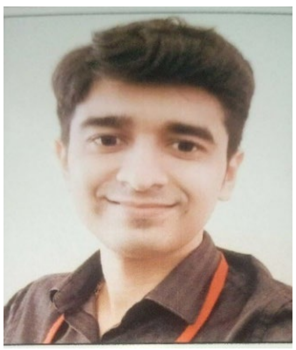

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