Heliyon 10 (2024) e25390

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Designing a medical information diagnosis platform with IoT integration

Hejian Liu [a,1], Xin Guan [b], Rong Bai [c,1], Tianqiao Qin [d], Yanrui Chen [e], Tao Liu [f,*]

[a] School of Education, Teachers College, Guangzhou University, Guangzhou, 510006, China
[b] Guangzhou Xinhua University, Dongguan, 523133, China
[c] Social Sciences Division, University of Chicago, Chicago, Chicago, 60637, United States
[d] School of Management, Guangzhou University, Guangzhou, 510006, China
[e] School of Public Administration, Guangzhou University, Guangzhou, 510006, China
[f] School of Journalism and Communication, Guangzhou University, Guangzhou, 510006, China

ARTICLE INFO

Keywords:
Internet of things technology
Bee colony and evolutionary algorithms
Medical information diagnosis platform
Reverse learning
Gaussian functions

ABSTRACT

In order to enhance the operational efficiency of the healthcare industry, this paper investigates a medical information diagnostic platform through the application of swarm and evolutionary algorithms. This paper begins with an analysis of the current development status of medical information diagnostic platforms based on Chat Generative Pre-trained Transformer (ChatGPT) and Internet of Things (IoT) technology. Subsequently, a comprehensive exploration of the advantages and disadvantages of swarm and evolutionary algorithms within the medical information diagnostic platform is presented. Further, the optimization of the swarm algorithm is achieved through reverse learning and Gaussian functions. The rationality and effectiveness of the proposed optimization algorithm are validated through horizontal comparative experiments. Experimental results demonstrate that the optimized model achieves favorable performance at the levels of minimum, average, and maximum algorithm fitness values. Additionally, preprocessing data in a 10 * 10 server configuration enhances the algorithm's fitness values. The minimum fitness value obtained by the optimized algorithm is 3.56, representing a 3 % improvement compared to the minimum value without sorting. In comparative experiments on algorithm stability, the optimized algorithm exhibits the best stability, with further enhancement observed when using sorting algorithms. Therefore, this paper not only provides a new perspective for the field of medical information diagnostics but also offers effective technical support for practical applications in medical information processing.

1. Introduction

In recent years, medical information diagnostic platforms based on Chat Generative Pre-trained Transformer (ChatGPT) and Internet of Things (IoT) technology have gradually emerged as a significant trend in the healthcare sector [1]. Leveraging advanced artificial intelligence and network technology, these platforms have substantially improved the efficiency and accuracy of medical data

* Corresponding author.
E-mail addresses: liuhejian@gzhu.edu.cn (H. Liu), guanxin@xhsysu.edu.cn (X. Guan), bairr@uchicago.edu (R. Bai), 32365400111@e.gzhu.edu.cn (T. Qin), chenyanrui@e.gzhu.edu.cn (Y. Chen), tao.liu@gzhu.edu.cn (T. Liu).
[1] These two authors considered as co-first authors: Hejian Liu, Rong Bai.

https://doi.org/10.1016/j.heliyon.2024.e25390
Received 28 October 2023; Received in revised form 18 January 2024; Accepted 25 January 2024
Available online 1 February 2024
2405-8440/© 2024 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

processing. However, existing technologies still face numerous challenges in handling large-scale and complex medical data, such as inefficient algorithms and insufficient accuracy [2]. In light of these challenges, this paper aims to design a more efficient and accurate medical information diagnostic platform. The proposed research combines swarm and evolutionary algorithms to enhance the performance of medical diagnostics through algorithm optimization. The motivation for this paper lies in the innovative fusion of algorithms, aiming not only to improve search efficiency and processing speed but also to enhance the adaptability and accuracy of the platform in complex medical data environments. This paper holds significant theoretical and practical implications for advancing medical diagnostic technology.

In the realm of IoT technology research, D'Souza [3] conducted an extensive survey addressing the research landscape of internet-based healthcare platforms. The investigation involved an analysis of interaction patterns, functional structures, and design characteristics of data visualization within healthcare platforms. This analysis was predicated on the distinctive attributes of medical users. D'Souza outlined fundamental principles and strategies governing the design of data visualization in healthcare platforms, encompassing considerations such as structural elements, charting techniques, typographic choices, color schemes, and grid structures. These principles served as valuable guidelines for the practical design implementation of medical management platforms. The design practice encompassed methodologies such as constructing user models, scrutinizing user behavioral trajectories, and utilizing functional framework diagrams, low-fidelity diagrams, and high-fidelity diagrams to elucidate the interaction structure of data visualization design within healthcare platforms. Conversely, Yang [4] provided a comprehensive definition of the nuanced implications surrounding the regulatory oversight of internet-based medical information platforms, approached from an economic law perspective. Yang summarized the distinctive characteristics inherent in the regulatory supervision of these platforms. A meticulous examination of the current status of regulatory oversight concerning internet-based medical information platforms in China was undertaken, considering practical implementation and pertinent policies, thereby identifying prevailing deficiencies. Additionally, scholars conducted an inquiry into regulatory systems in the United States, seeking insights and practices applicable to the regulatory supervision of internet-based medical information platforms in China. Ultimately, recommendations were proffered to enhance the regulatory supervision of these platforms in China, thereby serving as a valuable reference for future developments in the regulatory framework within this domain. Akhbarifar [5] directed attention to the challenge of task migration between terminal devices and Mobile Edge Computing (MEC) servers. Initial considerations involved determining the workload of terminal devices to ascertain the necessity for task migration. In instances of heightened load on a terminal device, tasks were earmarked for migration to proximate MEC servers. Subsequently, a matching model was devised to gauge resource compatibility between tasks and MEC servers, with a preference for migrating tasks to MEC servers demonstrating higher compatibility. Concluding the study, enhancements were introduced to the ant colony algorithm by incorporating load information, culminating in the resolution of the task migration problem through the implementation of the refined ant colony algorithm.

Wang [6], addressing the current situation of complex entrepreneurial enterprises in the cultural and creative industries, applied recommendation systems to decision-making and resource optimization in entrepreneurial projects. They employed neural network algorithms to model project characteristics, user behavior, and content features. Finally, they constructed an entrepreneurial project recommendation and resource optimization model, evaluating and analyzing the model's performance. Wang [7] optimized network systems using blockchain technology, constructed a risk management system with smart contracts, and employed risk association tree technology to track public opinion through smart ledgers. They implemented a blockchain-based non-profit organization risk management model and experimentally validate its effectiveness. Additionally, based on the public opinion risk prediction model, scholars optimized the theoretical framework for detecting the credibility of smart contracts. Wang [8] evaluated the digital economic growth of 277 Chinese cities from 2002 to 2019 using principal component analysis and difference-in-differences methods. The assessment aims to evaluate the impact of low-carbon city pilot policies on digital economic growth. Empirical results indicate that low-carbon city pilot policies encourage digital economic growth, thereby promoting green development. After several robustness tests, including parallel trends, placebo, and endogeneity tests, this conclusion still holds. Heterogeneity analysis shows that low-carbon city pilot policies have a more profound impact on the digital economic growth of coastal, non-resource-based, and large cities. Using panel data from 279 Chinese cities from 2002 to 2019, Li [9] employed a difference model to assess the impact of low-carbon city pilot policies on urban entrepreneurial activities. Results indicate that overall, low-carbon city pilot policies inhibit entrepreneurial activities. However, the level of green innovation can mitigate this inhibitory effect. Based on heterogeneity analysis, low-carbon city pilot policies have a more significant inhibitory effect on entrepreneurial activities in the central and western regions, resource-based cities, and non-central cities. Hu [10], utilizing event studies and bootstrap regression analysis, examined the impact of environmental, social, and governance (ESG) reports on the market performance of shale gas-related companies. The paper reveals that ESG reports exhibit heterogeneity in their impact on the shale gas resource management of relevant listed companies. The report provides short-term positive returns for issuers and potential related parties. The stock returns of private and small companies are significantly negatively affected by ESG announcements. Li [11] investigated the influence of regional digital financial development on corporate financing constraints. The research shows that regional digital finance can significantly alleviate corporate financing constraints, with a greater impact on small and medium-sized enterprises and private enterprises. Regional digital finance can partially correct the size discrimination and ownership discrimination against private small and medium-sized enterprises by traditional finance, as well as the misallocation of financial resources.

Therefore, traditional research on medical information diagnostic platforms often focuses on the application of a single algorithm, such as swarm algorithms or evolutionary algorithms, for processing healthcare data. These studies exhibit significant shortcomings, including low algorithm efficiency, limited capabilities in handling complex data, and insufficient search capabilities in high-dimensional data. This paper adopts an innovative approach by combining swarm algorithms and evolutionary algorithms, introducing Gaussian functions and a reverse learning mechanism to optimize algorithm performance. The novelty of this paper lies in enhancing the efficiency and accuracy of the algorithm in processing large-scale and complex medical data, particularly in improving global search capabilities and avoiding the pitfalls of local optimal solutions. This manuscript introduces a novel optimization algorithm, amalgamating bee colony and evolutionary algorithms, aimed at enhancing the functionality of the medical information diagnostic platform. Initially, the paper conducts an in-depth analysis of the functional dynamics and existing state of the medical information diagnostic platform within the framework of ChatGPT and IoT technology. Subsequently, the manuscript elucidates the constraints inherent in utilizing bee colonies and evolutionary algorithms within the context of the medical information diagnostic platform. Finally, optimization of the bee colony algorithm is achieved through the incorporation of Gaussian functions and the application of reverse learning principles. The efficacy of the proposed optimization algorithm is subsequently substantiated through rigorous comparative experiments.

2. Applications of ChatGPT and IoT technology in medical information diagnosis platform

2.1. Medical information diagnosis platform assisted by ChatGPT and IoT

ChatGPT represents a chatbot technology rooted in natural language processing, facilitating simulated human language communication. Its deployment in medical information diagnosis endeavors to augment the expeditious and precise acquisition of patient data by physicians, thereby elevating the efficiency and caliber of healthcare services. Firstly, the integration of ChatGPT technology streamlines the process of gathering patients' medical history, symptoms, and pertinent information through intelligent question-answering mechanisms. Doctors can pose relevant inquiries, and ChatGPT can adeptly analyze and furnish responses, thereby significantly mitigating physicians' workload and enhancing their efficiency. Secondly, ChatGPT technology contributes to the diagnostic and therapeutic phases by offering intelligent recommendations. Upon the input of patient symptom information by doctors, ChatGPT autonomously scrutinizes the patient's condition, providing corresponding diagnostic and treatment suggestions. This augmentation substantiates heightened diagnostic accuracy and treatment efficacy. Lastly, ChatGPT technology aids physicians in patient monitoring through intelligent surveillance. By inputting pertinent patient data, ChatGPT autonomously monitors changes in patient condition and promptly alerts physicians for necessary interventions. This feature substantially amplifies the efficiency of physicians' endeavors and the effectiveness of patient treatment. IoT technology, encompassing physical devices, sensors, networks, and cloud computing, embodies a synergistic framework that fosters device interconnectedness, thereby refining the efficiency and quality of healthcare services. The incorporation of IoT technology in medical information diagnosis facilitates real-time data collection, transmission, and analysis, thereby augmenting the efficiency and quality of healthcare services. Primarily, IoT technology facilitates the integration of medical devices, affording real-time data collection and transmission to improve the efficiency and quality of healthcare services. Secondary to this, IoT technology allows real-time monitoring and analysis of medical information [12]. Through the installation of sensors on patients, real-time monitoring of vital signs and changes in their condition can be executed, with

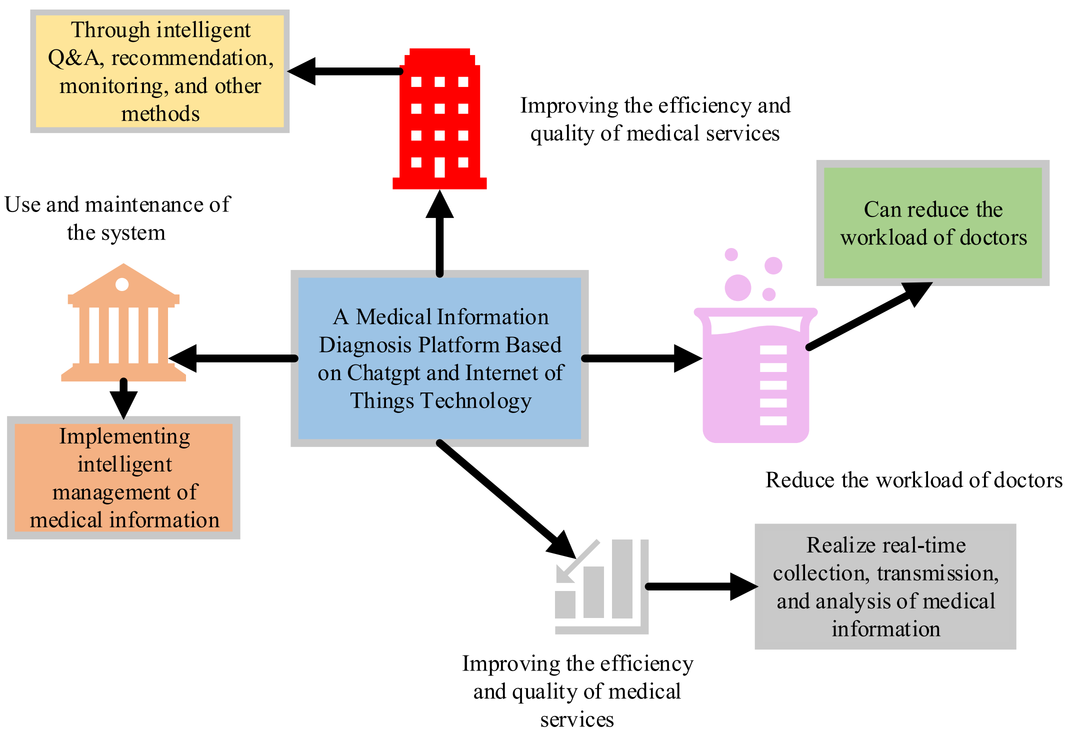

Fig. 1. Advantages of medical information diagnosis platform under ChatGPT and IoT technology.

relevant information transmitted to the medical information diagnosis platform for analysis and processing. This feature markedly alleviates the workload of physicians, thereby enhancing the efficiency and quality of healthcare services [13]. Finally, IoT technology enables intelligent management of medical information. Through the fusion of the medical information diagnosis platform with cloud computing technology, intelligent management of medical information becomes attainable, thereby further advancing the efficiency and quality of healthcare services [14]. The salient advantages of the medical information diagnosis platform under the amalgamation of ChatGPT and IoT technology are illustrated in Fig. 1.

In a broader context, the integration of ChatGPT and IoT technology within the medical information diagnosis platform displays significant promise and substantial developmental potential [15]. This integration augurs more streamlined, convenient, and precise healthcare services, thereby contributing to the preservation of individuals' health [16].

2.2. Artificial bee colony algorithm and evolutionary algorithm

The artificial bee colony (ABC) algorithm, functioning as an optimization algorithm rooted in swarm intelligence, holds distinctive attributes characterized by its algorithmic simplicity, minimal control parameters, and robust resilience. Consequently, it assumes a pivotal role as a significant optimization algorithm within the domain of bio-inspired intelligent optimization [17]. The fundamental underpinning of the bee colony algorithm finds inspiration in biological principles, with the key facets being division of labor and self-organization within an intelligent bee colony [18]. The colony consists of three distinct groups: employed bees, onlookers, and scouts. Their foraging activities are orchestrated to minimize energy consumption in the pursuit of locating food sources [19]. The employed bees bear the responsibility of investigating specific food sources and relaying information on the quality and location of these sources to the onlookers [20]. The quality of a food source is contingent on factors such as concentration, distance from the hive, and the complexity of nectar extraction [21]. Onlooker bees, stationed in the hive, make food source choices based on information shared by the employed bees, with their preference proportionate to the quality of the food source. In the event of resource depletion, an employed bee associated with that source transitions into a scout, undertaking a randomized exploration for new, superior food sources within the search space [22]. The detailed procedural steps are elucidated in Fig. 2.

Within the initialization phase of bee positions, the generation of initial food source information adheres to the formulation in Eq. (1):

$$x_{ij} = L_j + \mathrm{rand}(0,1) * (U_j - L_j) \tag{1}$$

In Eq. (1), x_{ij} signifies the value of the *j*-th dimension for the *i*-th bee after the search. U_j and L_j denote the upper and lower limits of the *j*-th dimensional space, respectively. $\mathrm{rand}(0,1)$ represents a random real number within the range of 0–1. Subsequently, during the employed bee search phase, the update of food source information is articulated by Eq. (2):

$$v_{ij} = x_{ij} + \varnothing * (x_{ij} - x_{kj}) \tag{2}$$

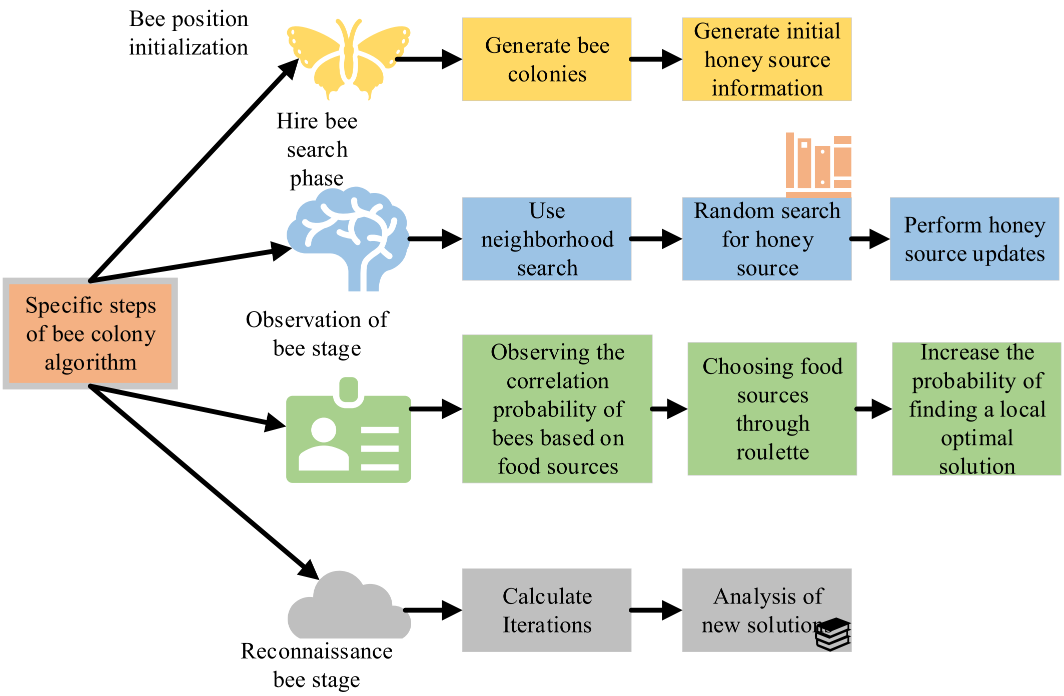

Fig. 2. Specific steps of bee colony algorithm.

In Eq. (2), v_{ij} signifies the updated value of the *j*-th dimension for the *i*-th bee. x_{kj} represents the value of the *j*-th dimension for the *k*-th bee, and φ is a real number within the range of −1 to 1.

Evolutionary algorithms, initially designed for the intelligent optimization of complex continuous nonlinear functions and capable of handling discrete variables, constitute a key methodology [23]. The standard evolutionary algorithm is compartmentalized into four sequential steps: initialization, mutation, recombination, and selection. The algorithm commences by setting the population size, mutation, and recombination operators. Subsequently, through iterations of mutation, recombination, and selection, the algorithm generates and retains high-quality solutions [24]. The initial step involves population initialization, achieved by uniformly generating a set of solutions within the search space, representing the algorithm's initial population [25]. Each individual within this population signifies a coordinate in the search space. Subsequently, three distinct individuals are selected from the population to generate new candidate solutions through mutation and recombination, as delineated in Eq. (3):

$$v_{i,g} = x_{r1,g} + F\left(x_{r2,g} - x_{r3,g}\right) \tag{3}$$

In Eq. (3), $v_{i,g}$ represents the mutated individual, F is the scaling factor, and $x_{r1,g}$, $x_{r2,g}$, and $x_{r3,g}$ are randomly chosen individuals [26]. The primary advantages of the bee colony algorithm lie in its efficient global search capability and straightforward implementation mechanism. However, this algorithm is prone to falling into local optima, especially when confronted with complex or multi-peaked search spaces. Additionally, the efficiency of the bee colony algorithm diminishes when dealing with large-scale data, and it exhibits sensitivity to parameter selection. Evolutionary algorithms, on the other hand, are renowned for their robust adaptability and flexibility, particularly well-suited for addressing high-dimensional and nonlinear problems. Nonetheless, they also possess some drawbacks, such as slow convergence, inconsistent performance in multi-objective optimization problems, and inefficiency due

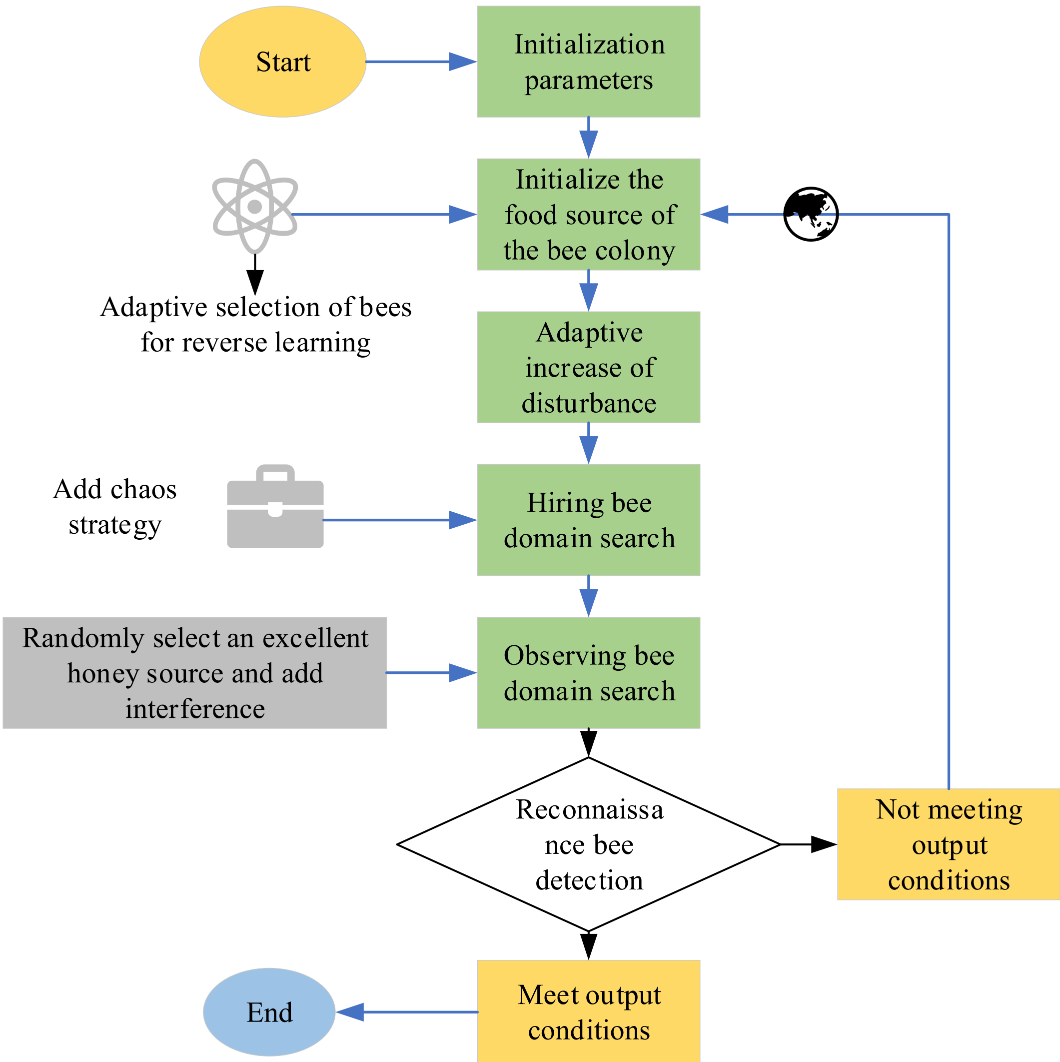

Fig. 3. Optimized bee colony algorithm.

to excessive exploration in the early stages.

2.3. Optimized bee colony algorithm and evolutionary algorithm for medical information diagnosis platform

In traditional ABC algorithms, the adoption of a greedy selection strategy often leads to premature iteration convergence towards the optimal solution, thereby constraining the algorithm's exploratory capabilities. To address this issue, reverse learning is introduced into the bee colony algorithm. This approach introduces disturbances to the algorithm, particularly in the early iterations, to enhance the population's diversity [27]. Gaussian functions are utilized in the optimization process to adjust the magnitude of disturbances. In the early stages of the algorithm, Gaussian functions help increase the diversity of the population, gradually reducing the magnitude of disturbances in later stages to facilitate quicker convergence to the optimal solution. This tuning approach balances the algorithm's exploration and exploitation capabilities, thereby improving overall search efficiency. The objective is to preserve the current optimal solution while expanding the search scope to escape local optima. By combining reverse learning and Gaussian functions, the bee colony algorithm demonstrates significantly enhanced performance when handling complex and diverse medical data. Reverse learning increases the algorithm's exploratory capabilities, preventing premature convergence to local optima, while Gaussian functions effectively balance exploration and exploitation, enabling faster convergence to the global optimum. This optimization method enhances the algorithm's adaptability and stability, particularly in handling large-scale and high-dimensional medical information data. The optimized bee colony algorithm is illustrated in Fig. 3.

Chaos methodology represents a fusion of quantitative analysis and qualitative research, designed for the examination of dynamic system behaviors necessitating the interpretation and prediction of overarching, continuous data relationships, as opposed to individual data relationships [28]. The calculation of the chaos algorithm is shown in Eq. (4):

$$C_{ij}(t+1) = \mu C_{ij}(t)[1 - C_{ij}(t)] \tag{4}$$

In Eq. (4), $C_{ij}(t)$ signifies the chaotic variable before the update, wherein μ denotes the control variable, and $C_{ij}(t+1)$ denotes the updated chaotic variable. Subsequent to this stage, the system undergoes a nonlinear transformation via unimodal mapping, entering a chaotic state [29]. The infusion of the chaotic variable into the exploration formula during the scout bee phase serves to augment the exploration capability of the solution space, as delineated in Eq. (5):

$$x_{ij}(t+1) = x_{ij}(t) + 2(C_n(t) - 0.5)\left(x_{bxtj}(t) - x_{kj}(t)\right) + 2(1 - C_n(t))\left(x_{kj}(t) - x_{mj}(t)\right) \tag{5}$$

In Eq. (5), $x_{bxtj}(t)$ signifies the value of the j-th dimension of the bee attaining the optimal global solution, where k and m represent mutually exclusive random integers, and $C_n(t)$ designates the chaotic operator. The optimization strategy introduces reverse learning as the initial step, wherein a reverse learning strategy is applied to each dimension of the selected food source. Given the greedy selection strategy inherent in the ABC algorithm, which defaults to choosing the current best food source and perpetuates selection based on it, local optima may either be global optima or suboptimal solutions. In cases where suboptimal solutions prevail, premature convergence becomes a potential concern. The integration of reverse learning into the bee colony algorithm serves a dual purpose. Firstly, it introduces perturbation to the algorithm in its early stages, enhancing population diversity and expanding the search range, thereby facilitating escape from local optima while preserving the current global optimal solution. Secondly, recognizing that the importance of population diversity diminishes in the algorithm's later stages due to increased algorithmic complexity, an adaptive

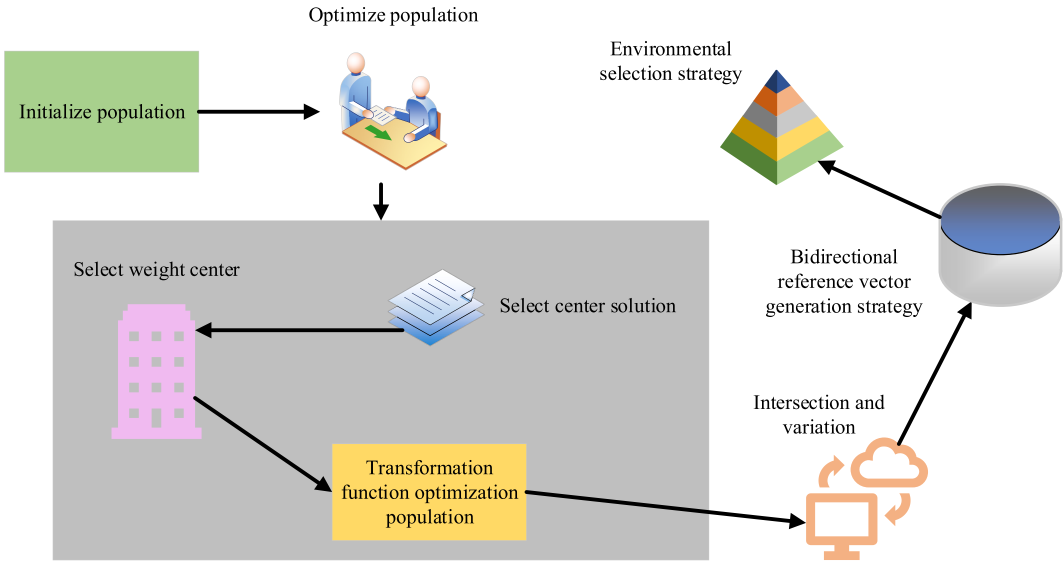

Fig. 4. Optimized evolutionary algorithm.

operator is introduced. Furthermore, the strategy encompasses the incorporation of the chaotic strategy and the global optimal solution. The chaotic strategy enhances the random search capability of scout bees, thereby improving local search capability near high-quality solutions based on information provided by employed bees. The inclusion of the optimal global solution and exploration of the search space around it enhances the algorithm's exploitation performance, expediting convergence. Finally, enhancements are introduced to the assignment process. While many current scout bee search formulas adopt the initialization selection formula, this approach proves impractical for scout bees that discover a depleted food source and remain in search stagnation during the later stages of the algorithm. In such cases, an array is employed to record the top 5 high-quality solutions. A random selection is made from this array, and the chosen high-quality solution is subjected to perturbation, thereby accelerating the search for the global optimal solution. Fig. 4 illustrates the optimization process of the evolutionary algorithm.

When confronted with a considerable number of individuals within the nondominated solution set, it becomes imperative to compute performance indicators, as expressed in Eq. (6):

$$C(x) = \sum_{i=1}^{m} f_i(x) \tag{6}$$

In Eq. (6), $C(x)$ represents the performance metric, where *m* signifies the number of objectives, *i* pertains to the objective, and $f_i(x)$ denotes the target value for the objective. A diminished value of the performance metric for an individual signifies superior quality [30]. The environmental selection strategy is devised to enhance the performance of large-scale multi-objective evolutionary algorithms while upholding a delicate equilibrium between diversity and convergence. Initially, reference vectors are introduced into the objective space, wherein population individuals undergo crossover and mutation operations with randomly selected counterparts. Each individual is affiliated with the reference vector characterized by the smallest angle, and subsequent population partitioning is executed [31]. Elite individuals are then chosen from each subpopulation to maintain a harmonious balance between diversity and convergence, as defined by Eqs. (7) and (8).

$$H_{i,j} = \left[1 + \eta \bullet \cos \min \text{angle}\left(x_i, R_j\right)\right] \bullet \parallel C(x_i) \parallel \tag{7}$$

$$\eta = \left(\frac{G}{G_{max}}\right)^m \tag{8}$$

The strategic use of variables significantly mitigates the consumption of computational resources. Diverging from prevalent coevolutionary methods, the problem transformation methodology diminishes the dimensionality of the search space by concurrently optimizing all variables within each group [32,33]. Within the optimization process, decision variables undergo alteration through the manipulation of weight values. This innovative approach approximates the optimal solution by optimizing the weight values rather than the solution itself [34]. The judicious selection of a central solution emerges as pivotal in problem optimization. The central solution, unaltered during the optimization of weight vectors, serves as the anchor, generating new solutions through the application of its steadfast decision variables. By incorporating a portion of perturbation in the early stages of the algorithm, our optimization approach enhances the diversity of the population, contributing to improved exploration of different solutions and mitigating the risk of local optima. Additionally, the optimization algorithm introduces significant perturbation in the initial phases to broaden the search space and explore new possibilities. Subsequently, the perturbation is gradually reduced in later stages to enable the algorithm to concentrate on optimizing the currently identified superior solutions, expediting the convergence process. These optimization measures collectively impact both the bee colony algorithm and evolutionary algorithm, markedly enhancing their performance in medical information diagnostic platforms, particularly in addressing complex and large-scale problems. Through these optimizations, the algorithm becomes more effective in handling medical information, providing more accurate and reliable diagnostic results.

3. Comparison of optimized bee algorithm and evolutionary algorithm performance in the medical information diagnosis platform

3.1. Comparison of fitness values of optimized algorithms in the medical information diagnosis platform

The experiments evaluate the effectiveness of various algorithmic solutions to system service composition problems using the minimum, average, and maximum values of the algorithm's fitness. The minimum fitness value represents the poorest-performing solution among all solutions, serving as a metric to assess the algorithm's performance under the most adverse conditions in optimization problems. The average fitness value signifies the average fitness level of all solutions found by the algorithm, serving as a crucial indicator to evaluate the overall performance of the algorithm, reflecting its general performance over multiple runs. A lower average fitness value typically indicates the algorithm's ability to consistently find high-quality solutions across multiple attempts. The maximum fitness value represents the fitness of the best-performing solution among all solutions, highlighting the algorithm's potential at its highest level. The comprehensive use of these three metrics allows for a thorough assessment of the algorithm's effectiveness, including its stability, overall performance, and potential optimal performance. This is particularly useful for understanding and comparing the strengths and weaknesses of different algorithms, especially when dealing with complex system service composition problems. The experiments are conducted for service scales of 1010, 2020, and 30 * 30, with 100 repetitions for each case, recording the minimum, average, and maximum fitness values for each algorithm. In practical applications, service scales may vary significantly. The selection of these three scales in the experiments better simulates scenarios of different scales that may be encountered in real-world applications, thereby enhancing the practical value of the research results. Conducting 100 repetitions and recording the data provides sufficient data for statistical analysis, ensuring the stability and reliability of the experimental results. This approach helps mitigate the impact of randomness on the experimental results, offering more robust evidence to support the performance evaluation of the algorithm. This paper conducts a comparative analysis of conventional algorithms, including Particle Swarm Optimization (PSO), Differential Evolution (DE), Independent Component Analysis (ICA), ABC, and Genetic Algorithm (GA). The parameter configurations for each algorithm are as follows: the PSO algorithm is equipped with an inertia weight of 0.75 and a cognitive coefficient of 1.5. The DE algorithm utilizes a scaling factor of 0.01 and a crossover rate of 0.5. The ICA algorithm employs an assimilation coefficient set at 2. For the ABC algorithm, an acceleration coefficient of 0.9 is applied. The GA algorithm incorporates a genetic factor of 2. Notably, the optimized bee algorithm introduced in this paper features an accelerated coefficient of 0.9. The chosen dataset for the experiments is the Quality of Web Services (QWS) dataset, comprising 2507 rows of relevant information about systems, including response time, availability, reliability, success rate, throughput, compliance, best practices, latency, and measurement documents, among various other classification criteria. The QWS dataset typically consists of web service data collected from the real world, originating from publicly available services or specific data collection projects. The QWS dataset is commonly employed in various research and practical applications, including service quality assessment, service selection, and service composition optimization. The sorting algorithm used in this paper is quicksort, which employs a divide-and-conquer strategy, breaking down a large problem into two or more smaller problems and recursively solving these subproblems. This approach significantly enhances the efficiency of the algorithm. Furthermore, quicksort is an in-place sorting algorithm, meaning it requires minimal additional storage space aside from the input data. This makes quicksort particularly outstanding in terms of space efficiency, especially suitable for situations with limited memory resources. The results of the 10 * 10 server size execution are shown in Fig. 5(a) and (b).

Fig. 5 illustrates that the optimized algorithm proposed in this paper attains the highest fitness value without employing sorting, surpassing PSO with the lowest average fitness value at 3.11. The optimized algorithm exhibits commendable outcomes in terms of minimum, average, and maximum fitness values, maintaining a stable fitness value of 3.51 and achieving a maximum of 3.54. This represents an improvement of 0.31 over PSO, 0.2 over DE, 0.17 over ICA, and 0.19 over ABC. The optimized algorithm's maximum fitness value exceeds that of ABC by 5.7 %, with the average value being 7.3 % higher and the minimum value 11.3 % higher. Following data preprocessing in comparison to unprocessed data, all algorithms demonstrate enhancements in their minimum and average fitness values. The optimized algorithm, under such conditions, registers a minimum value of 3.56, presenting a 3 % increase over the minimum value without sorting, and the average value also experiences a 3.1 % elevation. In the context of a server size of 10 × 10, the fitness value of the optimized algorithm remains stable at 3.62, reaching a maximum of 3.65. This is notably higher by 0.23 compared to PSO, 0.2 compared to DE, 0.12 compared to ICA, and 0.13 compared to ABC. Irrespective of whether sorting is employed, the optimized algorithm consistently exhibits superior effectiveness. The results pertaining to the execution with a server size of 20 × 20 are presented in Fig. 6(a) and (b).

In Fig. 6, the optimized algorithm proposed in this paper attains the highest fitness value without employing sorting, outperforming ICA and DE, while ABC records a fitness value approximately at 6.57, and PSO at 6.42. The optimized algorithm consistently exhibits commendable outcomes in terms of minimum, average, and maximum fitness values, maintaining a stable fitness value of 6.72 and achieving a maximum of 6.76. This reflects an improvement of 0.24 over PSO, 0.16 over DE, 0.08 over ICA, and 0.12 over ABC. Relative to the scenario without sorting, the fitness values of DE, PSO, ICA, GA, and ABC algorithms all exhibit improvement, with reduced discrepancies between the maximum, minimum, and average values. At this scale, the fitness value of the optimized algorithm remains stable at 6.74, reaching a maximum of 6.78, which is 0.19 higher than PSO, 0.13 higher than DE, 0.09 higher than ICA, and 0.15 higher than ABC. The results pertaining to the execution with a server size of 30 × 30 are presented in Fig. 7(a) and (b).

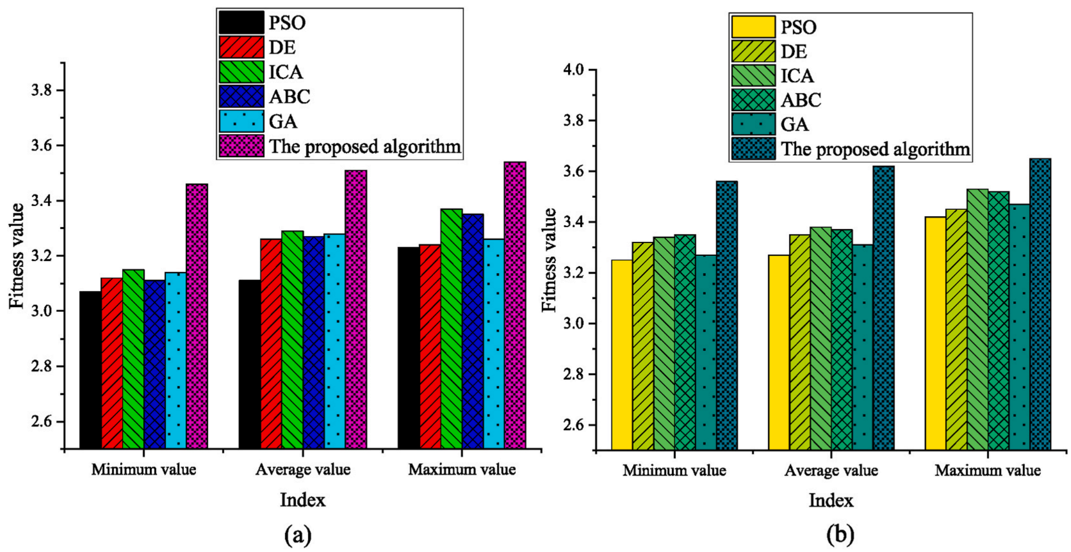

Fig. 5. 10 * 10 scale server execution results (a) Server combination not sorted; (b) Server combination sorting.

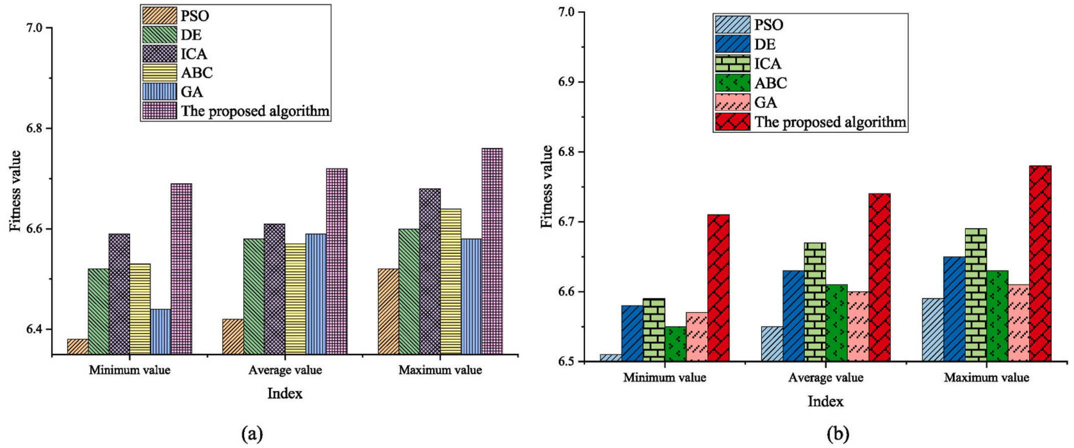

Fig. 6. 20 * 20 scale server execution results (a) Server combination not sorted; (b) Server combination sorting.

According to Fig. 7, the enhancement of fitness values associated with DE, PSO, ICA, GA, and ABC algorithms is discernible. The optimized algorithm presented in this paper exhibits more pronounced advantages, particularly in relation to minimum and average fitness values. Notably, the fitness value of the optimized algorithm remains consistently stable at 9.83, attaining a peak of 9.86. This represents an improvement of 0.33 over PSO, 0.25 over DE, 0.2 over ICA, and 0.3 over ABC.

3.2. Comparison of stability of optimized algorithms in the medical information diagnosis platform

Algorithmic stability, a crucial metric indicative of performance robustness during search operations, is a key consideration given the inherent randomness in heuristic algorithms. This paper employs the standard deviation of fitness values as a metric for stability assessment, where a diminished standard deviation implies heightened stability. Firstly, compute the mean of all fitness values. The mean is obtained by dividing the sum of all fitness values by the total number of fitness values. Next, calculate the difference between each fitness value and the mean, and square this difference. Determine the average of all squared differences, referred to as the variance. Finally, compute the square root of the variance to obtain the standard deviation. In order to quantify and illustrate the stability of the algorithms, the standard deviations of results derived from 100 iterations on a 10 × 10 server grid are presented in Fig. 8.

According to the data presented in Fig. 8, when considering a server size of 10 × 10, the optimized algorithm proposed in this paper exhibits the smallest standard deviation among all algorithms, even without the application of sorting. This finding indicates superior stability compared to alternative algorithms. Notably, the unenhanced ABC algorithm manifests the highest standard deviation, suggesting a susceptibility to local optima entrapment and a deficiency in exploration capabilities during the search process. Upon employing sorting algorithms, a noticeable reduction in standard deviations is observed for all algorithms, with the exception of the

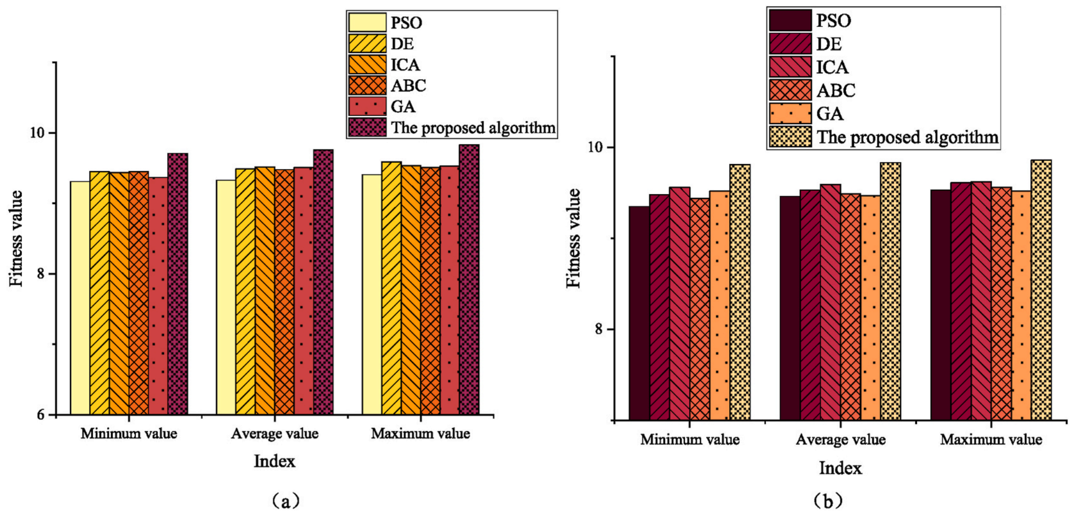

Fig. 7. 30 * 30 scale server execution results (a) Server combination not sorted; (b) Server combination sorting.

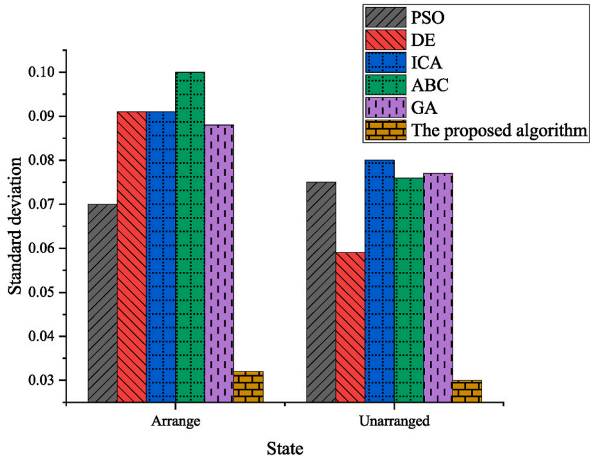

Fig. 8. Algorithm standard deviation for server size of 10 * 10.

optimized algorithm in this paper, in comparison to scenarios without sorting. Analyzing the execution outcomes reveals that the utilization of sorting algorithms contributes to an improvement in the minimum fitness value and accelerates convergence, mitigating the likelihood of convergence to suboptimal local optima. Consequently, this refinement enhances algorithmic stability. The standard deviations of results obtained from 100 iterations on a 20 * 20 server grid are depicted in Fig. 9.

In Fig. 9, with a server size of 20 × 20 and the absence of sorting algorithms, the optimized algorithm demonstrates a diminished standard deviation, indicative of heightened stability. Notably, both the PSO and ABC algorithms exhibit elevated standard deviations, suggesting a proclivity towards premature convergence as algorithmic complexity increases. Following the integration of sorting algorithms, there is an observable enhancement in the stability of all algorithms, except for the optimized algorithm in this paper. However, it is noteworthy that the ICA algorithm experiences an increase in standard deviation. Evaluation of execution results underscores the stabilizing influence of sorting algorithms, contributing to incremental improvements in solution quality. Furthermore, it is evident from the outcomes that the proposed algorithm in this paper excels in both exploratory behavior and stability at this scale. The standard deviation of results derived from 100 iterations on a 30 × 30 server is depicted in Fig. 10.

In Fig. 10, under a server size of 30 × 30 and the absence of sorting algorithms, the optimized algorithm featured in this paper reveals an elevated standard deviation. A comprehensive examination of the execution results suggests that heightened algorithmic complexity contributes to instability, primarily stemming from substantial disparities between the low and high fitness values identified by the optimized algorithm. This divergence amplifies the standard deviation. Consequently, with the integration of sorting algorithms leading to improved fitness values, there is a collective increase in the standard deviations across all algorithms. Nonetheless, owing to the adeptness of the optimized algorithm in locating relatively superior fitness values, its stability undergoes enhancement post the incorporation of sorting algorithms. In summary, the optimized algorithm consistently demonstrates commendable stability. However, as the operational scale expands, there is a propensity for an increase in standard deviation and a concomitant reduction in stability. It is noteworthy that this observed instability remains advantageous relative to other algorithms, and the application of sorted datasets contributes to an augmentation of stability.

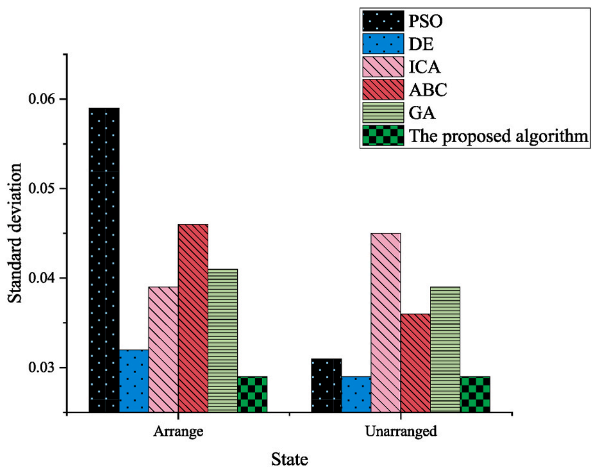

Fig. 9. Algorithm standard deviation for server size of 20 * 20.

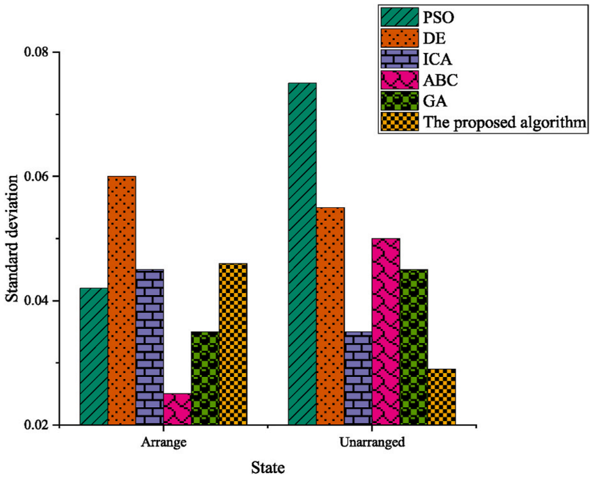

Fig. 10. Algorithm standard deviation for server size of 30 * 30.

4. Discussion

Based on the results of the experiments, the performance of the optimized algorithm presented in this paper surpasses that of comparable traditional algorithms across various service scales. The optimized algorithm consistently exhibits elevated performance in terms of minimum, average, and maximum fitness values. This indicates that the optimized algorithm not only performs well under optimal conditions but also maintains a high level of efficiency in general scenarios. The stability of the optimized algorithm's fitness values across different scales is evident from the limited fluctuation in fitness values. Particularly noteworthy is the algorithm's ability to maintain stability at a high level in the 30 $\times$ 30 scale. Even without the use of sorting, the fitness values of the optimized algorithm remain at a notably high level, further highlighting the algorithm's stability. Data preprocessing, specifically the application of sorting, results in improvements in the minimum and average values for all algorithms. This underscores the significant impact of sorting on enhancing algorithmic performance. The optimized algorithm, when subjected to sorting, exhibits particularly pronounced improvements in its minimum and average values, emphasizing the critical role of sorting in optimization algorithms. The performance advantage of the optimized algorithm grows progressively from small to large-scale services, suggesting its adaptability and sustained efficiency in handling larger-scale problems.

In stability comparative experiments on a 10 $\times$ 10 server scale, the optimized algorithm demonstrates the smallest standard deviation, indicating superior stability. This implies that the algorithm consistently exhibits minimal fluctuations in fitness values across multiple runs, showcasing a high degree of consistency and reliability. In contrast, the unimproved ABC algorithm exhibits the highest standard deviation, suggesting a propensity to converge prematurely to local optima, indicative of insufficient exploration. The application of sorting algorithms results in a decrease in standard deviation for all algorithms, except for the optimized algorithm, underlining the effectiveness of sorting in overall stability improvement, particularly in mitigating convergence to suboptimal local optima during iterations. For the optimized algorithm, the use of sorting algorithms further enhances its stability. In the context of a 20 $\times$ 20 server scale, the optimized algorithm continues to demonstrate notable stability, despite higher standard deviations observed for PSO and ABC algorithms, indicating a susceptibility to premature convergence in more complex scenarios. In the 30 $\times$ 30 scale, while the optimized algorithm exhibits a higher standard deviation, it is attributed to the significant disparities in the search for fitness values. After the application of sorting algorithms, an increase in standard deviation is observed for all algorithms, yet the optimized algorithm maintains an advantage in stability. In summary, the optimized algorithm consistently exhibits commendable stability across various service scales. The observed instability at larger scales is advantageous compared to other algorithms, and the use of sorted datasets contributes to the further enhancement of stability.

The optimization swarm algorithm and evolutionary algorithm employed in this paper demonstrate unique advantages in handling complex medical data compared to the intelligent fuzzy multi-criteria decision model used by Nabeeh [35]. Particularly, in algorithmic improvement and practical medical applications, our approach showcases a significant enhancement in the ability to address complex problems. In contrast to Mohamed's [36] study on the application of deep learning in organizational decision-making, this paper, through the integration of two distinct optimization algorithms, illustrates methodological innovation in the field of medical information processing. In comparison to Muthuswamy's [37] research focusing on the challenges and opportunities of sustainable supply chain management in the era of machine intelligence, the study concentrates more on the practical applications in the medical domain. Specifically, in the design and optimization of medical information diagnostic platforms, our contribution lies in providing an effective solution to tackle the complexity of current medical diagnostics and challenges in data processing. The innovation in methodology and application aspects of this paper, when compared to the aforementioned studies, not only presents novel approaches in algorithm optimization but also underscores the urgent need for precise and efficient algorithms in the field of medical information processing. Through direct comparison, the uniqueness of this paper's contribution and its significant impact on the real world can be highlighted.

The practical significance of this paper and its application in real-world medical information diagnostic platforms are evident in several aspects. Firstly, by combining the optimized swarm algorithm and evolutionary algorithm, this paper enhances the accuracy of medical information diagnostics. This is crucial for healthcare professionals as it assists them in making more precise diagnostic decisions, reducing the risks of misdiagnosis and underdiagnosis. Secondly, the research improves the efficiency of data processing through optimization algorithms, enabling quicker analysis of medical information. In emergency medical situations, rapid diagnostics can significantly improve patient survival rates and treatment outcomes. Thirdly, as the volume of medical data continues to grow, the proposed algorithm can effectively handle large-scale datasets, providing healthcare professionals with more comprehensive patient health information to support comprehensive disease analysis and treatment planning. Lastly, the optimized algorithm can handle and analyze various complex medical data, contributing to more personalized medical services. For example, it can offer customized treatment recommendations based on patient-specific health data. In conclusion, this paper not only brings important technological innovations but also has a significant positive impact on actual healthcare services and patient care, with the potential to play a crucial role in future medical information systems.

5. Conclusion

The optimized algorithm presented in this paper demonstrates superior stability, a quality further bolstered by the incorporation of sorting algorithms. As evidenced by the experimental outcomes herein, while the optimized algorithm consistently exhibits commendable stability, an observable trend reveals an inclination for an increase in standard deviation and a subsequent decrease in stability with the expansion of the scale, leading to intermittent instances of instability. Nonetheless, it maintains a substantial advantage over alternative algorithms. This paper, however, is not without limitations. Owing to the inherent complexity of the algorithm, the runtime of the optimized algorithm surpasses that of traditional algorithms. Subsequent research endeavors will concentrate on mitigating the algorithm's runtime, involving thorough exploration and refinement strategies.

Data availability statement

Data will be made available on request.

Funding statement

This work was supported by the 2022 Philosophy and Social Science Foundation of Guangdong Province of China (GD22XXW05) entitled “Study on niche selection of Guangdong mainstream media in Guangdong-Hong Kong-Macao Greater Bay Area”; This work was supported by the 2018 Social Science Foundation of Guangzhou city of China (2018GZMZYB39) entitled “Research on Guangzhou city brand building and communication strategy under UGC production paradigm”.

CRediT authorship contribution statement

Hejian Liu: Writing – review & editing, Project administration, Methodology, Conceptualization. **Xin Guan:** Writing – original draft, Formal analysis, Data curation, Conceptualization. **Rong Bai:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Tianqiao Qin:** Writing – original draft, Visualization. **Yanrui Chen:** Writing – original draft, Validation. **Tao Liu:** Writing – review & editing, Resources, Methodology, Funding acquisition, Conceptualization.

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.

References

[1] Z. Ahmed, et al., Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine, Database 2020 (2020).
[2] Y. Pan, et al., Enhanced deep learning assisted convolutional neural network for heart disease prediction on the internet of medical things platform, IEEE Access 8 (2020) 189503–189512.
[3] R.S. D'Souza, et al., YouTube as a source of medical information on the novel coronavirus 2019 disease (COVID-19) pandemic, Global Publ. Health 15 (7) (2020) 935–942.
[4] T. Yang, et al., Combining Point-Of-Care Diagnostics and Internet of Medical Things (IoMT) to Combat the COVID-19 Pandemic, MDPI, 2020, p. 224.
[5] S. Akhbarifar, et al., A Secure Remote Health Monitoring Model for Early Disease Diagnosis in Cloud-Based IoT Environment, Personal and Ubiquitous Computing, 2020, pp. 1–17.
[6] Z. Wang, et al., Achieving sustainable development goal 9: a study of enterprise resource optimization based on artificial intelligence algorithms, Sci. Dircet 80 (2023) 103212.
[7] Z. Wang, et al., Risk prediction and credibility detection of network public opinion using blockchain technology, Technol. Forecast. Soc. Change 187 (2023) 122177.
[8] Z. Wang, et al., Does China's low-carbon city pilot policy promote green development? Evidence from the digital industry, J. Innov. Knowl. 8 (2) (2023) 100339.
[9] C. Li, et al., Low-carbon strategy, entrepreneurial activity, and industrial structure change: evidence from a quasi-natural experiment, J. Clean. Prod. 427 (2023) 139183.
[10] H. Hu, et al., Green financial regulation and shale gas resources management, Resour. Pol. 85 (2023) 103926.
[11] C. Li, et al., Digital finance and enterprise financing constraints: structural characteristics and mechanism identification, J. Bus. Res. 165 (2023) 114074.

[12] M. Senbekov, et al., The recent progress and applications of digital technologies in healthcare: a review, Int. J. Telemed. Appl. 2020 (2020).
[13] A. Asadzadeh, et al., Information technology in emergency management of COVID-19 outbreak, Inform. Med. Unlocked 21 (2020) 100475.
[14] M. Abdel-Basset, et al., A novel group decision making model based on neutrosophic sets for heart disease diagnosis, Multimed. Tool. Appl. 79 (2020) 9977–10002.
[15] F. Shi, et al., Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for COVID-19, IEEE Rev. Biomed. Eng. 14 (2020) 4–15.
[16] S. Guinez-Molinos, et al., A web platform (MOSAICO) to design, perform, and assess collaborative clinical scenarios for medical students, JMIR Med. Educ. 7 (1) (2021) e23370.
[17] Ş. Öztürk, R. Ahmad, N. Akhtar, Variants of artificial bee colony algorithm and its applications in medical image processing, Appl. Soft Comput. 97 (2020) 106799.
[18] H. Wang, et al., Improving artificial bee colony algorithm using a new neighborhood selection mechanism, Inf. Sci. 527 (2020) 227–240.
[19] A.H. Alaidi, C.S. Der, Y.W. Leong, Systematic review of enhancement of artificial bee colony algorithm using ant colony pheromone, Int. J. Inter. Mob. Technol. 15 (16) (2021) 173.
[20] F. Ezazi, et al., A new method for multicomponent mixture separation cascade optimization using artificial bee colony algorithm, Prog. Nucl. Energy 124 (2020) 103371.
[21] G. Hu, et al., Genghis Khan shark optimizer: a novel nature-inspired algorithm for engineering optimization, Adv. Eng. Inf. 58 (2023) 102210.
[22] M. Ghasemi, et al., Geyser inspired algorithm: a new geological-inspired meta-heuristic for real-parameter and constrained engineering optimization, J. Bionic Eng. 5 (2023) 1–35.
[23] A.E. Ezugwu, et al., Prairie dog optimization algorithm, Neural Comput. Appl. 34 (22) (2022) 20017–20065.
[24] J.O. Agushaka, et al., Dwarf mongoose optimization algorithm, Comput. Methods Appl. Mech. Eng. 391 (2022) 114570.
[25] J.O. Agushaka, et al., Gazelle optimization algorithm: a novel nature-inspired metaheuristic optimizer, Neural Comput. Appl. 35 (5) (2023) 4099–4131.
[26] G. Hu, et al., DETDO: an adaptive hybrid dandelion optimizer for engineering optimization, Adv. Eng. Inf. 57 (2023) 102004.
[27] M. Zare, et al., A global best-guided firefly algorithm for engineering problems, J. Bionic Eng. 1 (2023) 1–30.
[28] L. Abualigah, et al., Modified elite opposition-based artificial hummingbird algorithm for designing FOPID controlled cruise control system, Intellig. Autom. Soft Comp. 5 (2023) 94–99.
[29] Z. Han, et al., Improved artificial bee colony algorithm-based path planning of unmanned autonomous helicopter using multi-strategy evolutionary learning, Aero. Sci. Technol. 122 (2022) 107374.
[30] X. Xu, J. Hao, Y. Zheng, Multi-objective artificial bee colony algorithm for multi-stage resource leveling problem in sharing logistics network, Comput. Ind. Eng. 142 (2020) 106338.
[31] B.K. Dedeturk, B. Akay, Spam filtering using a logistic regression model trained by an artificial bee colony algorithm, Appl. Soft Comput. 91 (2020) 106229.
[32] B. Akay, et al., A survey on the artificial bee colony algorithm variants for binary, integer and mixed integer programming problems, Appl. Soft Comput. 106 (2021) 107351.
[33] T. Ye, et al., Artificial bee colony algorithm with efficient search strategy based on random neighborhood structure, Knowl. Base Syst. 241 (2022) 108306.
[34] S. Xiao, et al., Artificial bee colony algorithm based on adaptive neighborhood search and Gaussian perturbation, Appl. Soft Comput. 100 (2021) 106955.
[35] N. Nabeeh, Assessment and contrast the sustainable growth of various road transport systems using intelligent neutrosophic multi-criteria decision-making model, Sustain. Machine Intellig. J. 2 (2023) 102.
[36] M. Mohamed, Empowering deep learning based organizational decision making: a survey, Sustain. Machine Intellig. J. 3 (2023) 125.
[37] M. Muthuswamy, et al., Sustainable supply chain management in the age of machine intelligence: addressing challenges, capitalizing on opportunities, and shaping the future landscape, Sustain. Machine Intellig. J. 3 (2023) 42.