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Development of an IoT-Integrated Platform for Medical Diagnosis and Information Management

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ABSTRACT

To improve operational efficiency within the healthcare sector, this study explores the development of a medical information diagnostic platform leveraging swarm intelligence and evolutionary algorithms. The paper first reviews the current state of medical diagnostic platforms that integrate Chat Generative Pre-trained Transformer (ChatGPT) models with Internet of Things (IoT) technology. It then provides a detailed analysis of the strengths and limitations of employing swarm and evolutionary algorithms in such platforms. Optimization of the swarm algorithm is achieved using reverse learning and Gaussian functions. The validity and effectiveness of this optimized approach are demonstrated through horizontal comparative experiments. Results indicate that the enhanced model performs well across minimum, average, and maximum algorithm fitness metrics. Furthermore, preprocessing data on a 10 × 10 server arrangement further improves algorithm fitness, with the optimized algorithm achieving a minimum fitness value of 3.56—a 3% improvement compared to unsorted data. Stability tests reveal that the optimized algorithm maintains superior stability, which is further strengthened by applying sorting techniques. Overall, this study provides new insights into medical information diagnostics and offers practical technical support for applications in medical data processing.

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

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Introduction

In recent years, medical information diagnostic platforms integrating Chat Generative Pre-trained Transformer (ChatGPT) and Internet of Things (IoT) technologies have become an emerging trend in the healthcare sector [1]. By harnessing advanced artificial intelligence and network capabilities, these platforms have significantly enhanced the speed and accuracy of medical data processing. Despite these advancements, existing systems still encounter substantial challenges when managing large-scale and complex medical datasets, including algorithmic inefficiencies and limitations in accuracy [2]. To address these issues, this study proposes the design of a more efficient and precise medical information diagnostic platform. The approach involves the integration of swarm intelligence and evolutionary algorithms, aiming to optimize algorithmic performance. The key motivation behind this research is the innovative combination of these algorithms to not only improve computational efficiency and processing speed but also to increase the adaptability and diagnostic accuracy of the platform in handling complex medical data. This work carries both theoretical significance and practical implications for advancing medical diagnostic technologies.

In the field of IoT-based healthcare research, D'Souza [3] conducted a comprehensive survey on internet-driven healthcare platforms, analyzing interaction patterns, functional architectures, and data visualization designs tailored to the specific needs of medical users. D'Souza outlined essential principles and strategies for designing effective data visualization in healthcare platforms, including structural components, charting methodologies, typography, color schemes, and grid systems. These guidelines provided practical support for implementing

medical management platforms. The design process involved constructing user models, examining user behavior patterns, and employing functional framework diagrams, as well as low- and high-fidelity prototypes, to illustrate the interaction structure of data visualization within healthcare systems.
In contrast, Yang [4] examined the regulatory oversight of internet-based medical information platforms from the perspective of economic law. Yang highlighted the unique characteristics of regulatory supervision in this context and conducted an in-depth analysis of the current regulatory environment for such platforms in China, evaluating practical implementation and relevant policies while identifying existing shortcomings. Comparative insights were drawn from regulatory frameworks in the United States, and recommendations were made to strengthen regulatory oversight in China, offering guidance for future policy development in this area.
Akhbarifar [5] addressed the challenge of task migration between terminal devices and Mobile Edge Computing (MEC) servers. The study initially assessed terminal device workloads to determine when task migration was necessary. Under high-load conditions, tasks were transferred to nearby MEC servers. A matching model was developed to evaluate the compatibility between tasks and MEC server resources, favoring migration to servers with higher compatibility. Furthermore, the ant colony algorithm was improved by incorporating load information, resulting in a refined approach that effectively solved the task migration problem.
Wang [6] investigated how recommendation systems can support decision-making and resource allocation in complex entrepreneurial projects within the cultural and creative industries. By employing neural networks to model project attributes, user interactions, and content characteristics, Wang developed a system that integrates project recommendations with resource optimization, subsequently evaluating its performance. In a related study, Wang [7] applied blockchain technology to enhance network system efficiency and built a smart contract-based risk management framework. Using risk association trees to monitor public sentiment via smart ledgers, the study proposed a blockchain-driven risk management model for non-profit organizations and experimentally verified its effectiveness. Furthermore, the research refined methods for assessing smart contract credibility through a predictive model of public opinion risks.
Wang [8] analyzed the digital economic growth trajectories of 277 Chinese cities from 2002 to 2019, combining principal component analysis with difference-in-differences methods to examine the effects of low-carbon city pilot policies. The study found that such initiatives foster digital economic growth and encourage sustainable urban development. The results held under multiple robustness tests, including parallel trends, placebo, and endogeneity checks, with a stronger effect observed in coastal, non-resource-based, and larger cities. Similarly, Li [9] evaluated the impact of low-carbon pilot policies on urban entrepreneurial activity using data from 279 cities over the same period. The study revealed that these policies generally suppress entrepreneurship, although cities with higher green innovation capabilities experienced reduced negative effects. Further analysis indicated that the inhibitory effects were more pronounced in central and western regions, resource-dependent cities, and non-central cities.
Hu [10] explored the influence of ESG (environmental, social, and governance) reporting on the market performance of shale gas companies using event studies and bootstrap regression. Findings indicated a heterogeneous impact: ESG disclosures led to short-term gains for issuers and related stakeholders, while private and smaller firms faced significant negative stock returns. Li [11] examined the role of regional digital financial development in alleviating corporate financing constraints. Results showed that digital finance effectively reduces these constraints, especially for private and small- to medium-sized enterprises, while partially correcting biases in traditional financial systems related to firm size and ownership.
Traditional approaches to medical information diagnostic platforms tend to focus on single-algorithm applications, such as swarm intelligence or evolutionary computation, to process healthcare data. These approaches often suffer from low efficiency, inadequate handling of complex datasets, and limited search capability in high-dimensional spaces. Addressing these limitations, this study introduces a hybrid framework that combines swarm and evolutionary algorithms, enhanced with Gaussian functions and a reverse learning mechanism, to improve computational performance. The proposed approach is designed to strengthen global search capacity and reduce convergence to local optima, thereby improving both the accuracy and efficiency of large-scale medical data processing. Specifically, the study presents a novel algorithm that integrates bee colony optimization with evolutionary strategies for application within medical diagnostic platforms. The work begins by analyzing the functional status of current medical information platforms within the context of ChatGPT and IoT integration, identifies limitations in conventional algorithmic approaches, and then optimizes the bee colony algorithm using Gaussian-based enhancements and reverse learning. The effectiveness of the proposed hybrid

algorithm is validated through systematic comparative experiments, demonstrating improvements in both accuracy and stability.

Applications of ChatGPT and IoT technology in medical information diagnostic platforms
Medical information diagnostic platforms enhanced by ChatGPT and IoT
ChatGPT is a chatbot system built on natural language processing (NLP), enabling human-like communication and interaction. When applied to medical information diagnostic platforms, ChatGPT aims to improve the speed and accuracy of patient data collection, thereby enhancing both the efficiency and quality of healthcare services.
Firstly, integrating ChatGPT streamlines the collection of patients' medical histories, symptoms, and other relevant information through intelligent question-and-answer interactions. Physicians can pose targeted questions, and ChatGPT can efficiently analyze responses and provide relevant information, significantly reducing doctors' workload and improving operational efficiency.
Secondly, ChatGPT supports the diagnostic and treatment process by generating intelligent recommendations. Upon receiving patient symptom data from physicians, ChatGPT analyzes the information autonomously and suggests possible diagnoses and treatment plans, contributing to improved diagnostic precision and therapeutic outcomes.
Finally, ChatGPT aids in patient monitoring via intelligent surveillance. By continuously processing patient data, ChatGPT can track changes in patient conditions and promptly alert physicians to critical developments, thereby enhancing the effectiveness of patient care and the efficiency of medical interventions.
IoT technology, encompassing physical devices, sensors, communication networks, and cloud computing, provides a connected infrastructure that further improves healthcare service delivery. Its integration into medical information diagnostic platforms enables real-time collection, transmission, and analysis of patient data, thereby increasing operational efficiency and service quality.
Primarily, IoT facilitates the seamless connection of medical devices, allowing real-time data acquisition and transmission that supports timely and accurate healthcare delivery. In addition, IoT enables continuous monitoring and analysis of patient information [12]. By equipping patients with sensors, vital signs and other physiological indicators can be tracked in real time, with data transmitted directly to the diagnostic platform for processing. This capability reduces physicians' workload while enhancing healthcare service efficiency [13].
Moreover, IoT supports intelligent management of medical information. Through integration with cloud computing, the platform can manage patient data more effectively and securely, further improving the overall quality and efficiency of healthcare services [14].
The key advantages of combining ChatGPT and IoT technologies within medical information diagnostic platforms are summarized in **Figure 1**.

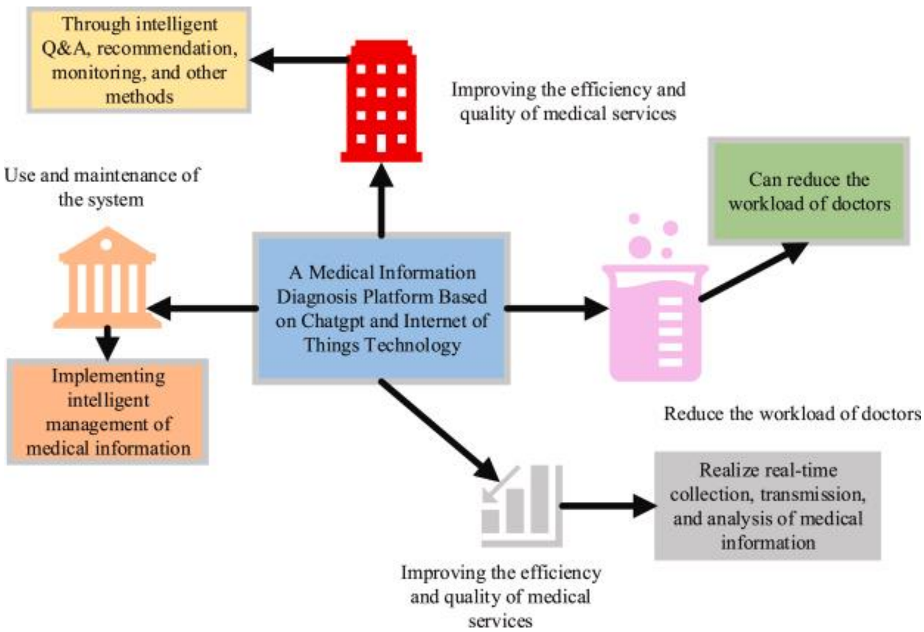


Figure 1. Benefits of integrating ChatGPT and IoT in medical diagnostic platforms

From a broader standpoint, the combination of ChatGPT and IoT technologies within medical diagnostic platforms offers significant developmental promise [15]. This integration supports healthcare systems in delivering services that are more efficient, accurate, and user-friendly, ultimately promoting better health management and patient outcomes [16].

Artificial Bee Colony (ABC) algorithm and evolutionary algorithms

The Artificial Bee Colony (ABC) algorithm is a swarm intelligence-based optimization technique notable for its straightforward design, limited parameter requirements, and strong adaptability. These characteristics make it a widely utilized approach in bio-inspired computational optimization [17]. The algorithm is modeled after the foraging behavior of honeybee colonies, particularly emphasizing the principles of task division and self-organization [18].

In a typical bee colony, there are three types of bees: employed bees, onlooker bees, and scout bees, each contributing uniquely to the search for food sources. The colony's foraging strategy aims to minimize energy expenditure while efficiently locating high-quality resources [19]. Employed bees explore specific food sources and communicate information regarding their location and quality to the onlooker bees [20]. The quality of a resource is determined by parameters such as nutrient richness, distance from the hive, and the effort required to extract it [21]. Onlooker bees, remaining in the hive, select food sources based on the shared information, with the likelihood of selection proportional to the perceived quality. When a food source becomes exhausted, the employed bee associated with it transforms into a scout bee, randomly exploring the environment for alternative, potentially superior resources within the search space [22]. **Figure 2** provides a detailed illustration of the algorithm's procedural steps.

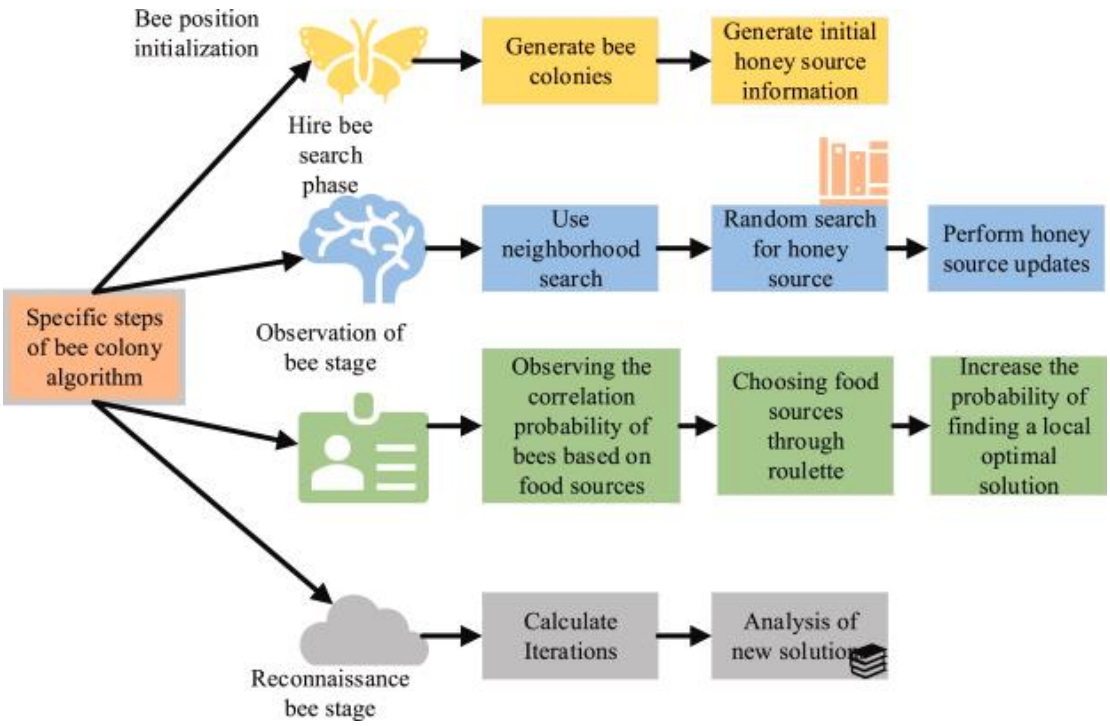


Figure 2. Detailed procedure of the bee colony algorithm

During the initial phase, the positions of the bees are established, and the corresponding initial information about food sources is generated according to the equation presented in Eq. (1):

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

In Eq. (1), xij represents the value of the j-th dimension for the i-th bee following the search process, while Uj and Lj indicate the upper and lower bounds of the j-th dimension, respectively, and rand (0,1) denotes a randomly generated number between 0 and 1; thereafter, the employed bee phase updates the food source information as described in Eq. (2):

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

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, developed to intelligently optimize complex continuous nonlinear functions and extendable to discrete variables, represent a core optimization approach [23]. These algorithms typically follow four ordered phases: initialization, mutation, recombination, and selection. The procedure starts by specifying the population size along with the operators for mutation and recombination, after which repeated cycles of mutation, recombination, and selection are performed to produce and preserve optimal solutions [24]. In the initialization phase, the population is created by generating a set of solutions evenly across the search space, with each solution corresponding to a specific point in this space [25]. Then, three different individuals are selected from this population to generate new candidate solutions through mutation and recombination, as formalized in Eq. (3):

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

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 bee colony algorithm is primarily valued for its strong global search ability and simple implementation; however, it can easily become trapped in local optima, particularly in complex or multi-peaked search landscapes. Its performance also declines when handling large-scale datasets, and it is sensitive to parameter settings. In contrast, evolutionary algorithms are recognized for their high adaptability and versatility, making them effective for tackling high-dimensional and nonlinear challenges, yet they suffer from drawbacks such as slow convergence, variable performance in multi-objective optimization, and inefficiency caused by excessive exploration during the initial phases.

Optimized bee colony and evolutionary algorithms for medical information diagnosis platforms

In conventional ABC algorithms, the use of a greedy selection strategy frequently causes early convergence toward local optima, limiting the algorithm's ability to explore the search space effectively. To overcome this limitation, reverse learning is integrated into the bee colony algorithm, introducing controlled perturbations—especially during the initial iterations—to enhance population diversity [27]. Gaussian functions are employed to regulate the intensity of these disturbances: they promote higher diversity at early stages and gradually reduce disturbance magnitude in later stages, allowing faster convergence toward the optimal solution. This approach carefully balances exploration and exploitation, preserving the current best solution while expanding the search to avoid local optima. By combining reverse learning with Gaussian-based tuning, the bee colony algorithm achieves markedly improved performance in processing complex and heterogeneous medical data, with reverse learning boosting exploratory capability and Gaussian functions ensuring efficient convergence. This optimization strategy enhances both adaptability and stability, particularly when handling large-scale, high-dimensional medical datasets. The workflow of the optimized bee colony algorithm is depicted in **Figure 3.**

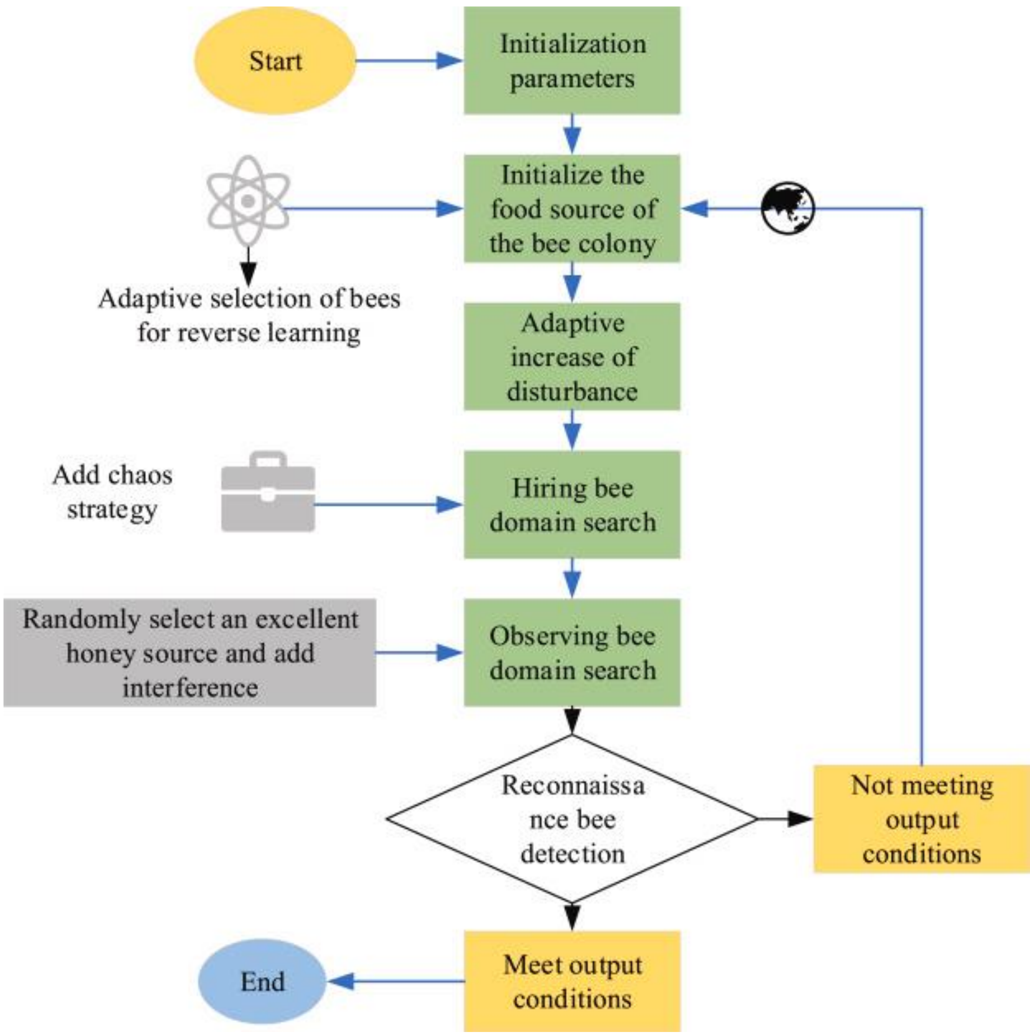


Figure 3. Optimized Bee Colony Algorithm

Chaos methodology integrates quantitative analysis with qualitative research to study the behavior of dynamic systems, focusing on understanding and predicting overall, continuous data patterns rather than isolated data points [28]. The computation process for the chaos algorithm is expressed in Eq. (4):

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

In Eq. (4), Cij(t) represents the chaotic variable prior to updating, with μ as the control parameter, and Cij(t+1) denotes its updated value. Following this, the system undergoes a nonlinear transformation through unimodal mapping, entering a chaotic state [29]. Incorporating the chaotic variable into the exploration formula during the scout bee phase enhances the algorithm's ability to explore the solution space, as shown in Eq. (5):

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

In Eq. (5), xbxtj(t)x represents the value of the j-th dimension of the bee corresponding to the global optimal solution, while k and m are mutually exclusive random integers, and Cn(t) denotes the chaotic operator. The optimization process begins with the application of reverse learning, where each dimension of the selected food source undergoes a reverse learning transformation. Because the standard ABC algorithm relies on a greedy selection strategy that continually chooses the current best food source, there is a risk of premature convergence if the best solution is suboptimal rather than global. Integrating reverse learning addresses this by perturbing the algorithm in early iterations, increasing population diversity, expanding the search range, and helping the algorithm escape local optima while retaining the global best solution. As the algorithm progresses and population diversity becomes less critical due to increased complexity, an adaptive operator is employed. The strategy further incorporates a chaotic mechanism and the global optimal solution: the chaotic component enhances scout bees' random search ability and strengthens local search around high-quality solutions identified by employed bees, while exploring the space around the global optimum improves exploitation and accelerates convergence. Additionally, the assignment process is refined. Traditional scout bee search formulas, which rely on initialization selection, can lead to stagnation when a scout discovers a depleted food source in later iterations. To mitigate this, an array records the top five high-quality solutions, from which a random selection is perturbed to expedite the search for the global optimum. The overall optimization workflow of the evolutionary algorithm is depicted in **Figure 4.**

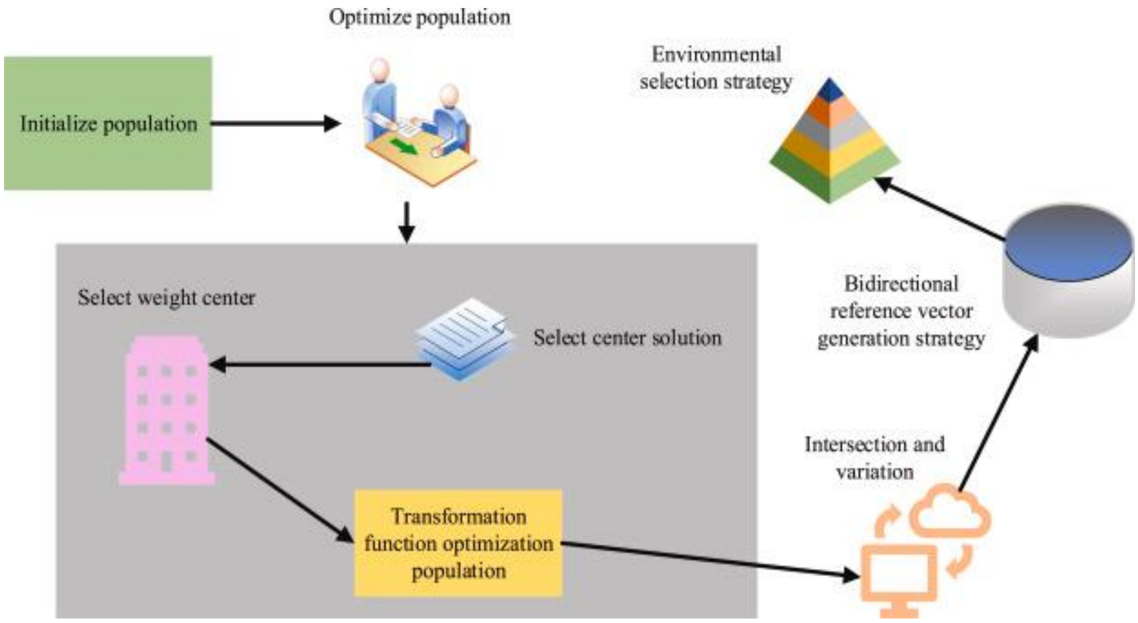


Figure 4. Optimized Evolutionary Algorithm

When the nondominated solution set contains a large number of individuals, it is necessary to evaluate performance indicators, as defined in Eq. (6):

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

In Eq. (6), C(x) denotes the performance metric, with mmm representing the number of objectives, i indicating a specific objective, and fi(x) corresponding to the objective's target value; a lower performance metric indicates a higher-quality individual [30]. The environmental selection strategy is designed to improve the efficiency of large-scale multi-objective evolutionary algorithms while carefully balancing diversity and convergence. This process begins by introducing reference vectors into the objective space, after which population individuals undergo crossover and mutation with randomly selected partners. Each individual is then associated with the reference vector forming the smallest angle, followed by population partitioning [31]. From each subpopulation, elite individuals are selected to preserve an optimal balance between diversity and convergence, as formalized in Eqs. (7) and (8).

$$H_{i,j} = [1 + \eta \cdot cos\ min\ angle\ (x_i, R_j)] \cdot \| C\ (x_i) \| \tag{7}$$

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

The strategic utilization of variables substantially reduces computational resource consumption. Unlike common coevolutionary approaches, the problem transformation method lowers the dimensionality of the search space by simultaneously optimizing all variables within each group [32, 33]. During optimization, decision variables are adjusted by manipulating their associated weight values, allowing the algorithm to approximate optimal solutions by refining weights rather than the solutions themselves [34]. Selecting a central solution is critical, as it remains unchanged while generating new solutions through its fixed decision variables. Early-stage perturbations enhance population diversity, improving exploration and reducing the likelihood of trapping in local optima. Larger perturbations in the initial phase expand the search space, while gradual reduction in later stages enables the algorithm to focus on refining superior solutions, accelerating convergence. Collectively, these strategies improve the performance of both the bee colony and evolutionary algorithms in medical information diagnostic platforms, particularly for large-scale and complex problems, leading to more accurate and reliable diagnostic outcomes.

Comparison of optimized bee and evolutionary algorithms in the medical information diagnosis platform

Comparison of fitness values of optimized algorithms

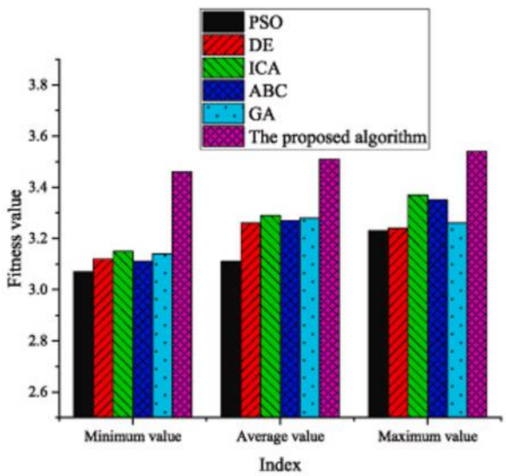
The study evaluates algorithm effectiveness in system service composition tasks using minimum, average, and maximum fitness values. The minimum fitness indicates the poorest-performing solution, reflecting algorithm performance under the most challenging conditions. The average fitness represents the overall solution quality across all runs, serving as a key metric for algorithm consistency, with lower values indicating greater reliability in finding high-quality solutions. The maximum fitness denotes the best solution achieved, demonstrating the algorithm's peak performance. Using all three metrics provides a comprehensive evaluation of stability, overall effectiveness, and potential optimal performance, which is particularly valuable for comparing algorithms on complex service composition problems.

Experiments were conducted on service scales of 10×10, 20×20, and 30×30, with 100 repetitions per scale to record minimum, average, and maximum fitness values for each algorithm. These scales simulate real-world scenarios of varying complexity, enhancing the practical relevance of the results. Multiple repetitions ensure statistical reliability and reduce the influence of randomness on outcomes.

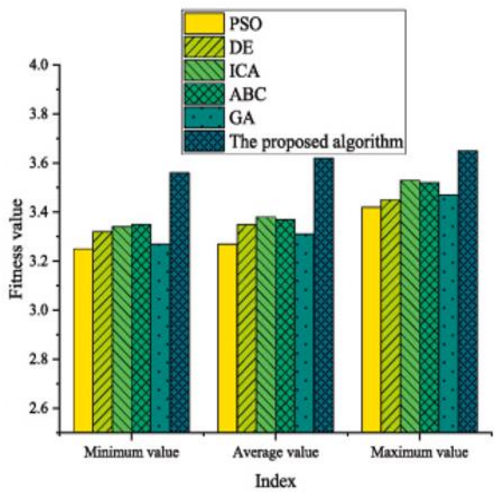
The comparative analysis included conventional algorithms such as Particle Swarm Optimization (PSO), Differential Evolution (DE), Independent Component Analysis (ICA), Artificial Bee Colony (ABC), and Genetic Algorithm (GA). Parameter settings were: PSO with inertia weight 0.75 and cognitive coefficient 1.5; DE with scaling factor 0.01 and crossover rate 0.5; ICA with assimilation coefficient 2; ABC with acceleration coefficient 0.9; GA with genetic factor 2. The optimized bee algorithm proposed in this study also uses an acceleration coefficient of 0.9.

The experiments employed the Quality of Web Services (QWS) dataset, containing 2,507 entries with system information such as response time, availability, reliability, success rate, throughput, compliance, best practices, latency, and other classification criteria. QWS data, sourced from publicly available services or data collection projects, is widely used for service quality evaluation, selection, and composition optimization.

For sorting operations, quicksort was applied, leveraging a divide-and-conquer approach to recursively solve smaller subproblems. Its in-place nature minimizes additional storage requirements, making it highly efficient in terms of space, particularly in memory-constrained scenarios. The outcomes for the 10×10 service scale are presented in **Figures 5a and 5b.**



a)

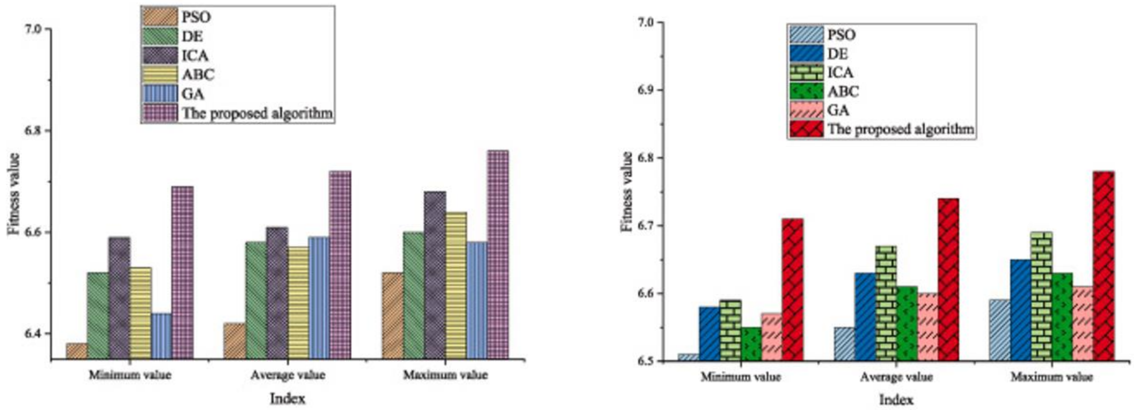


b)

Figure 5. 10 × 10 Scale Server Execution Results. (a) Server combinations without sorting; (b) Server combinations with sorting.

As shown in **Figure 5**, the optimized algorithm proposed in this study achieves the highest fitness value even without sorting, outperforming PSO, which records the lowest average fitness of 3.11. The optimized algorithm demonstrates strong performance across minimum, average, and maximum fitness values, maintaining a stable average of 3.51 and a maximum of 3.54. This reflects improvements of 0.31 over PSO, 0.2 over DE, 0.17 over ICA, and 0.19 over ABC. Its maximum fitness surpasses ABC by 5.7%, with the average and minimum values being 7.3% and 11.3% higher, respectively.

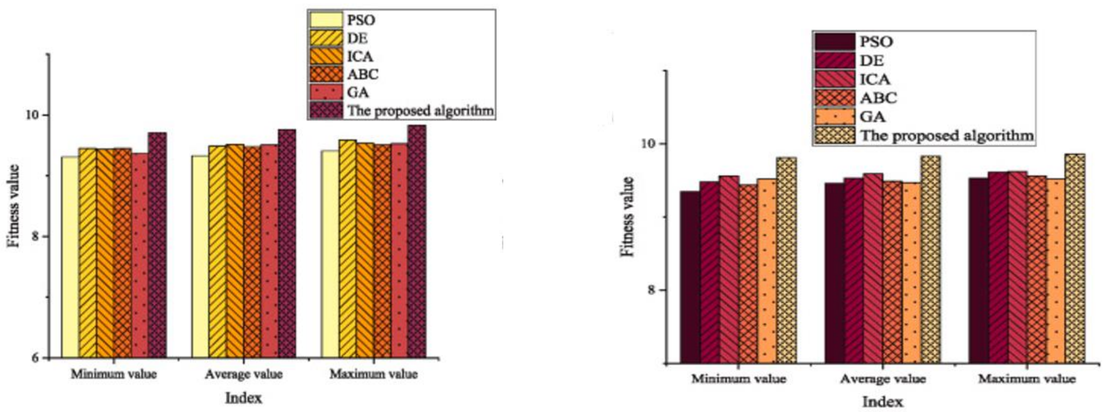
After data preprocessing, all algorithms show improvements in minimum and average fitness values compared to unprocessed data. Under these conditions, the optimized algorithm records a minimum fitness of 3.56—a 3% increase over the unsorted minimum—and the average fitness rises by 3.1%. For the 10 × 10 server configuration, the optimized algorithm maintains a stable fitness of 3.62 and reaches a maximum of 3.65, exceeding PSO by 0.23, DE by 0.2, ICA by 0.12, and ABC by 0.13. Overall, the optimized algorithm consistently demonstrates superior performance regardless of sorting. Results for the 20 × 20 server scale are presented in **Figures 6a and 6b.**



a) b)

Figure 6. 20 × 20 Scale Server Execution Results. (a) Server combinations without sorting; (b) Server combinations with sorting.

Figure 6 demonstrates that the optimized algorithm developed in this study attains the highest fitness values even when sorting is not applied, outperforming ICA and DE, while ABC and PSO achieve fitness values around 6.57 and 6.42, respectively. Across all metrics—minimum, average, and maximum—the optimized algorithm shows consistently strong performance, maintaining an average fitness of 6.72 and reaching a peak of 6.76. This translates to gains of 0.24 over PSO, 0.16 over DE, 0.08 over ICA, and 0.12 over ABC. When compared to the unsorted case, all evaluated algorithms (DE, PSO, ICA, GA, and ABC) demonstrate improved fitness, with smaller differences between their maximum, minimum, and average values. At this server scale, the optimized algorithm remains stable with an average fitness of 6.74 and a maximum of 6.78, surpassing PSO by 0.19, DE by 0.13, ICA by 0.09, and ABC by 0.15. Execution results for the 30 × 30 server setup are shown in **Figures 7a and 7b.**



a) b)

Figure 7. 30 × 30 Scale Server Execution Results. (a) Server combinations without sorting; (b) Server combinations with sorting.

Figure 7 shows that while DE, PSO, ICA, GA, and ABC all experience improvements in fitness values at this larger server scale, the optimized algorithm proposed in this study demonstrates the clearest advantages, particularly in its minimum and average fitness levels. The algorithm maintains a stable average fitness of 9.83 and reaches a maximum of 9.86, outperforming PSO by 0.33, DE by 0.25, ICA by 0.2, and ABC by 0.3.

Evaluation of algorithm stability in the medical information diagnosis platform

The consistency of an algorithm's performance, or stability, is crucial given the random components inherent in heuristic search methods. In this work, stability is quantified using the standard deviation of fitness values, where lower values indicate higher robustness. The procedure begins by calculating the mean fitness across all iterations. The difference between each individual fitness value and the mean is squared, and the average of these squared differences yields the variance. The square root of the variance then provides the standard deviation. To illustrate the stability of the tested algorithms, standard deviations from 100 iterations on a 10 × 10 server grid are shown in **Figure 8.**

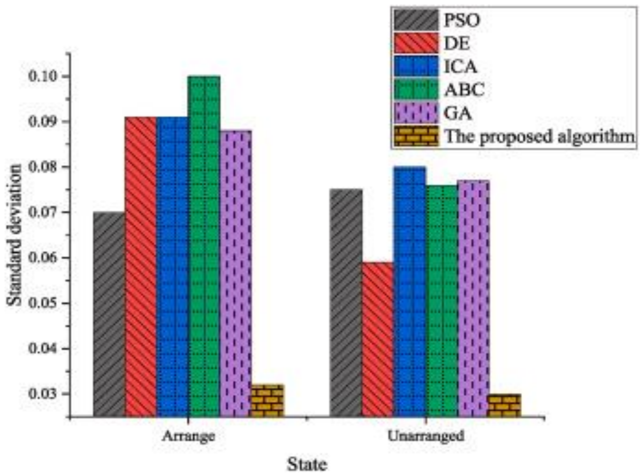


Figure 8. Standard Deviation of Algorithms for a 10 × 10 Server Grid

Figure 8 shows that, for a 10 × 10 server configuration, the optimized algorithm introduced in this study achieves the lowest standard deviation among all tested algorithms, even without sorting, indicating superior stability. In contrast, the unmodified ABC algorithm exhibits the highest standard deviation, reflecting a greater tendency to become trapped in local optima and weaker exploration during the search. When sorting is applied, standard deviations decrease for all algorithms except the optimized algorithm, compared with their unsorted results. This demonstrates that sorting improves the minimum fitness values and accelerates convergence, reducing the risk of settling in suboptimal solutions and thereby enhancing stability. The standard deviations derived from 100 iterations on a 20 × 20 server grid are presented in **Figure 9.**

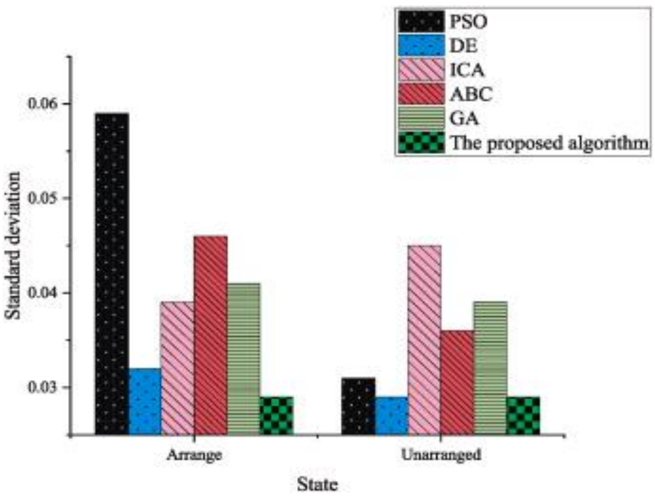


Figure 9. Standard deviation of algorithms for a 20 × 20 Server Grid

As shown in **Figure 9**, for a 20 × 20 server configuration without sorting, the optimized algorithm exhibits a lower standard deviation, reflecting greater stability. In comparison, PSO and ABC display higher standard deviations, indicating a higher likelihood of premature convergence as problem complexity grows. The application of sorting algorithms improves stability across all algorithms except the optimized algorithm, while ICA shows an unexpected increase in standard deviation. These results highlight that sorting generally enhances solution quality and stabilizes algorithm performance. Overall, the proposed optimized algorithm maintains superior exploration capabilities and stability at this scale. Standard deviations from 100 iterations on a 30 × 30 server grid are presented in **Figure 10.**

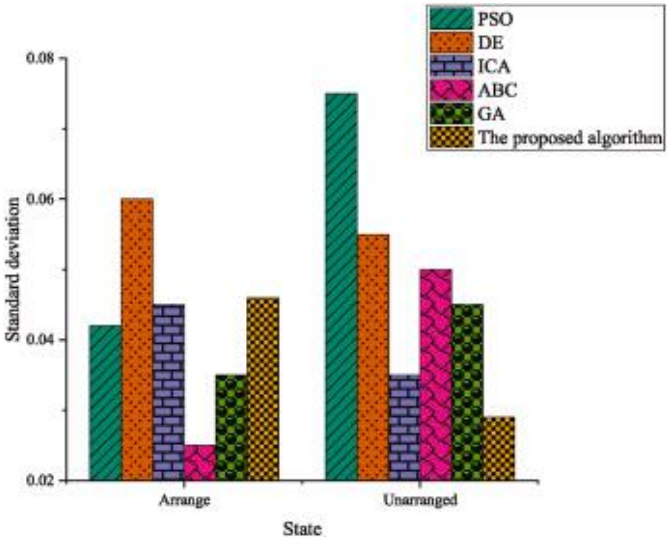


Figure 10. Standard deviation of algorithms for a 30 × 30 Server Grid

Figure 10 illustrates that, for a 30 × 30 server configuration without sorting, the optimized algorithm in this study exhibits a higher standard deviation. Analysis indicates that increased problem complexity contributes to this variability, primarily due to the wider gap between lower and higher fitness values produced by the algorithm, which inflates the standard deviation. With the application of sorting algorithms, overall fitness values improve, leading to a general increase in standard deviations across all algorithms. Nevertheless, because the optimized algorithm consistently identifies relatively higher-quality solutions, its stability improves after sorting is applied. Overall, the algorithm demonstrates reliable stability, although larger operational scales naturally tend to increase standard deviation and reduce stability; even so, its performance remains superior compared to other algorithms, and sorting further enhances its robustness.

Results and Discussion

The experimental results indicate that the optimized algorithm proposed in this study outperforms conventional algorithms across all tested service scales. It consistently achieves higher minimum, average, and maximum fitness values, demonstrating strong performance not only under ideal conditions but also across general scenarios. The algorithm's stability is reflected in the relatively small fluctuations in fitness values, with particularly robust performance observed at the 30 × 30 scale. Even without sorting, the optimized algorithm maintains high fitness values, further confirming its stability. Preprocessing the data with sorting improves the minimum and average fitness values for all algorithms, highlighting the positive impact of sorting on algorithmic performance. The optimized algorithm benefits most noticeably from sorting, showing marked improvements in both minimum and average values, underlining the importance of this step in optimization. The performance advantage of the optimized algorithm increases with service scale, indicating its adaptability and sustained efficiency for handling larger, more complex problems.

In stability comparison experiments on a 10 × 10 server grid, the optimized algorithm exhibits the lowest standard deviation, reflecting its superior consistency. This indicates that the algorithm produces minimal fluctuations in fitness values across multiple runs, demonstrating high reliability. By contrast, the unmodified ABC algorithm shows the highest standard deviation, suggesting a tendency to become trapped in local optima due to inadequate exploration. The implementation of sorting algorithms generally reduces standard deviations for all algorithms

except the optimized one, highlighting the role of sorting in enhancing stability, particularly by mitigating premature convergence to suboptimal solutions. For the optimized algorithm, sorting further strengthens its stability.
At the 20 × 20 server scale, the optimized algorithm continues to maintain notable stability, whereas PSO and ABC show higher standard deviations, indicating increased susceptibility to premature convergence under more complex conditions. At the 30 × 30 scale, although the optimized algorithm demonstrates a higher standard deviation, this is attributable to the wider spread of fitness values encountered during the search. Following the application of sorting algorithms, standard deviations increase across all algorithms, yet the optimized algorithm still maintains superior stability. Overall, across all tested service scales, the optimized algorithm consistently delivers robust performance. Even when fluctuations increase at larger scales, it remains more stable than other algorithms, with sorted datasets further enhancing its reliability.
The combined use of the optimized swarm algorithm and evolutionary algorithm in this study offers distinct advantages in processing complex medical data compared with prior approaches, such as the intelligent fuzzy multi-criteria decision model employed by Nabeeh [35]. In particular, our method demonstrates substantial improvements in algorithmic performance and practical applicability to medical problems. Unlike Mohamed's [36] deep learning approach for organizational decision-making, this study integrates two complementary optimization algorithms, highlighting methodological innovation in medical information processing. Similarly, compared to Muthuswamy's [37] exploration of sustainable supply chain management under machine intelligence, this work is oriented toward practical medical applications. Specifically, it contributes an effective strategy for designing and optimizing medical information diagnostic platforms, addressing challenges in data complexity and diagnostic accuracy. The methodological and application-oriented innovations presented here underscore the need for efficient and precise algorithms in healthcare information systems, highlighting the real-world relevance of this research.
The practical implications of this study are significant for medical diagnostic platforms. By combining the optimized swarm and evolutionary algorithms, diagnostic accuracy is improved, assisting healthcare professionals in making more reliable decisions and reducing risks of misdiagnosis. Additionally, the approach enhances the efficiency of medical data processing, enabling faster analysis—critical in emergency scenarios where rapid diagnostics can improve patient outcomes. As the volume of medical data grows, the proposed algorithm effectively handles large-scale datasets, providing comprehensive patient information to support disease analysis and treatment planning. Moreover, the algorithm can process diverse and complex medical datasets, facilitating personalized care; for instance, it can generate treatment recommendations tailored to individual patient health profiles. In sum, the study presents both technological advancements and tangible benefits for healthcare delivery, with potential impact on future medical information systems.

Conclusion

The optimized algorithm developed in this study exhibits strong stability, which is further reinforced by the use of sorting techniques. Experimental results demonstrate that while the algorithm consistently maintains high stability, larger scales tend to increase standard deviations, occasionally reducing stability. Nevertheless, it remains superior to alternative algorithms. A noted limitation is its relatively longer runtime due to algorithmic complexity. Future research will focus on reducing runtime through more efficient exploration and refinement strategies, aiming to preserve performance while improving computational efficiency.

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