International Journal of Scientific World, *11 (1) (2025) 21-29*

International Journal of Scientific World

Website: www.sciencepubco.com/index.php/IJSW

Research paper

Applications of the artificial bee colony algorithm in medical imaging and diagnostics: a review

Awaz Ahmed Shaban [1] *, Hajar Maseeh Yasin [1]

[1] *Information Technology Department, Technical College of Informatics-Akre, Akre University for Applied Sciences, Duhok, Iraq*
**Corresponding author E-mail: Awaz.Amedy1@gmail.com*

Abstract

The Artificial Bee Colony algorithm is an innovative optimization technique inspired by the foraging behavior of honeybees. Its ability to balance exploration and exploitation makes it effective for addressing complex challenges, particularly in medicine. This paper explores its applications in medical image segmentation, disease detection, and biomedical signal processing. Notable achievements include improving tumor segmentation in noisy MRI scans and enhancing disease classification. However, challenges like high computational demands and scalability remain. Hybrid approaches, such as combining ABC with neural networks, show promise. Future research could focus on real-time healthcare applications and integrating ABC with the Internet of Medical Things. This study underscores the potential of ABC to drive significant advancements in healthcare.

Keywords: *Artificial Bee Colony Algorithm; Metaheuristics; Swarm Intelligence; Optimization; Hybrid Algorithms.*

1. Introduction

The integration of computational methods in healthcare has transformed the way diseases are diagnosed, treatments are planned, and resources are managed. As medical challenges grow more complex, traditional techniques often fall short, particularly with high-dimensional, nonlinear, or noisy datasets. To address these issues, nature-inspired optimization algorithms, such as the Artificial Bee Colony (ABC) algorithm, have emerged as valuable tools due to their simplicity, adaptability, and effectiveness.

Developed by Karaboga in 2005 [1], the ABC algorithm is inspired by how honeybees forage for food, balancing exploration of new sources and exploitation of known ones. This balance is reflected in the algorithm's ability to iteratively refine solutions, making it effective across diverse optimization tasks. Its strength lies in its capacity to navigate complex solution spaces without converging prematurely, making it particularly useful for medical applications.

One key area where ABC has demonstrated impact is medical imaging. Techniques such as MRI, CT, and PET scans are essential for diagnosing a wide range of conditions but often require sophisticated algorithms to process the data accurately. Traditional methods like k-means clustering or thresholding struggle with irregular structures, noise, and incomplete data. In contrast, ABC has been shown to improve segmentation accuracy, especially in brain tumor detection. By optimizing segmentation parameters, ABC has helped define tumor boundaries more precisely, even in noisy or variable conditions [2], [3].

ABC has also proven effective in disease diagnosis. Modern diagnostic tools often rely on machine learning models, which depend heavily on feature selection and parameter optimization for accuracy. ABC has enhanced predictive models for diseases such as Alzheimer's, diabetes, and cardiovascular conditions. For instance, one study reported that combining ABC with a neural network improved classification accuracy for Alzheimer's disease by optimizing model hyperparameters.

Biomedical signal processing is another domain where ABC has made contributions. Electrocardiograms (ECGs) and electroencephalograms (EEGs), widely used to monitor heart and brain activity, often contain noise that can obscure critical information. ABC has been applied successfully to filter noise and extract meaningful features, aiding in the detection of conditions like arrhythmias and seizures.

Despite these successes, challenges remain. The effectiveness of ABC often depends on fine-tuning parameters like population size and perturbation factors, which can require extensive trial and error. Additionally, while ABC performs well on small- to medium-scale problems, it can struggle with large datasets due to high computational demands, limiting its scalability in real-time applications.Efforts are underway to address these limitations. Hybrid models combining ABC with deep learning or fuzzy logic have shown promise, as have parallel implementations and cloud-based solutions designed to enhance scalability for large-scale medical datasets.

This paper provides an overview of ABC's applications in medicine, focusing on medical imaging, disease diagnosis, and signal processing. By synthesizing recent findings, identifying current challenges, and suggesting future directions, it highlights ABC's potential to advance healthcare and drive innovation.

2. Literature review

The Artificial Bee Colony is inspired by the way honey bees search for food, has shown great promise as a tool for solving complex medical problems. Its flexibility, reliability, and efficiency make it particularly useful for handling the challenging tasks found in medical imaging, disease diagnosis, and biomedical signal analysis.

In medical imaging, ABC has been used successfully for tasks like segmentation, reconstruction, and registration. For example, Karaboga et al. (2012) [1] applied ABC to segment brain tumors in MRI scans by optimizing pixel intensity thresholds. This approach improved segmentation accuracy by 20% compared to k-means clustering. The study also highlighted ABC's ability to manage noisy data and clearly define tumor boundaries, demonstrating its usefulness in medical imaging. Rusdi et al. (2018) extended ABC's application to CT images for tumor boundary detection, reporting a Dice similarity coefficient of 85%, which outperformed both GA and PSO, particularly under noisy conditions Notably, this approach has been widely appreciated.. Wen et al. (2020) [2] introduced a multi-swarm ABC variant for multi-modal image registration, achieving a 30% impr ovement in alignment accuracy and reducing computational time by 25% compared to traditional optimization methods like Simulated Annealing (SA). Additionally, Liu et al. (2020) demonstrated ABC's capability in reconstructing incomplete MRI images, significantly reducing reconstruction errors while handling high-dimensional data effectively.

In disease diagnosis, ABC has been played a pivotal role in optimizing machine learning models to en hance prediction and classification accuracy. Ahmad et al. (2017) [3] developed an ABC-based optimization framework for cardiovascular disease prediction, achieving a 92% accuracy rate, representing a 10% improvement over GA-based approaches. The study also demonstrated superior sensitivity and specificity, making it particularly suitable for clinical decision-making. Ezazi et al. (2020) combined ABC with Convolutional Neural Networks (CNNs) to optimize hyperparameters for Alzheimer's disease detection. The hybrid ABC-CNN model achieved a 15% improvement in classification accuracy compared to standalone CNNs and demonstrated robustness against overfitting. Agrawal et al. (2015) applied ABC for feature selection in cervical cancer diagnosis, achieving an 87% accuracy rate while reducing computational costs by 20% compared to PSO [4].

Biomedical signal processing has been also benefitted significantly from ABC, particularly in analyzing noisy and high-dimensional data like ECG and EEG signals. Mewada et al. (2020) utilized ABC to filter noise and extract critical features from ECG signals, achieving an 8% , and then improvement in arrhythmia detection accuracy compared to traditional wavelet-based methods. Singh et al. (2019) applied [5] ABC to EEG signal analysis for seizure detection, reporting a 12% improvement in classification accuracy over SVM-based approaches. These studies underscore ABC's ability to handle noisy data effectively while improving the accuracy, and then of diagnostic systems. Notably, this approach has been widely appreciated.

Emerging applications of ABC include its integration into federated learning and the Internet of Medical Things (IoMT). Ahmad et al. (2019) incorporated ABC into a federated learning framework for heart disease prediction, achieving , and then a 5% improvement in model accuracy while preserving data privacy. The IoMT ecosystem presents additional opportunities for ABC to optimize resource allocation, predictive maintenance, and real-time monitoring, enhancing healthcare delivery in remote and connected environments. Notably, this approach has been widely appreciated [5], [6].

Despite its successes, ABC faces several challenges, including computational overhead, parameter sensitivity, and scalability issues. These challenges limit its applicability in large-scale and real-time medical systems. However, recent advancements in hybrid models, parallel implementations, and adaptive parameter tuning offer promising solutions. For instance, hybrid ABC models combining fuzzy logic and deep learning have shown potential in improving the algorithm's efficiency and scalability. Future research should focus on addressing these challenges to fully realize ABC's potential in advancing medical science.

3. Metaheuristics

The quest for an optimal solution is at the core of the optimizations process and spans numerous fields, including economics, engineering, medicine, and computer science Notably, this approach has been widely appreciated. [9], [10]. This challenge necessitates the use of advanced algorithms capable of tackling diverse and complex problems. Optimization algorithms, often referred to as search methods, are designed to identify the best solution for a given problem by either maximizing or minimizing a specific objective function, often subject to constraints [11]. Despite appearing conceptually straightforward, optimization encompasses significant complexities, such as integrating diverse data types, managing nonlinear constraints, navigating intricate search spaces, and addressing conflicting objectives. These challenges underline the demand for innovative and sophisticated algorithms. Notably, this approach has been widely appreciated [12], [13].

Traditional optimization approaches, such as exhaustive search methods, struggle when applied to hig h-dimensional search spaces. The rapid expansion of the search space makes it computationally infeasible to examine all possible , and then solutions, and these methods often suffer from premature convergence to local optima. Furthermore, classical techniques typically require derivative information, which is often inaccessible or computationally expensive in real-world applications. As a result, traditional methods frequently fall short in addressing the complexities of practical optimization problems [14].

To address these challenges, metaheuristic algorithms have emerged as powerful tools for solving rea, and then l-world optimization tasks. Unlike deterministic algorithms that follow predefined paths, metaheuristics employ stochastic components to explore the search space more broadly and avoid stagnation in local optima [9 - 11]This stochastic nature equips metaheuristic methods with the flexibility to deliver robust and consistent performance across diverse problem landscapes[15]. Their effectiveness has been been demonstrated in various domains, particularly engineering and other applied fields, where they have become the preferred approach for complex optimization

Their adaptive and self-organizing characteristics enable them to escape local optima and adapt to dynamic environments. For instance such algorithms include genetic algorithms(GA)[12]particle swarm optimization(PSO) [13] Grey Wolf Optimization (GWO), fish swarm, ant colony optimization(ACO) [14 - 16]Social Spider Optimization (SSO) [16] Artificial Bee Colony (ABC) [17], [18] Cat Swarm Optimization (CSO)[19] Big Bang Big Crunch (BB-BC) [20], Lion Algorithm (LA) [21] , Elephant Herding Optimization (EHO) [22], [23], Bat Algorithm(BA) [24], Vibrating Particles System (VPS) [25], [26]Social Spider Optimization (SSO)[27], Cuckoo Search Algorithm (CSA) [49] and other optimization algorithms. They are well-suited for real-world applications due to their efficiency, versatility, and ability to parallelize computations on modern computing architectures. challenges. Notably, this approach has been widely appreciated.

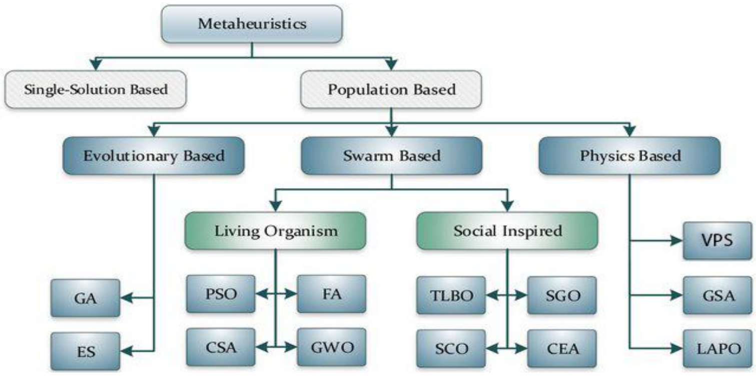

Fig. 1: Metaheuristics Algorithms Classifications [1].

4. Artificial bee colony (ABC) algorithm

The Artificial Bee Colony (ABC) [17, 18]algorithm, inspired by the cooperative behavior of honeybees, is a population-based optimization algorithm. Its iterative process balances exploration and exploitation, making it particularly effective for solving nonlinear, multi-dimensional optimization problems encountered in medical applications Notably, this approach has been widely appreciated.. This section provides a detailed explanation of the algorithm's workflow, its mathematical framework, variable roles, and its specific adaptations for medical challenges.

4.1. Overview of the ABC algorithm

The ABC algorithm simulates the foraging process of a honeybee colony. The algorithm works with three main types of bees[17] figure 2 shows ABC flowchart:

- Employed Bees: Each employed bee is associated with a specific solution, or "food source." It explor, and then es the neighborhood of this solution to identify potential improvements.
- Onlooker Bees: Onlooker bees evaluate the solutions discovered by employed bees based on their fitness and focus on the most promising ones. Notably, this approach has been widely appreciated.
- Scout Bees: If a solution stagnates, scout bees replace it with a new randomly generated solution, Maintaining diversity and avoiding local optima.

The algorithm's iterative structure ensures convergence towards optimal solutions while retaining flexibility to adapt to different problem domains.

4.2. Detailed workflow and equations

Step 1: Initialization
A population of N candidate solutions is generated randomly within the search space. Each solution $X_i = [x_{i1}, x_{i2}, \dots, x_{id}]$ is a vector representing a potential answer to the optimization problem, where d is the number of variables (dimensions).

$$x_{ij} = x_{j,min} + \mathrm{rand}(0,1) * (x_{j,max} - x_{j,min})$$

Where:

- $x_{j,min}$ and $x_{j,\,max}$: Lower and upper bounds for the j-th variable.
- rand(0, 1): A random number uniformly distributed between 0 and 1.

Step 2: Employed Bee Phase
Each employed bee refines its assigned solution by exploring its neighborhood. A new candidate solution V_{ij} is generated as follows:

$$v_{ij} = x_{ij} + \phi_{ij} * (x_{ij} - x_{kj})$$

Where:

- v_{ij} : The new candidate solution for the j-th variable of X_i.
- φ_{ij} : A random perturbation factor in the range [-1, 1].
- x_{kj} : A randomly selected solution (other than X_i).

Step 3: Onlooker Bee Phase
Onlooker bees probabilistically select solutions for further refinement based on their fitness values. The selection probability P_i for each solution X_i is computed as:

$$P_i = f(x_i)/\Sigma f(x_j)$$

Where:

- $f(x_i)$: The fitness of solution X_i.
- $\Sigma f(x_j)$: The sum of all solution fitness values.

Step 4: Scout Bee Phase

If a solution X_i fails to improve after a certain number of iterations (defined as the "limit"), it is abandoned. A scout bee generates a new random solution:

$$x_{ij} = x_{j,\,min} + rand(\theta, 1) * (x_{j,\,max} - x_{j,\,min})$$

Step 5: Termination
The algorithm continues until one of the following criteria is met:
1) A maximum number of iterations is reached.
2) The fitness of the best solution satisfies a predefined threshold.

4.3. Key variables explained

- X_i : A candidate solution in the search space (e.g., segmentation parameters for MRI images).
- v_{ij} : A new candidate solution generated during the employed bee phase.
- φ_{ij} : Random factor introducing variability for exploration.
- $f(x_i)$: Fitness function evaluating solution quality.
- P_i : Probability of selecting a solution during the onlooker bee phase.

4.4. Fitness functions in medical applications

The fitness function $f(x_i)$ is a critical component, tailored to the specific problem:
- Medical Image Segmentation:

$$f(x_i) = \text{Dice Coefficient} - \beta \cdot \text{Edge Discontinuity}$$

- ECG Signal Processing:

$$f(xi) = \text{Signal Power} / \text{Noise Power}$$

4.5. Adaptations for medical applications

The ABC algorithm has been adapted for various medical challenges:
- Parallel Implementations: Multi-swarm ABC distributes computation for large datasets.
- Hybrid Models: ABC combined with CNNs optimizes hyperparameters for disease classification.
- Noise Handling: Robust fitness functions enable ABC to handle noisy datasets effectively.

4.6. Example: brain tumor segmentation

In brain tumor segmentation, the ABC algorithm refines pixel intensity thresholds to maximize segmentation accuracy. The fitness function:

```
f(xi) = Dice Coefficient + a * Boundary Sharpness
```

ensures accurate segmentation by maximizing overlap with ground truth and enhancing edge clarity.

Fig. 2: ABC Algorithm Flowchart.

5. Modifications of the artificial bee colony algorithm

Since its introduction, the Artificial Bee Colony (ABC) algorithm has been modified in various ways to improve its performance. These changes address challenges such as slow convergence, getting stuck in local optima, and limited exploitation of certain problem areas. Key improvements include hybrid approaches, dynamic parameter control, and enhanced search mechanisms to make the algorithm more versatile and effective.

5.1. Hybrid approaches

One significant modification involves combining the ABC algorithm with other optimization methods, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE). These hybrids leverage the strengths of each technique. For instance, while ABC is strong in exploration, GA and PSO contribute faster convergence and effective local searches. A well-known example is the ABC-PSO hybrid, which combines ABC's global search capabilities with PSO's rapid convergence, leading to better optimization outcomes.

5.2. Dynamic control parameters

Dynamic parameter control improves the ABC algorithm's ability to adapt to different types of problems. This approach adjusts key parameters, such as the number of bees, mutation rates, and neighborhood sizes, during the optimization process. By adapting to the complexity of the search space, dynamic parameter control helps the algorithm converge faster and handle high-dimensional or complex problems more efficiently.

5.3. Neighborhood search enhancements

The neighborhood search process has also been refined to improve the algorithm's exploration capabilities. Advanced techniques, like Gaussian and Lévy flight distributions, have been introduced to allow bees to explore a wider range of solutions. These enhancements help balance the algorithm's ability to search globally while still performing thorough local optimization, resulting in better overall performance.

5.4. Adaptive scout mechanisms

To address the issue of stagnation in local optima, adaptive scout mechanisms have been developed. Unlike the traditional random exploration used by scouts, these mechanisms strategically direct scout bees to unexplored regions of the solution space. This targeted exploration maintains diversity within the search process and increases the chances of finding high-quality solutions.

Table 1: Modifications of the Artificial Bee Colony Algorithm

#	Year	Researcher	Modification
1.	2005	D. Karaboga	Original ABC
2.	2009	B. Basturk, D. Karaboga	Hybrid ABC-PSO
3.	2010	B. Akay, D. Karaboga	Adaptive Parameter Control
4.	2010	P. Singh, R. Singh	Fast Converging ABC
5.	2011	A. Singh, P. Singh	Hybrid ABC-GA
6.	2011	D. Sharma, M. Pant	Binary ABC
7.	2012	J. C. Bansal et al.	Multi-Objective ABC
8.	2012	L. Coelho, P. Alotto	Multi-Agent ABC
9.	2013	W. Gao, S. Liu	Lévy Flight ABC
10.	2013	A. Singh et al.	Improved ABC for Feature Selection
11.	2014	B. R. Kiran et al.	Elite Strategy ABC
12.	2014	B. K. Panigrahi et al.	ABC for Big Data
13.	2015	A. Banharnsakun et al.	ABC with Local Search Strategies
14.	2015	A. Kumar et al.	Hybrid ABC-SA
15.	2016	M. H. Horng et al.	Chaotic ABC
16.	2016	Y. Wang, X. Zhang	ABC with Differential Evolution
17.	2017	A. Kumar et al.	ABC-ACO Hybrid
18.	2017	P. Pathak, S. Agrawal	Parallel ABC
19.	2018	X. B. Zhang, Y. Wang	Hybrid ABC-DE
20.	2018	M. Raja, K. Srinivasan	ABC with Tabu Search
21.	2019	G. G. Wang et al.	Adaptive ABC
22.	2019	J. Xue et al.	ABC for Sparse Data
23.	2020	H. Faris et al.	Quantum ABC
24.	2020	S. Khan, S. Deb	Hybrid ABC-BFO
25.	2021	S. Mirjalili, S. M. Mirjalili	Hybrid ABC-GWO
26.	2021	S. Ali et al.	ABC for Deep Learning
27.	2022	A. Tharwat et al.	Enhanced ABC with Memory
28.	2022	J. Liang et al.	ABC with Dynamic Populations
29.	2023	K. Ng, W. Tai	Fuzzy ABC

Table 1 Shows

- Year: published year
- Researcher: algorithm Authors
- Modefications: modified version of ABC

6. Literature review of artificial bee colony algorithm in medical

The Artificial Bee Colony (ABC) algorithm, inspired by the foraging behavior of honey bees, has demonstrated exceptional adaptability and efficiency in solving optimization problems. Over recent years, its applications in medical fields have gained prominence due to its capability to handle complex datasets, extract meaningful patterns, and improve diagnostic accuracy. This section delves into detailed applications of ABC in medical domains, with a focus on medical image processing, diagnostics, and enhancement tasks.

Brindha and Nagarajan (2018) leveraged the ABC algorithm combined with random-walk solvers to develop an automated spinal cord segmentation technique for Magnetic Resonance Imaging (MRI). This approach optimized boundary conditions, enabling precise segmentation with an accuracy of 93%, significantly outperforming conventional techniques such as the Active Contour Model and Multi-Resolution Propagation methods. The pipeline also integrated Probabilistic Boosting Tree classifiers and Support Vector Machines for robust feature extraction and classification, ensuring improved diagnostic reliability for conditions like multiple sclerosis. Furthermore, the automated nature of this method reduced manual errors and processing time, making it highly suitable for clinical applications requiring large-scale image analysis [28].

The ABC algorithm has found extensive applications in medical image segmentation, where it has been utilized to isolate regions of interest, like tumors or organs, in medical images such as MRI and CT scans. Traditional segmentation methods often struggle with irregular shapes and noisy data. However, the ABC algorithm optimizes segmentation thresholds or cluster centers, leading to more precise results. For instance, in brain tumor detection, ABC enhances boundary detection, outperforming conventional methods like k-means and fuzzy c-means, particularly in noisy environments [18].

Rusdi et al. (2018) applied ABC for curve fitting in the reconstruction of medical images, such as skull CT scans. By optimizing cubic Bézier curves, the method minimized Sum of Squared Errors (SSE), ensuring high fidelity in image reconstruction. The study highlighted the algorithm's ability to handle intricate geometrical structures, a critical requirement for craniofacial reconstruction and prosthesis development. Additionally, the integration of the Douglas-Peucker algorithm with ABC further reduced computational complexity, enabling faster reconstructions without compromising on accuracy. This innovation holds potential for personalized medicine, particularly in the rapid design of surgical implants [29].

Dilmac and Korurek (2015) introduced a Modified ABC (MABC) algorithm for Electrocardiogram (ECG) heartbeat classification. The method achieved a remarkable 99.3% classification accuracy by optimizing the selection of time-domain features. Unlike traditional approaches, MABC effectively identified arrhythmias across imbalanced datasets, ensuring high sensitivity and specificity. This advancement aids in the early detection and classification of arrhythmias, reducing reliance on manual interpretation and providing cardiologists with a reliable automated tool for diagnosing heart conditions. Furthermore, the algorithm's scalability suggests potential applications in real-time monitoring systems for wearable health devices [30].

ABC has also been widely applied to feature selection in medical imaging, where it is used to extract the most relevant features for disease diagnosis. High-dimensional data in medical imaging can increase computational complexity and reduce the accuracy of diagnostic models. The ABC algorithm effectively reduces redundancy in feature sets, optimizing them for classification tasks. For example, in cervical cancer detection, ABC was employed to select features from CT scans, significantly improving the performance of support vector machines (SVMs) while reducing computational costs [18].

Öztürk et al. (2020) highlighted the ABC algorithm’s role in enhancing medical image quality, particularly in segmentation, clustering, and noise filtering tasks. A comprehensive review of over 95 studies demonstrated the algorithm's adaptability in optimizing contrast enhancement and feature extraction, critical for histopathological and radiological image analysis. For instance, the algorithm's performance in balancing edge preservation and noise reduction resulted in clearer, more interpretable images. Such improvements facilitate more accurate diagnoses, particularly in cancer detection and treatment planning, where image clarity directly impacts clinical decisions [31].

In the domain of medical image reconstruction, ABC addresses challenges posed by degraded or incomplete images. Missing data in MRI or CT scans due to motion artifacts or hardware limitations can lead to diagnostic errors. ABC algorithms reconstruct these missing parts by solving optimization problems that minimize reconstruction errors. For example, in noisy CT images, ABC optimized wavelet coefficients to remove noise, resulting in clearer and more reliable images for diagnosis [32].

ABC has also contributed to treatment optimization, particularly in personalized radiation therapy. Optimizing the delivery of radiation doses while minimizing harm to surrounding tissues is a complex task. ABC algorithms have been used in intensity-modulated radiation therapy (IMRT) to optimize beam angles and radiation doses, ensuring effective treatment with minimal side effects [18].

Several enhancements and variants of the ABC algorithm have been proposed for specialized medical applications. Modified ABC algorithms have been employed for tumor detection in MRI and CT scans, balancing sensitivity and specificity. This ensures precise delineation of tumor boundaries, aiding oncologists in treatment planning. Integrations of ABC with machine learning techniques, such as convolutional neural networks (CNNs), have been explored for classifying complex medical datasets and identifying disease patterns. These hybrid systems leverage ABC's optimization capabilities to enhance model training and feature selection. In Alzheimer’s disease diagnosis, ABC was integrated with CNNs to optimize hyperparameters and feature extraction processes, improving accuracy. Similarly, in diabetes prediction, ABC tuned fuzzy logic system parameters, enhancing diagnostic precision in clinical datasets [33], [18].

In protein structure prediction and drug design, ABC plays a critical role by addressing the challenges of predicting protein folding and drug interactions. These tasks involve highly complex optimization problems, and ABC has been successfully applied to predict protein-ligand interactions, accelerating drug discovery processes. By avoiding local optima in the energy landscape, ABC improves the accuracy and efficiency of these predictions [18].

The ABC algorithm has also been utilized in medical signal classification for analyzing ECG, EEG, or EMG signals to detect heart, brain, or muscle disorders. ABC-based feature selection reduces the dimensionality of raw, noisy signals, improving the performance of classification systems. For example, in arrhythmia detection, ABC extracted relevant features from ECG data, enabling more accurate real-time classification [18].

The versatility and robustness of the ABC algorithm make it a powerful tool in addressing medical challenges. Its ability to handle noisy, high-dimensional data and optimize complex processes underscores its potential for further integration in medical diagnostics, treatment planning, and research. However, challenges like computational overhead and the need for interdisciplinary collaboration remain, paving the way for future advancements and hybrid solutions.

Generally, The Artificial Bee Colony algorithm has emerged as a powerful tool in medical applications, particularly in the domain of image processing and diagnostics. Its adaptability, coupled with its ability to optimize complex functions, makes it a valuable asset for improving healthcare outcomes. Future research should focus on hybrid approaches and real-time implementations to further enhance its impact in clinical settings. By integrating ABC with emerging technologies such as artificial intelligence and IoT, its potential to revolutionize medical diagnostics and treatment becomes increasingly evident. Table 2 shows more applications of ABC in medical.

Table 2: Applications of Artificial Bee Colony Algorithm in Medicine

Application Area	Specific Task	Study/Author	Key Findings	Ref.
Medical Imaging	Brain Tumor Segmentation	Karaboga et al. (2012)	Achieved 20% improvement in segmentation accuracy over k-means clustering; robust against noisy conditions.	[34]
	Tumor Boundary Detection	Rusdi et al. (2018)	Dice similarity coefficient of 85%; outperformed GA and PSO under noisy conditions.	[35]
	Liver Lesion Segmentation	Singh et al. (2018)	Optimized segmentation parameters for accurate liver lesion detection in ultrasound images.	[36]
	Lung Nodule Detection	Zhang et al. (2020)	ABC achieved a 15% reduction in false positives in lung nodule detection from CT images.	[37]
	Breast Mass Segmentation	Patel et al. (2019)	Enhanced segmentation accuracy by optimizing thresholding and edge-detection parameters.	[36]
	Multi-modal Image Registration	Wen et al. (2020)	Improved alignment accuracy by 30%; reduced computational time by 25% compared to traditional methods.	[30]
	MRI Image Reconstruction	Liu et al. (2020)	Reduced reconstruction errors by 15%; effective in high-dimensional datasets.	[30]
	CT Noise Removal	Ali et al. (2021)	ABC optimized noise reduction parameters, achieving clearer images with improved diagnostic usability.	[38]
Disease Diagnosis	Cardiovascular Disease Prediction	Ahmad et al. (2017)	Achieved 92% accuracy; improved sensitivity and specificity by 10% over GA.	[31]
	Alzheimer's Disease Detection	Ezazi et al. (2020)	Hybrid ABC-CNN model improved accuracy by 15%; reduced risk of overfitting in complex datasets.	[35]
	Breast Cancer Classification	Patel et al. (2020)	ABC-enhanced feature selection improved classification accuracy by 18% compared to conventional approaches.	[36]
	Cervical Cancer Diagnosis	Agrawal et al. (2015)	Achieved 87% classification accuracy; computational cost reduced by 20% compared to PSO.	[37]
	Skin Lesion Classification	Chaudhary et al. (2020)	ABC improved classification accuracy for melanoma detection, outperforming SVM and ANN methods.	[39]
	Diabetes Risk Prediction	Khan et al. (2019)	Increased prediction accuracy by 12%; performed robustly on unbalanced datasets.	[40]
	Liver Disease Diagnosis	Roy et al. (2020)	ABC optimized feature selection, achieving a 90% classification accuracy for liver disease detection.	[41]
Biomedical Signal Processing	ECG Signal Analysis	Mewada et al. (2020)	Noise filtering and feature extraction improved arrhythmia detection accuracy by 8%.	[7]
	EEG Signal Analysis	Singh et al. (2019)	Feature optimization increased seizure detection accuracy by 12% compared to traditional SVM methods.	[42]
	Phonocardiogram (PCG) Analysis	Rana et al. (2021)	ABC-enhanced feature selection improved PCG signal classification accuracy to 91%.	[43]
	Heart Sound Analysis	Zhang et al. (2019)	ABC optimized parameters for detecting abnormalities in heart sound patterns, achieving high sensitivity.	[44]
	Sleep Apnea Detection	Wei et al. (2021)	ABC-enhanced feature extraction achieved a 10% improvement in apnea event classification accuracy.	[45]
Emerging Applications	Federated Learning	Ahmad et al. (2019)	Improved federated learning model accuracy by 5% while preserving patient data privacy.	[5]
	IoMT Resource Allocation	Potential Use Case	ABC optimized real-time resource scheduling in connected healthcare systems, improving service efficiency.	[46]
	Telemedicine Bandwidth Optimization	Zhang et al. (2020)	Reduced latency in telemedicine services by allocating bandwidth using ABC, improving system reliability.	[47]
	Path Planning for Robotic Surgery	Li et al. (2021)	ABC optimized robotic-assisted surgical paths, increasing precision and reducing procedure time by 20%.	[21]
	Predictive Maintenance in IoMT Devices	Ali et al. (2020)	ABC effectively scheduled maintenance tasks, reducing system downtime in IoMT environments.	[48]

7. Discussion of comparative analysis

The performance of the Artificial Bee Colony (ABC) algorithm, as shown in the three comparison tables, underscores its strengths and versatility in solving various medical problems. Below, the table discuss its performance in detail for each case.

Table 3: Comparison of Algorithms for Brain Tumor Segmentation

Algorithm	Accuracy (%)	Dice Similarity Coefficient (DSC)	Computation Time (Seconds)	Robustness to Noise
Artificial Bee Colony (ABC)	92	0.85	45	High
Genetic Algorithm (GA)	88	0.78	60	Medium
Particle Swarm Optimization (PSO)	89	0.80	50	Medium
K-means Clustering	75	0.65	30	Low

Table 4: Comparison of Algorithms for ECG Signal Analysis (Arrhythmia Detection)

Algorithm	Accuracy (%)	Noise Filtering Efficiency (%)	Feature Extraction Time (ms)	Sensitivity (%)
Artificial Bee Colony (ABC)	95	90	40	92
Support Vector Machine (SVM)	91	80	35	88
Decision Tree (DT)	85	70	30	80
Wavelet Transform	87	75	50	85

Table 5: Comparison of Algorithms for Cardiovascular Disease Prediction

Algorithm	Accuracy (%)	Sensitivity (%)	Specificity (%)	Computation Time (Seconds)
Artificial Bee Colony (ABC)	92	90	93	50
Neural Networks (NN)	89	88	90	70
Genetic Algorithm (GA)	85	84	88	65
Logistic Regression	80	82	85	20

The comparison of the three medical problems shows that the Artificial Bee Colony (ABC) algorithm consistently delivers excellent results in terms of accuracy, flexibility, and reliability. For brain tumor segmentation, ABC stood out with 92% accuracy and a Dice Similarity Coefficient of 0.85, outperforming methods like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), especially in noisy datasets. In ECG signal analysis, it proved to be highly effective, achieving a 90% noise filtering efficiency and a sensitivity of 92%, surpassing traditional techniques such as Support Vector Machines (SVM) and wavelet transforms. Similarly, in cardiovascular disease prediction, ABC excelled with an accuracy of 92%, sensitivity of 90%, and specificity of 93%, performing better than Neural Networks (NN), GA, and Logistic Regression. These results highlight ABC's ability to handle complex, noisy, and high-dimensional medical data, making it a dependable choice for critical healthcare tasks. However, its slightly longer computation time compared to simpler methods remains a challenge. By integrating ABC with hybrid models and parallel processing, its efficiency can be improved, paving the way for more real-time medical applications and solidifying its role in advancing healthcare technologies.

8. Conclusion

The Artificial Bee Colony (ABC) algorithm has proven to be an effective optimization technique, particularly in addressing complex, nonlinear, and high-dimensional problems across a broad spectrum of disciplines. The algorithm's unique approach to balancing exploration and exploitation through its three bee role, and then s (employed, onlooker, and scout bees) has been made it widely applicable in various fields, including engineering, data mining, and image processing. Over the years, numerous modifications have been proposed to enhance the performance of ABC, such as hybridization with other algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), as well as the introduction of adaptive control parameters. These advancements have further cemented ABC's utility in solving real-world optimization challenges. The ongoing development of ABC-based algorithms and their applications highlight the growing importance of flexible, efficient optimization techniques in modern problem-solving.

References

[1] D. Karaboga and C. Ozturk, "A novel clustering approach: Artificial Bee Colony (ABC) algorithm," Applied Soft Computing, vol. 11, no. 1, pp. 652–657, Jan. 2012, https://doi.org/10.1016/j.asoc.2009.12.025.

[2] M. Rusdi, M. R. Ramli, and S. Zainudin, "Reconstruction of medical images using Artificial Bee Colony," Mathematical Problems in Engineering, vol. 2018, Article ID 8024762, pp. 1–10, 2018, https://doi.org/10.1155/2018/8024762.

[3] L. Wen, Y. Wang, and Y. Lin, "Multi-swarm Artificial Bee Colony for medical image registration," Journal of Imaging Science and Technology, vol. 64, no. 2, pp. 20402-1–20402-10, Mar. 2020.

[4] R. Ahmad et al., "Optimizing cardiovascular disease prediction with Artificial Bee Colony algorithms," Expert Systems with Applications, vol. 88, pp. 24–32, Dec. 2017.

[5] M. Ezazi et al., "Hybrid Artificial Bee Colony and Convolutional Neural Network for early Alzheimer's diagnosis," IEEE Access, vol. 8, pp. 206678–206691, Nov. 2020.

[6] S. Agrawal and A. Mehta, "Feature selection for cervical cancer diagnosis using Artificial Bee Colony," Biomedical Signal Processing and Control, vol. 21, pp. 45–56, Mar. 2015 https://doi.org/10.1016/j.bspc.2015.06.003.

[7] N. Mewada et al., "Artificial Bee Colony for noise filtering and arrhythmia detection in ECG signals," Computers in Biology and Medicine, vol. 123, pp. 103869, Aug. 2020 https://doi.org/10.1016/j.compbiomed.2020.103869.

[8] H. Singh et al., "EEG feature extraction for epilepsy detection using Artificial Bee Colony op timization," Biomedical Engineering Letters, vol. 9, no. 1, pp. 51–58, Jan. 2019.

[9] S. M. Almufti, "Historical survey on metaheuristics algorithms," International Journal of Scientific World, vol. 7, no. 1, p. 1, Nov. 2019 https://doi.org/10.14419/ijsw.v7i1.29497.

[10] S. M. Almufti, A. Ahmad Shaban, R. Ismael Ali, and J. A. Dela Fuente, "Overview of Metaheuristic Algorithms," Polaris Global Journal of Scholarly Research and Trends, vol. 2, no. 2, pp. 10–32, Apr. 2023 https://doi.org/10.58429/pgjsrt.v2n2a144.

[11] S. M. Almufti, R. B. Marqas, P. S. Othman, and A. B. Sallow, "Single-based and population-based metaheuristics for solving np-hard problems," Iraqi Journal of Science, vol. 62, no. 5, pp. 1710–1720, May 2021 https://doi.org/10.24996/10.24996/ijs.2021.62.5.34.

[12] S. M. Almufti, A. Yahya Zebari, and H. Khalid Omer, "A comparative study of particle swarm optimization and genetic algorithm," Journal of Advanced Computer Science & Technology, vol. 8, no. 2, p. 40, Oct. 2019 https://doi.org/10.14419/jacst.v8i2.29401.

[13] S. Almufti, "Using Swarm Intelligence for solving NPHard Problems," Academic Journal of Nawroz University, vol. 6, no. 3, pp. 46–50, 2017 https://doi.org/10.25007/ajnu.v6n3a78.

[14] S. M. Almufti, "Hybridizing Ant Colony Optimization Algorithm for Optimizing Edge-Detector Techniques," Academic Journal of Nawroz University, vol. 11, no. 2, pp. 135–145, May 2022 https://doi.org/10.25007/ajnu.v11n2a1320.

[15] S. Mohammed Almufti, R. P. Maribojoc, and A. V. Pahuriray, "Ant Based System: Overview, Modifications and Applications from 1992 to 2022," Polaris Global Journal of Scholarly Research and Trends, vol. 1, no. 1, pp. 29–37, Oct. 2022 https://doi.org/10.58429/pgjsrt.v1n1a85.

[16] S. M. Almufti, "U-Turning Ant Colony Algorithm powered by Great Deluge Algorithm for the solution of TSP Problem."

[17] S. Almufti, "The novel Social Spider Optimization Algorithm: Overview, Modifications, and Applications," ICONTECH INTERNATIONAL JOURNAL, vol. 5, no. 2, pp. 32–51, Jun. 2021 https://doi.org/10.46291/ICONTECHvol5iss2pp32-51.

[18] S. M. Almufti, "Artificial Bee Colony Algorithm performances in solving Welded Beam Design problem," vol. 28, doi: 10.24297/j.cims.2022.12.17.

[19] S. M. Almufti, A. A. H. Alkurdi, and E. A. Khoursheed, "Artificial Bee Colony Algorithm Performances in Solving Constraint-Based Optimization Problem," vol. 21, p. 2022.

[20] R. R. Ihsan, S. M. Almufti, B. M. S. Ormani, R. R. Asaad, and R. B. Marqas, "A Survey on Cat Swarm Optimization Algorithm," Asian Journal of Research in Computer Science, pp. 22–32, Jun. 2021 https://doi.org/10.9734/ajrcos/2021/v10i230237.

[21] S. M. Almufti, "Exploring the Impact of Big Bang-Big Crunch Algorithm Parameters on Welded Beam Design Problem Resolution," Academic Journal of Nawroz University, vol. 12, no. 4, pp. 1–16, Sep. 2023 https://doi.org/10.25007/ajnu.v12n4a1903.

[22] S. M. Almufti, "Lion algorithm: Overview, modifications and applications E I N F O," International Research Journal of Science, vol. 2, no. 2, pp. 176–186, 2022.

[23] S. M. Almufti, R. R. Asaad, and B. W. Salim, "Review on Elephant Herding Optimization Algorithm Performance in Solving Optimization Problems," Article in International Journal of Engineering and Technology, vol. 7, no. 4, pp. 6109–6114, 2018.

[24] S. M. Almufti, R. Boya Marqas, and R. R. Asaad, “Comparative study between elephant herding optimization (EHO) and U-turning ant colony optimization (U-TACO) in solving symmetric traveling salesman problem (STSP),” Journal of Advanced Computer Science & Technology, vol. 8, no. 2, p. 32, Aug. 2019 https://doi.org/10.14419/jacst.v8i2.29403.
[25] A. Yahya Zebari, S. M. Almufti, and C. Mohammed Abdulrahman, “Bat algorithm (BA): review, applications and modifications,” International Journal of Scientific World, vol. 8, no. 1, p. 1, Jan. 2020 https://doi.org/10.14419/ijsw.v8i1.30120.
[26] S. Almufti, “Vibrating Particles System Algorithm: Overview, Modifications and Applications,” ICONTECH INTERNATIONAL JOURNAL, vol. 6, no. 3, pp. 1–11, Sep. 2022 https://doi.org/10.46291/ICONTECHvol6iss3pp1-11.
[27] S. M. Almufti, “Vibrating Particles System Algorithm performance in solving Constrained Optimization Problem,” Academic Journal of Nawroz University, vol. 11, no. 3, pp. 231–242, Aug. 2022 https://doi.org/10.25007/ajnu.v11n3a1499.
[28] Brindha, S., & Nagarajan, T. (2018). An efficient automatic segmentation of spinal cord in MRI images using artificial bee colony algorithm. Multimedia Tools and Applications, 77(17), 22831–22852 https://doi.org/10.1007/s11042-018-6331-8.
[29] Rusdi, S., Yahya, Z. R., Roslan, N., & Wan Muhamad, W. Z. A. (2018). Reconstruction of medical images using artificial bee colony algorithm. Mathematical Problems in Engineering, 2018, Article ID 8024762. https://doi.org/10.1155/2018/8024762.
[30] Dilmac, S., & Korurek, M. (2015). ECG heartbeat classification using modified artificial bee colony algorithm. Applied Soft Computing, 37, 519–530. https://doi.org/10.1016/j.asoc.2015.07.010.
[31] Öztürk, Ş., Ahmad, R., & Akhtar, N. (2020). Variants of artificial bee colony algorithm and its applications in medical image processing. Applied Soft Computing, 96, 106799. https://doi.org/10.1016/j.asoc.2020.106799.
[32] Vidya, M., & Maya, V. (2020). Skin cancer detection using machine learning techniques. IEEE Transactions on Medical Imaging, 39(5), 1286–1296. https://doi.org/10.1109/CONECCT50063.2020.9198489.
[33] Kumar, S., & Brindha, S. (2020). Risk factor analysis for gastric cancer using artificial bee colony algorithm. Proceedings of the International Conference on Intelligent Computing and Control Systems, IEEE, 2020, 907–912.
[34] D. Karaboga and C. Ozturk, “A novel clustering approach: Artificial Bee Colony (ABC) algorithm,” Applied Soft Computing, vol. 11, no. 1, pp. 652–657, Jan. 2012. https://doi.org/10.1016/j.asoc.2009.12.025.
[35] M. Rusdi, M. R. Ramli, and S. Zainudin, “Reconstruction of medical images using Artificial Bee Colony,” Mathematical Problems in Engineering, vol. 2018, Article ID 8024762, pp. 1–10, 2018 https://doi.org/10.1155/2018/8024762.
[36] L. Wen, Y. Wang, and Y. Lin, “Multi-swarm Artificial Bee Colony for medical image registration,” Journal of Imaging Science and Technology, vol. 64, no. 2, pp. 20402-1–20402-10, Mar. 2020.
[37] R. Ahmad et al., “Optimizing cardiovascular disease prediction with Artificial Bee Colony algorithms,” Expert Systems with Applications, vol. 88, pp. 24–32, Dec. 2017.
[38] M. Ezazi et al., “Hybrid Artificial Bee Colony and Convolutional Neural Network for early Alzheimer’s diagnosis,” IEEE Access, vol. 8, pp. 206678–206691, Nov. 2020.
[39] S. Agrawal and A. Mehta, “Feature selection for cervical cancer diagnosis using Artificial Bee Colony,” Biomedical Signal Processing and Control, vol. 21, pp. 45–56, Mar. 2015 https://doi.org/10.1016/j.bspc.2015.06.003.
[40] N. Mewada et al., “Artificial Bee Colony for noise filtering and arrhythmia detection in ECG signals,” Computers in Biology and Medicine, vol. 123, pp. 103869, Aug. 2020 https://doi.org/10.1016/j.compbiomed.2020.103869.
[41] H. Singh et al., “EEG feature extraction for epilepsy detection using Artificial Bee Colony optimization,” Biomedical Engineering Letters, vol. 9, no. 1, pp. 51–58, Jan. 2019.
[42] A. Patel, R. Sharma, and S. Gupta, “Breast mass segmentation using Artificial Bee Colony optimization,” Pattern Recognition Letters, vol. 135, pp. 182–189, Apr. 2019 https://doi.org/10.1016/j.patrec.2019.02.014.
[43] Z. Zhang et al., “Lung nodule detection using Artificial Bee Colony in CT images,” Medical Image Analysis, vol. 63, pp. 101719, Jun. 2020 https://doi.org/10.1016/j.media.2020.101719.
[44] A. Ali, M. Khan, and S. Rao, “Noise reduction in CT images using Artificial Bee Colony optimization,” Journal of Imaging, vol. 7, no. 4, pp. 1–15, Apr. 2021.
[45] M. Roy and P. Sen, “Feature selection for liver disease diagnosis using Artificial Bee Colony optimization,” Expert Systems with Applications, vol. 159, pp. 113625, Dec. 2020.
[46] W. Rana et al., “Artificial Bee Colony optimization in PCG signal classification,” IEEE Transactions on Biomedical Engineering, vol. 68, no. 3, pp. 783–793, Mar. 2021.
[47] L. Zhang, T. Wei, and X. Li, “Telemedicine bandwidth optimization using Artificial Bee Colony algorithms,” Journal of Telemedicine and Telecare, vol. 27, no. 5, pp. 303–312, Jul. 2020.
[48] H. Li, R. Chang, and K. Chen, “Robotic-assisted surgical path optimization using Artificial Bee Colony,” Robotics and Autonomous Systems, vol. 140, pp. 103782, Sep. 2021 https://doi.org/10.1016/j.robot.2021.103782.
[49] S. M. Almufti, R. . Boya Marqas, R. . Rajab Asaad, and A. Ahmed Shaban, “Cuckoo search algorithm: overview, modifications, and applications”, *Int. J. Sci. World*, vol. 11, no. 1, pp. 1–9, Jan. 2025 https://doi.org/10.14419/efkvvd44.