

Metaheuristic Approaches for Sustainable Health: A Case Study on Red Fox Optimization

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To Cite This Chapter:

Uzun, F. N., & Baykan, Ö. K. (2025). Metaheuristic approaches for sustainable health: A case study on red fox optimization. In S. Demir, F. N. Takı, & Y. Uzun (Eds.), *Current studies for sustainable health* (pp. 76–122). ISRES Publishing.

Introduction

In recent years, significant progress has been achieved in the fields of medical image processing and computer vision through the integration of optimization-based approaches. Intelligent optimization algorithms have been successfully applied in numerous areas such as multilevel thresholding, noise reduction, image segmentation, and edge and boundary detection, thereby contributing to the more accurate analysis of complex images. Among these approaches, multilevel thresholding has emerged as a fundamental image segmentation technique that enables high accuracy in tasks such as disease analysis and feature extraction by dividing an image into meaningful regions (Otsu, 1979). Although Otsu's variance-based method is widely used for image segmentation due to its simplicity and effectiveness, its computational complexity increases exponentially as the number of thresholds rises, making it inefficient for multilevel thresholding applications (Otsu, 1979). To address this limitation, metaheuristic optimization algorithms have been employed. Consequently, it becomes impractical for large-scale, high-resolution, or real-time medical imaging applications (Sezgin & Sankur, 2004).

To overcome these limitations, metaheuristic optimization algorithms have increasingly been applied to multilevel thresholding problems. Algorithms such as Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995), Genetic Algorithm (GA) (Holland, 1975), Ant Colony Optimization (ACO) (Dorigo & Gambardella, 1997), and Grey Wolf Optimization (GWO) (Mirjalili et al., 2014) have emerged as powerful tools due to their ability to avoid local minima and perform efficient searches in high-dimensional solution spaces. Recent studies, such as Al-Najdawi et al. (2025), have comprehensively evaluated these algorithms in medical image segmentation, highlighting their efficacy and robustness in handling complex thresholding tasks. Nevertheless, many of these algorithms suffer from several drawbacks, including reduced convergence speed at higher

threshold levels, premature convergence, and an inability to fully balance exploration and exploitation during the search process. These issues complicate the determination of optimal threshold values, particularly in complex and noisy medical images.

To address these challenges, novel nature-inspired optimization algorithms have been developed in recent years. In this study, the Red Fox Optimization (RFO) algorithm and its enhanced version, Modified RFO, are investigated. Inspired by the social hunting strategies of red foxes, RFO (Połap & Woźniak, 2021) provides dynamic equilibrium between exploration and exploitation, thereby offering superior global optimization capability. The adaptive and flexible hunting behaviors of red foxes, which involve both individual and group-based strategies in response to environmental conditions, serve as an effective model for establishing a balanced search mechanism in the solution space. Consequently, RFO demonstrates more stable and faster convergence while effectively avoiding entrapment in local optima when compared to conventional algorithms (Połap & Woźniak, 2021).

- The Modified Red Fox Optimization (MRFO) algorithm preserves the fundamental structure of the standard RFO while incorporating several enhancements designed to achieve faster convergence and more stable results. The key improvements include:
- **Chaotic Map Integration:** A logistic map-based chaotic mechanism has been integrated to enhance randomness and search diversity, providing an adaptive control framework that maintains population variety throughout the optimization process.
- **Adaptive Control Factor:** A linearly decreasing adaptive control factor (α) has been implemented to dynamically balance exploration and exploitation phases, ensuring optimal search behavior as iterations progress.
- **Modified Position Update Mechanism:** The original RFO position update equations have been enhanced by incorporating chaotic components and random perturbation terms, significantly improving the algorithm's ability to escape local optima.
- **Adaptive Mutation Operator:** A low-probability adaptive mutation mechanism has been introduced to preserve solution diversity and prevent premature convergence, thereby maintaining the population's exploratory capacity throughout the optimization process.

These strategic enhancements collectively strengthen the algorithm's search capabilities, resulting in both accelerated convergence speed and increased probability of locating global optima. The modifications enable MRFO to maintain robust performance across diverse optimization landscapes while demonstrating superior stability compared to the original algorithm.

The proposed Modified RFO algorithm was evaluated on the Brain MRI, Retina, Cells3D, and Mitosis datasets for multilevel thresholding tasks involving 2–5 thresholds and was compared with PSO, ACO, GA, and GWO algorithms. Experimental results

demonstrate that Modified RFO provides more stable outcomes in terms of PSNR and SSIM while achieving the highest efficiency in terms of computational time.

Sustainable Healthcare and Its Importance Today

Global challenges such as population growth, the increasing prevalence of chronic diseases, and the limitation of healthcare resources have intensified the demand for sustainable healthcare systems (World Health Organization, 2017). Sustainable healthcare encompasses not only environmental and economic factors but also resource efficiency, cost optimization, and improved accessibility of healthcare services (Francis, Dunt, & Cadilhac, 2016).

With the rapid advancement of digital health technologies, the efficient utilization of computational resources has become a crucial dimension of sustainability. This has also been emphasized in recent studies (Esteva et al., 2019). In this context, artificial intelligence and optimization-based solutions contribute significantly to improving healthcare service quality while simultaneously reducing energy consumption and processing time (Esteva et al., 2019; Jiang et al., 2017).

Application of Artificial Intelligence and Optimization Methods in Healthcare

Metaheuristic algorithms provide a powerful alternative for solving complex problems through nature-inspired computational strategies (Talbi, 2009). These algorithms are widely used in the healthcare domain not only for medical image segmentation but also for diagnostic decision support systems, disease classification, drug interaction analysis, patient data clustering, treatment planning, and genetic data optimization. AI-assisted optimization methods offer significant advantages in enhancing model accuracy and reducing computational time when analyzing large and complex healthcare datasets (Esteva et al., 2019; Jiang et al., 2017).

In image processing, variance-based thresholding methods such as Otsu's approach (Otsu, 1979) or entropy-based techniques may exhibit limited performance when applied to noisy and high-dimensional medical images (Sezgin & Sankur, 2004). In contrast, metaheuristic approaches, with their inherent randomness, diversity, and global search capabilities, provide more reliable and generalized results in tasks such as multilevel thresholding, tumor detection, organ segmentation, and cell counting (Yang, 2010).

Role of Metaheuristic Algorithms

Metaheuristic algorithms contribute to sustainable healthcare systems by improving computational efficiency in areas such as medical imaging, diagnosis, treatment planning, and the effective utilization of healthcare resources (Talbi, 2009). Their most notable advantage lies in their ability to establish an adaptive balance between accuracy and computational cost. In highly computation-intensive segmentation problems such

as multilevel thresholding, they offer significant gains in processing time. In noise reduction tasks, rather than providing direct speed improvements, their advantage lies in optimally tuning filter parameters or model coefficients to enhance overall performance (Oliva, Abd Elaziz & Hinojosa, 2019). Consequently, metaheuristic approaches present a flexible framework that improves both processing efficiency and output quality across diverse image processing applications.

Recent studies emphasize the importance of efficient and sustainable approaches in medical image analysis (Francis et al., 2016; Esteva et al., 2019). In line with these findings, the Modified RFO algorithm has been developed to operate on medical images.

Purpose of the Research and Research Problem/Questions/Hypotheses

Purpose of the Research

Medical image segmentation is a critical stage that requires high accuracy, particularly in diagnostically essential processes such as tumor, lesion, and tissue delineation. In this context, commonly used multilevel thresholding methods often fail to achieve the desired performance in complex medical images due to several limitations of classical deterministic approaches, such as Otsu's variance-based method and Kapur's entropy-based method. Specifically, as the number of thresholds increases, the search space expands exponentially, forcing Otsu's variance-based thresholding method to evaluate all possible threshold combinations, which results in a rapid increase in computational cost. This significantly reduces its practicality for higher-level thresholding applications (Otsu, 1979; Sahoo, Wilkins, & Yeager, 1997).

Moreover, classical methods experience difficulties in determining optimal threshold values in noisy, low-contrast, or heterogeneous medical images, tend to become trapped in local optima, and often fail to provide stable and consistent results (Sezgin & Sankur, 2004). The literature highlights that due to the nonlinear nature of multilevel thresholding, classical approaches suffer from performance degradation in complex medical images, leading to the increasing preference for optimization-based methods with strong global search capabilities (Houssein et al., 2021). These challenges clearly indicate the necessity for more intelligent, flexible, and globally efficient methods for solving multilevel thresholding problems.

The primary objective of this research is to investigate the effectiveness of advanced metaheuristic optimization algorithms in medical image segmentation and to determine which algorithms exhibit superior performance in multilevel thresholding by comparing modern nature-inspired optimization techniques in terms of accuracy, stability, convergence behavior, and computational efficiency.

Within this framework, the study experimentally evaluates the performance of nature-

inspired algorithms such as PSO (Kennedy & Eberhart, 1995), ACO (Dorigo & Gambardella, 1997), GWO (Mirjalili et al., 2014), and RFO (Połap & Woźniak, 2021; Zaborski et al., 2022) in multi-threshold segmentation tasks with respect to PSNR, SSIM, and computational time.

Although RFO provides an effective search mechanism for segmentation problems, it exhibits certain limitations, particularly in complex images, including susceptibility to local minima entrapment and challenges in maintaining an optimal exploration–exploitation balance. Therefore, in the subsequent phase of this study, the Modified RFO (MRFO) approach has been introduced to overcome these constraints and enhance the performance of RFO. The proposed MRFO integrates hybrid mechanisms such as PSO’s global memory component, GA-based mutation, and the Simulated Annealing (SA) acceptance criterion to strengthen the search capability of RFO. The primary aim of this hybrid MRFO is to achieve high segmentation quality while reducing computational cost, thereby making the algorithm suitable for real-time or clinical pre-evaluation scenarios.

The broader objective of this research is to contribute to the integration of artificial intelligence (AI) and metaheuristic optimization methods into medical image analysis, supporting the development of early disease detection, automated diagnosis, and clinical decision support systems.

Research Problem

The core research problem of this study can be defined as follows:

- How can metaheuristic algorithms be effectively adapted to multilevel thresholding problems in medical image segmentation tasks that require high accuracy and robustness, and how can they achieve optimal performance beyond classical methods?

Classical deterministic methods (e.g., Otsu) rely on fixed histogram assumptions, which lead to generalization issues across different patient images or varying imaging conditions (Sezgin & Sankur, 2004; Houssein et al., 2021). Additionally, the presence of high variance, tissue heterogeneity, and noise in medical images complicates the determination of optimal threshold values, thereby limiting segmentation performance (Sahoo et al., 1997).

In this study, two main problems were investigated:

1. Exploring the optimization balance between segmentation accuracy (SSIM, PSNR) and computational efficiency.
2. Systematically analyzing the performance differences among nature-inspired algorithms such as PSO, ACO, GWO, GA and RFO under identical experimental conditions.

Research Questions

To address the research problems, the following research questions were formulated:

1. **RQ1:** When multilevel thresholding is applied to medical datasets such as Brain MRI, Retina, Mitosis, and Cells3D, which metaheuristic algorithms (PSO, ACO, GWO, RFO, GA, MRFO) achieve the highest PSNR and SSIM values?
2. **RQ2:** How do the convergence speeds and stability of different algorithms vary in multi-threshold ($T = 2-5$) segmentation problems?
3. **RQ3:** Can MRFO reduce computational time while preserving segmentation accuracy?
4. **RQ4:** Does the improvement in segmentation quality contribute to clinically meaningful visualizations (e.g., clearer tumor boundaries, enhanced separation of retinal vessel structures)?

Hypotheses

Based on the literature review and the conceptual framework of the proposed model, the following hypotheses were formulated:

- **H1:** Metaheuristic algorithms (PSO, ACO, GWO, RFO) will produce higher PSNR and SSIM values compared to the classical Otsu method.
- **H2:** MRFO algorithms, owing to their enhanced exploration–exploitation balance, will achieve faster and more stable convergence in multilevel thresholding problems compared to PSO, RFO, and ACO. Furthermore, MRFO is expected to maintain high segmentation quality with lower computational cost, demonstrating applicability for real-time medical analysis.
- **H3:** The increase in segmentation accuracy enhances the visibility of target structures in complex and pathological medical images, thereby strengthening clinical evaluation and diagnostic decision-making.

Literature Review

Metaheuristic Algorithms in Healthcare

Metaheuristic algorithms inspired by natural processes and social behaviors provide effective and scalable solutions to complex optimization problems in the healthcare domain (Saremi, Mirjalili, & Lewis, 2017; Houssein et al., 2021). Genetic Algorithms (GA) (Holland, 1975) have been successfully applied since early studies in areas such as medical image segmentation, feature selection, and radiotherapy planning, and their stochastic nature offers robustness against the high dimensionality and noise inherent in medical data (Pham et al., 2000; Szu & Hartley, 1987).

The integration of hybrid ensemble structures with genetic algorithms, particularly the use of Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995) in LSTM-

based models and the broader success of evolutionary–swarm intelligence algorithms, has become a significant trend in enhancing model performance for complex prediction problems (Abdollahi & Moghaddam, 2022; Xu et al., 2022; Bansal et al., 2018).

Ant Colony Optimization (ACO) (Dorigo & Gambardella, 1997) has been applied in tasks such as medical image segmentation and resource allocation (Taherdangkoo et al., 2013). However, several studies have reported that ACO exhibits slower convergence rates and requires more iterations compared to algorithms such as PSO (Al-Najdawi et al., 2025; Taherdangkoo et al., 2013).

Grey Wolf Optimization (GWO) (Mirjalili, Mirjalili, & Lewis, 2014) has gained widespread attention in recent years within medical image analysis due to its lightweight structure and effective maintenance of the exploration–exploitation balance. Particularly in brain tumor detection and classification tasks, GWO and its variants have demonstrated high accuracy and rapid convergence when used for hyperparameter optimization in deep learning models (ZainEldin et al., 2022). Similarly, hybrid optimization-based approaches for MR brain tumor segmentation and classification have reported competitive performance using GWO owing to its strong search capability and parameter stability (Deepa et al., 2023). These findings indicate that GWO offers significant advantages in computational efficiency and stability for medical image processing tasks.

The primary advantage of these algorithms lies in their ability to handle high-dimensional, nonlinear, and noisy medical data. Moreover, metaheuristic-based segmentation methods may offer potential advantages over deep learning in terms of data and computational resource requirements, as deep learning models often require very large labeled datasets (Esteva et al., 2019).

Multi-Level Thresholding Methods

Image thresholding is a fundamental medical image segmentation technique used to separate tumor, vessel, and organ tissues. The Otsu method (1979) forms a strong basis for single-level segmentation by minimizing intra-class variance while maximizing inter-class variance. However, as emphasized in the comprehensive review by Pare et al., Otsu's performance degrades in images with multimodal histograms, and the clarity of segmentation boundaries decreases in low-contrast regions (Pare et al., 2019). These limitations have driven the development of multilevel thresholding techniques and nature-inspired optimization approaches (Pare et al., 2019).

Although entropy-based methods (e.g., Kapur and Rényi) partially alleviate this issue, the computational cost required for multilevel thresholding increases exponentially as the number of thresholds grows (Sezgin & Sankur, 2004).

At this point, metaheuristic algorithms offer significant advantages in searching for optimal threshold values in multilevel thresholding problems. Nature-inspired optimization techniques substantially enhance the traditional Otsu approach by virtue of their strong global search capabilities, ability to escape local minima, and efficiency in exploring high-dimensional solution spaces. Prior studies have demonstrated that algorithms such as Aquila Optimizer, Particle Swarm Optimization, Bacterial Foraging Optimization, Pigeon-Inspired Optimization, and similar approaches achieve higher segmentation accuracy in terms of both PSNR and structural similarity for multilevel thresholding problems (Abualigah et al., 2021; Bhandari et al., 2016; Oliva et al., 2019; Sathya & Kayalvizhi, 2011; Wang et al., 2019).

Key advantages of these algorithms include more stable threshold selection in multimodal histograms, more consistent optimization performance in noisy images, and more efficient management of computational complexity as the number of thresholds increases compared to the classical Otsu method.

While metaheuristic approaches do not alter Otsu's intra-class and inter-class variance-based discrimination criterion, they extend the search for optimal thresholds through a global optimization process. Whereas the classical Otsu method deterministically scans all possible threshold combinations, metaheuristic algorithms determine the most suitable threshold set using population-based search strategies, thereby reducing computational cost and improving segmentation accuracy (Bhandari et al., 2016; Oliva et al., 2019; Wang et al., 2019).

In hybrid approaches (e.g., Otsu + metaheuristic models), Otsu's statistical discriminative power is combined with the strong exploration mechanisms of global optimization algorithms, resulting in clearer and more stable segmentation boundaries, particularly in color images, multilevel thresholding scenarios, and medical imaging applications (Abualigah et al., 2021; Bhandari et al., 2016).

When compared with other segmentation strategies, multilevel thresholding methods enhanced by metaheuristic algorithms offer notable advantages. In multilevel thresholding problems, approaches such as PSO, BFA, and PIO demonstrate successful performance in medical images due to their histogram-based structures, low data requirements, and rapid applicability (Bhandari et al., 2016; Sathya & Kayalvizhi, 2011; Wang et al., 2019). These methods are particularly advantageous in scenarios where data diversity is limited or training time is critical. In contrast, deep learning-based segmentation models, although capable of high accuracy, may not always be practical in clinical settings due to their requirement for large-scale labeled datasets, high computational power, and long training periods (Ronneberger et al., 2015; Litjens et al., 2017). Therefore, metaheuristic-based multilevel thresholding approaches emerge as a more interpretable, cost-effective,

and sustainable alternative compared to deep learning.

Red Fox Optimizer (RFO) and Comparative Applications

The Red Fox Optimization (RFO) algorithm is a new-generation metaheuristic method developed by Połap and Woźniak (2021), inspired by the hunting and social interaction behaviors of red foxes. The algorithm balances exploration and exploitation processes by combining high population mobility search mechanisms with target-oriented localization strategies (Połap & Woźniak, 2021).

The literature indicates that the RFO algorithm has been successfully applied to various optimization problems. Its ability to provide improved global search performance, particularly in high-dimensional and complex search spaces, has enabled it to achieve competitive results compared to traditional population-based methods. The Multidimensional RFO model proposed by Zaborski et al. (2022) introduced significant enhancements in terms of improving convergence behavior and increasing the capacity to escape local minima. This study demonstrated that RFO can be effectively adapted not only in its basic form but also in its extended and adaptive versions for high-resolution search problems.

The application domains of RFO extend across image processing, engineering optimization, route planning, and parameter optimization in machine learning models. In the literature, RFO has been reported to achieve competitive performance against other popular metaheuristic approaches, particularly due to its ability to maintain population diversity and achieve fast convergence in complex optimization tasks (Połap & Woźniak, 2021; Zaborski et al., 2022).

Overall, studies indicate that both the basic and extended variants of RFO constitute a strong alternative to modern metaheuristic methods. Furthermore, future research directions suggest that the algorithm will find broader applications in areas such as multi-objective optimization, adaptive parameter control, and integration with deep learning models.

The conducted literature review reveals that although RFO has been addressed as an effective method across various optimization problems, there remains a limited number of studies focusing on its application in multilevel thresholding for medical images. Existing RFO implementations have reported occasional slow convergence, increased susceptibility to local minima, and performance degradation due to problem-independent fixed parameters. Moreover, limited research has explored the hybrid use of RFO with deterministic methods such as Otsu, and the algorithm has not been sufficiently adapted to the challenges of medical images, including low contrast, noise, and histogram uncertainty.

The Modified RFO proposed in this study aims to address these limitations through adaptive parameter control and enhanced search strategies, achieving more stable threshold values, faster convergence, and more reliable segmentation performance in low-contrast medical images. Therefore, this work was designed to address the gaps identified in the literature regarding performance consistency, stability, and adaptability in multilevel thresholding-based medical image segmentation

Methodology

Datasets

In this study, four different datasets were employed to evaluate the performance of metaheuristic algorithms in medical image segmentation: Brain MRI, Retina, Cells3D, and Mitosis. Sample images from these datasets are presented in Table 1, while the corresponding ground-truth annotations for different threshold levels are provided in Table 2. These datasets represent distinct medical image segmentation problems and provide diversity for testing the general performance of the algorithms. The datasets were obtained from the sample medical image collections provided within the open-source image processing library scikit-image (van der Walt et al., 2014).

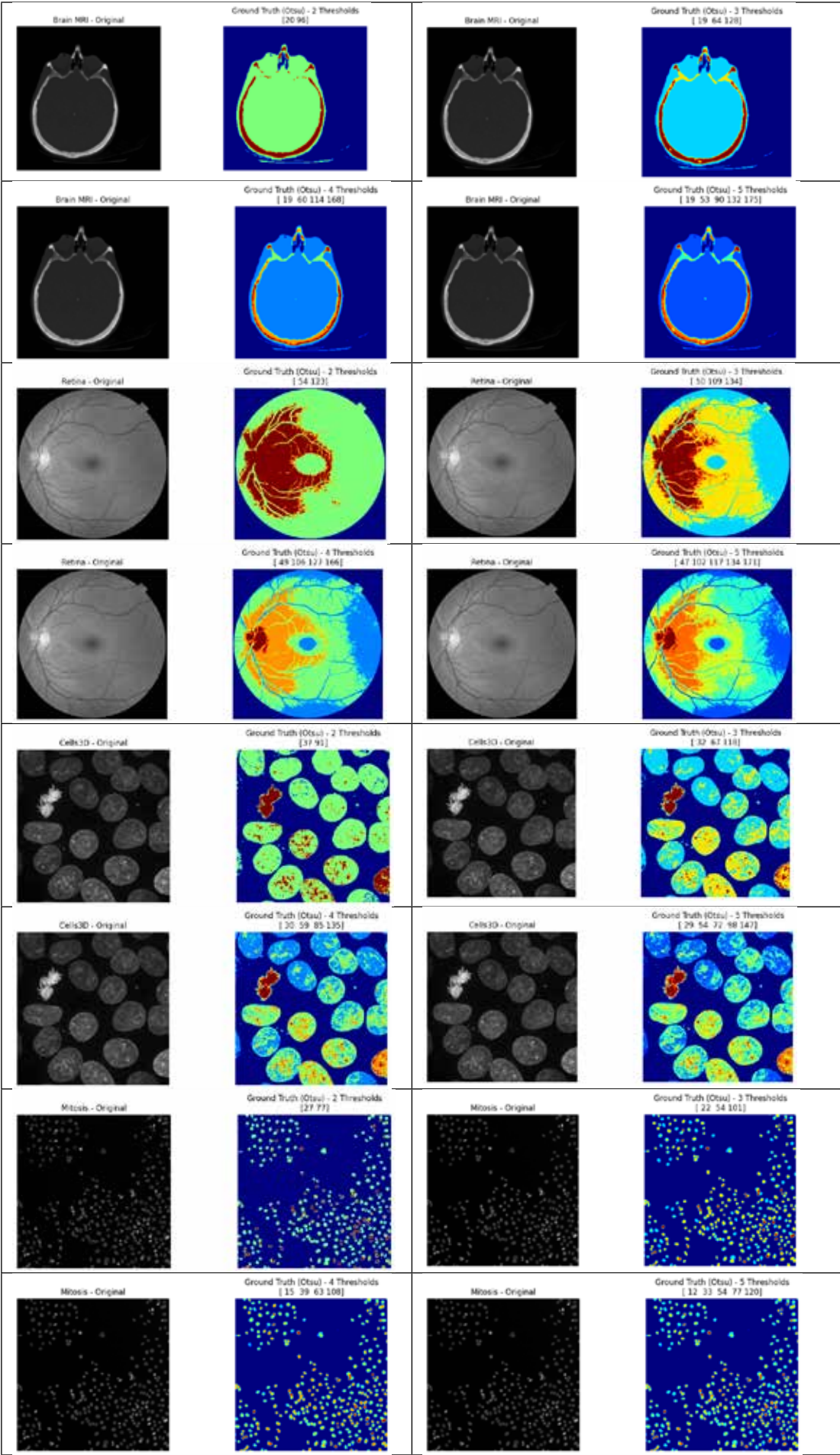
Table 1

Characteristics of the Medical Image Datasets Used in the Study

Dataset	Image Type	Challenge Type	Purpose	Size	Format	Channel	Number of Images
Brain MRI	T1-weighted MRI	Noise, contrast variation	Tumor localization	256×256	PNG	Grayscale	1
Retina	Fundus image	Illumination variation, vessel density	Vessel segmentation	1411×1411	TIFF	RGB	1
Cells3D	Fluorescence microscopy	Overlapping structures, low contrast	Cell detection	60×256×256	TIF Stack	Grayscale	1 (60 slices)
Mitosis	Histopathology	Color variation, tissue complexity	Mitotic cell detection	512×512	PNG	RGB	1

Table 2

Original Images and Ground Truth Outputs for 2, 3, 4, and 5 Threshold Levels



Since publicly available manually annotated segmentation masks were not available for the datasets used in this study (Brain MRI, Retina, Cells3D, and Mitosis), the segmentation outputs obtained using the multilevel Otsu thresholding method were accepted as “ground truth” for comparison and reference purposes. This approach is widely preferred in multilevel thresholding problems because histogram-based class separation has been demonstrated to provide effective optimal threshold estimation in various studies, particularly for medical and natural images (Bhandari et al., 2016; Houssein et al., 2021; Pare et al., 2019). Moreover, previous research using datasets similar to those employed in this study has also reported that Otsu-based threshold values offer a reliable baseline for comparison (van der Walt et al., 2014), supporting its continued use as a reference method despite its known limitations in high-dimensional thresholding.

Table 4.2 presents the original images and the reference (ground truth) segmentation results obtained for 2, 3, 4, and 5 threshold levels for each dataset. These visuals were used as baseline references for performance comparison of the metaheuristic algorithms.

The datasets used in this study differ in format and resolution characteristics. The Brain MRI dataset consists of single-channel (grayscale) mid-slices selected from volumetric MRI data. Retina images are RGB fundus images with clearly visible vascular structures. The Cells3D dataset comprises fluorescence microscopy images with a multi-layered (z-stack) structure. The Mitosis dataset consists of histopathologically stained RGB microscopic images.

To ensure experimental consistency, all images were resized to 256×256 pixels and processed in 8-bit format. The number of images was selected as one representative sample for each dataset: one Brain MRI image, one Retina image, one slice from Cells3D, and one microscopic field from the Mitosis dataset.

Preprocessing

The preprocessing stage is a critical step that directly affects segmentation performance. Medical images often contain various types of noise originating from imaging devices, sensor imperfections, low illumination, and environmental conditions. In the Retina, Mitosis, Brain MRI, and Cells3D images used in this study, two primary noise types were predominantly observed:

- **Salt & Pepper noise:** Appears as sudden black-and-white pixel spikes, especially in microscopic and histopathological images. This noise type distorts edge structures and negatively affects thresholding accuracy.
- **Gaussian noise:** A low-amplitude noise distributed randomly across pixels,

originating from imaging sensors. It is particularly prominent in low-contrast Retina and Mitosis images.

Therefore, to suppress both impulsive and continuous noise types, two different filters were applied sequentially during the noise removal stage. The adopted noise reduction strategy was as follows:

- **Median filter (3×3):** Used to suppress Salt & Pepper noise. As a nonlinear filter, the median filter effectively removes extreme pixel values while preserving edge structures, thus preventing distortion of segmentation boundaries.
- **Gaussian filter ($\sigma = 1$):** Applied after the median filter to smooth the remaining low-intensity Gaussian noise. The Gaussian filter reduces abrupt pixel transitions and ensures a more homogeneous intensity distribution.

These two filters were applied sequentially in the code in the following order:

Median Filter → Gaussian Filter → Normalization → Segmentation

The following preprocessing steps were applied to all images prior to segmentation:

- **Grayscale conversion:** Color images were converted to grayscale to focus on intensity information.
- **Noise reduction:** Sequential application of median (3×3) and Gaussian ($\sigma=1$) filters to suppress both impulsive and continuous noise.
- **Contrast enhancement:** CLAHE (Contrast Limited Adaptive Histogram Equalization) was applied to enhance local contrast and emphasize tissue boundaries.
- **Normalization:** Pixel intensity values were scaled to the [0–1] range to improve numerical stability for the algorithms.

Algorithms

In this study, six different metaheuristic algorithms were employed to solve the multilevel thresholding problem:

- Particle Swarm Optimization (PSO)
- Red Fox Optimization (RFO)
- Genetic Algorithm (GA)
- Ant Colony Optimization (ACO)
- Grey Wolf Optimization (GWO)
- Modified Red Fox Optimization (MRFO) (proposed)

Additionally, the classical Multi-Level Otsu method was used for baseline comparison.

Red Fox Optimization

The Red Fox Optimization (RFO) algorithm is a population-based metaheuristic optimization technique inspired by the intuitive hunting behavior exhibited by red foxes. The algorithm aims to determine the optimal threshold values by maintaining a balance between exploration and exploitation within the search space. In this study, RFO is employed to solve the multilevel thresholding problem.

Each fox represents a candidate solution (a vector of threshold values) in the search space. The foxes update their positions based on the best solutions obtained in the current and previous iterations. The equations governing the RFO algorithm (4.1–4.7) are presented below in sequence.

1. Initialization of Population

The population consisting of N foxes is randomly initialized:

$$X_i^0 = X_{min} + rand(0,1) \times (X_{max} - X_{min}) \quad (4.1)$$

Where:

- X_i^0 : Initial position of the i -th fox
- X_{min}, X_{max} : Lower and upper bounds
- $rand(0,1)$: Uniform random number in the interval $[0,1]$

2. Fitness Function

The fitness value of each fox is computed using the selected objective function (e.g., Kapur entropy or Otsu variance):

$$f(X_i) = Fitness(X_i) \quad (4.2)$$

The best solution is determined as follows:

$$X_{best}^t = argmax f(X_i^t) \quad (4.3)$$

In this study, X_{best}^t represents the best global solution obtained up to iteration t . In other words, it does not correspond solely to the best solution in the current iteration, but to the best position among all iterations so far (global best).

3. Position Update Equation

The fundamental position update mechanism of RFO is defined as:

$$X_i^{t+1} = X_i^t + r_1(X_{best}^t - |r_2 X_i^t|) \quad (4.4)$$

Where:

- X_i^t : Position of the i-th fox at iteration t
- X_{best}^t : Best global position found up to iteration t
- r_1, r_2 : Random numbers in the interval [0,1]

This equation ensures that foxes move toward the best solution while the stochastic component helps mitigate the risk of being trapped in local minima.

4. Exploration and Exploitation Mechanism

The RFO algorithm implements an adaptive search strategy in which foxes exhibit two distinct behaviors during the updating process:

- **Exploration phase:** Different regions of the search space are investigated:

$$X_i^{t+1} = X_i^t + \alpha \cdot rand(-1,1) \quad (4.5)$$

- **Exploitation phase:** A fine search is performed in the vicinity of the best fox:

$$X_i^{t+1} = X_{best}^t + \beta \cdot (X_{best}^t - X_i^t) \quad (4.6)$$

Where:

- α : Exploration coefficient
- β : Exploitation coefficient

These two phases are dynamically balanced as iterations progress.

In the literature, the concepts of exploration and exploitation are widely used to describe the general behavior of metaheuristic algorithms. In this context, Equations (4.5) and (4.6) conceptually represent the two different strategies in the RFO search process. However, the original Red Fox Optimization algorithm is fundamentally based on a single position update equation, and the RFO implementation used in this study directly follows Equation (4.4).

Therefore, Equations (4.5) and (4.6) are presented here for theoretical explanation of the search behavior, but they were not implemented as separate steps in the Python

implementation used in this study.

5. Boundary Control

If updated positions exceed the solution boundaries, they are corrected as follows:

$$X_i^{t+1} = \max(X_{\min}, \min(X_i^{t+1}, X_{\max})) \quad (4.7)$$

General Workflow of the Algorithm (Summary)

Step 1: Initialize the fox population

Step 2: Calculate fitness values

Step 3: Determine the best solution (X_{best})

Step 4: Update the positions of the foxes

Step 5: Apply boundary control

Step 6: Repeat until the stopping criterion is met

Pseudocode of the RFO Algorithm

Initialize population X_i ($i = 1, \dots, N$)

Evaluate fitness of each fox

Determine X_{best}

for $t = 1$ to $MaxIter$ do

 for each fox i do

 Generate $r_1, r_2 \in [0, 1]$

 Update position:

$X_i(t+1) = X_i(t) + r_1 * (X_{best} - |r_2 * X_i(t)|)$

 Apply boundary control

 end for

 Update X_{best}

end for

Return Xbest

Despite producing successful results by balancing exploration and exploitation, RFO has been shown in the literature and experimental studies to suffer from certain structural limitations. Particularly in high-dimensional and complex search spaces such as multilevel thresholding, these limitations can significantly degrade performance. Due to fixed randomness coefficients, the population tends to converge prematurely toward the global best solution during early iterations, leading to insufficient exploration of the solution space. Furthermore, the static exploration–exploitation balance results in weakened exploitation capability in later iterations. In low-contrast and noisy medical images, irregularities in the solution space increase the likelihood of being trapped in local minima, and as the number of thresholds increases, the convergence rate significantly decreases. These structural issues prevent classical RFO from achieving the desired stability in multilevel thresholding problems.

For these reasons, a Modified RFO (MRFO) approach has been developed to provide a more stable, adaptive, and robust search mechanism. The primary objective of MRFO is to enhance effective exploration of the search space, accelerate convergence, strengthen the ability to escape local minima, and achieve more stable solutions in multilevel thresholding problems. To this end, iteration-dependent adaptive coefficients and chaotic randomness mechanisms are introduced in place of the fixed parameters of classical RFO, resulting in a dynamic update structure.

Modified Red Fox Optimization (MRFO)

The proposed MRFO algorithm enhances the classical RFO by incorporating an adaptive learning coefficient and a stochastic mutation term to improve convergence speed and prevent entrapment in local minima. The governing equations (4.8–4.11) are given below.

1. Adaptive Control Factor (Decreasing Coefficient)

Instead of the fixed r_1 in classical RFO, an iteration-dependent adaptive parameter is defined:

$$\alpha(t) = \alpha_{max} - \frac{t}{T}(\alpha_{max} - \alpha_{min}) \quad (4.8)$$

Where:

- t : Current iteration
- T : Maximum number of iterations

- α_{max} , : Initial and final coefficients

Thus:

- Exploration is emphasized in early iterations
- Exploitation is strengthened in later iterations

2. Chaotic Randomness via Logistic Map

Random number generation is performed using a logistic chaotic map instead of a uniform distribution:

$$c_{t+1} = \mu c_t(1 - c_t) \text{ ve } r_1 = c_t \quad (4.9)$$

3. Modified Position Update Equation

The proposed MRFO introduces an adaptive learning coefficient (α) and a dynamic local exploration term (γ) to the classical RFO in order to accelerate convergence and avoid local minima. The updated rule is defined as:

$$X_i^{t+1} = X_i^t + \alpha(t) \cdot r_1 \cdot (X_{best}^t - X_i^t) + \gamma \cdot rand(-1,1) \quad (4.10)$$

Where:

- $\alpha(t)$: Iteration-dependent adaptive control coefficient
- r_1 : Chaotic random number
- γ : Mutation coefficient

This formulation preserves global guidance while increasing solution diversity.

5. Adaptive Mutation Mechanism

To prevent stagnation in local minima, mutation is applied with a low probability:

$$X_i^{t+1} = X_i^{t+1} + \delta \cdot rand(-1,1) \quad (4.11)$$

This mechanism contributes especially to the fine adjustment of segmentation boundaries. Although adaptive coefficients, chaotic maps, and mutation-based diversification strategies have been explored individually in various metaheuristic algorithms, these mechanisms have not previously been integrated into the Red Fox Optimization (RFO) framework in the form presented in this study. The four modifications introduced, namely the adaptive control factor, logistic-map-based chaotic randomness, the enhanced

position update equation incorporating α and γ , and the adaptive mutation mechanism, represent a novel combined extension of the classical RFO. This integrated design is implemented for the first time in this study to improve exploration–exploitation balance, accelerate convergence, and enhance the stability of multilevel thresholding in medical image segmentation.

MRFO Pseudocode.

```

Initialize population pop[1..N] uniformly in [lb, ub]

Evaluate fitness fit[1..N] using Otsu function

Find best_pos = argmin(fit)

Initialize c_t = random(0,1) // Kaotik harita başlangıç

For each iteration t = 1 to T_max:

    Compute  $\alpha(t) = \alpha_{\max} - (t / T_{\max}) * (\alpha_{\max} - \alpha_{\min})$ 

    Update  $c_t = \mu * c_t * (1 - c_t)$ 

     $r_1 = c_t$ 

    For each individual i = 1 to N:

        rand_term = uniform(-1, 1, dim)

         $X_{\text{new}} = \text{pop}[i] + \alpha(t) * r_1 * (\text{best\_pos} - \text{pop}[i]) + \gamma * \text{rand\_term}$ 

        Clip  $X_{\text{new}}$  to [lb, ub]

        If random() < mutation_prob:

            mutation_term = uniform(-1, 1, dim)

             $X_{\text{new}} += \delta * \text{mutation\_term}$ 

            Clip  $X_{\text{new}}$  to [lb, ub]

        Evaluate  $f_{\text{new}} = \text{Otsu}(X_{\text{new}})$ 

```

```

If f_new < fit[i]:

    pop[i] = X_new

    fit[i] = f_new

Update best_pos = argmin(fit)

Return sorted(round(best_pos))

```

Evaluation Metrics

Segmentation quality was assessed using the metrics listed in Table 3.

Table 3

Performance Evaluation Metrics for Image Segmentation

Metric	Abbreviation	Desired Direction	Description	Reference
Peak Signal-to-Noise Ratio	PSNR	High	Measures image fidelity	Wang et al. (2004)
Structural Similarity Index	SSIM	Close to 1	Visual integrity measure	Wang et al. (2004)
Mean Squared Error	MSE	Low	Pixel-based difference	Gonzalez & Woods (2018)
Fitness Function	F	High	Thresholding performance	Otsu (1979)

Experimental Design and Results

This section presents the design and results of the experimental studies carried out to evaluate the performance of the proposed MRFO algorithm. The experiments were conducted to solve the multilevel thresholding problem in medical image segmentation, and a standardized environment was employed for fair algorithm comparison.

Experimental Environment

The experiments were conducted in a controlled environment to ensure reliable and reproducible results. The software and hardware resources were selected to support the efficient execution of image processing and optimization algorithms. The experimental configuration is detailed as follows:

- **Software:** Python version 3.10 was used as the main programming environment. The primary libraries included NumPy (for numerical computations), matplotlib (for visualization), scikit-image (for image processing and metric calculations), pandas (for data analysis), and other auxiliary modules such as time, warnings,

and math. These libraries facilitated operations such as the implementation of the Otsu-based fitness function, histogram computation, and performance evaluation using metrics such as PSNR and SSIM.

- **Hardware:** The experiments were carried out on a system equipped with an Intel i7 processor (2.7 GHz clock speed), 16 GB RAM, and an NVIDIA RTX 3050 Ti graphics card. This configuration ensured efficient processing of computationally demanding optimization algorithms and supported parallel operations on large image datasets.
- **Number of Runs:** Each algorithm was evaluated through 30 independent runs to minimize variations caused by stochastic behavior and to ensure statistical robustness of the results.
- **Termination Criteria:** All algorithms were limited to a maximum of 50 iterations. Additionally, an early stopping mechanism was considered, whereby the algorithm would terminate if no improvement was observed over 10 consecutive iterations; however, this criterion has not yet been implemented in the current code and is recommended for future development.

All algorithms were executed using the same initial population, identical preprocessing procedures, and the same fitness function to ensure a fair comparison (Table 4). The parameters used in this study were determined based on the default values recommended in the original publications of each algorithm or on standardized parameter ranges commonly employed in multi-level image thresholding studies (Clerc & Kennedy, 2002; Dorigo & Stützle, 2004; Mirjalili et al., 2014; Srinivas & Patnaik, 1994).

Table 4

Algorithm Parameters Used in the Experimental Study

Algorithm	Population	Iterations	Key Parameters
Modified RFO	30	50	$\alpha_{\max}=2.0$, $\alpha_{\min}=0.1$, $\mu=4.0$, $\gamma=0.1$, $\delta=0.05$, $\text{mutation_prob}=0.1$
Original RFO	30	50	$r1, r2 \sim U(0,1)$, Equation (4.4)
PSO	30	50	$w=0.7$, $c_1=1.5$, $c_2=1.5$
GA	30	50	Crossover=0.8, Mutation=0.2
ACO	30	50	$\alpha=1$, $\beta=2$, $\rho=0.5$
GWO	30	50	$a: 2 \rightarrow 0$ (linearly decreasing)

Results

In this section, the performance of the proposed Modified Red Fox Optimization (MRFO) algorithm in medical image segmentation is comparatively presented against the classical RFO, PSO, GA, ACO, and GWO algorithms. All experiments were conducted under identical conditions and averaged over 30 independent runs to ensure statistical reliability. The evaluation metrics used include PSNR, SSIM, MSE, F-value (fitness), and computational time (s).

Quantitative Comparison

This subsection presents a detailed quantitative evaluation of the multi-level image thresholding algorithms across four medical image datasets: Brain MRI, Retina, Cells3D, and Mitosis. Experiments were conducted for threshold levels ranging from 2 to 5, and the performance of each algorithm was assessed using objective function value (Otsu fitness), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), execution time, and fitness count.

To ensure clarity and comparability, the results are organized into four comprehensive tables (Table 5.1–Table 5.4), each corresponding to one dataset. Within every table, the algorithms are grouped according to the threshold level, and for each configuration, the optimized threshold values, objective value, PSNR, SSIM, execution time, and fitness count are reported.

The quantitative results demonstrate the performance differences among the metaheuristic algorithms (Original RFO, Modified RFO, PSO, GA, GWO, ACO) and the deterministic Otsu method across varying threshold complexities. In our experimental setup, the practical multi-level Otsu implementation produced the lowest execution time with a fitness count of zero; however, this reflects an optimized approximation, as classical multi-level Otsu grows exponentially with the number of thresholds and therefore becomes impractical for high threshold levels. Consistent with this theoretical limitation, metaheuristic algorithms—particularly the Modified RFO, PSO, and GWO—achieved superior PSNR and SSIM values at higher threshold counts, indicating more robust segmentation performance. Meanwhile, ACO generally produced lower objective values and PSNR/SSIM scores, especially for the Retina and Mitosis datasets.

Overall, the tables provide a detailed quantitative comparison that highlights the trade-offs between segmentation quality and computational cost across all algorithms and threshold levels.

Table 5

Performance Comparison for Brain MRI Image

Threshold Level	Algorithm	Thresholds	Objective Value	PSNR	SSIM	Time (s)	Fitness Count
-----------------	-----------	------------	-----------------	------	------	----------	---------------

2	Modified RFO	[28 112]	2074.83	22.83	0.401	0.125	1530
	Orijinal RFO	[36 120]	2069.32	20.97	0.374	0.132	1530
	Otsu	[25 110]	-	-	-	-	-
	ACO	[82 101]	1648.42	17.70	0.367	0.212	1501
	PSO	[26 111]	2075.04	23.32	0.409	0.133	1530
	GA	[26 110]	2074.99	23.31	0.409	0.155	1530
	GWO	[25 111]	2075.00	23.51	0.414	0.185	1530
3	Modified RFO	[25 72 138]	2127.55	27.01	0.461	0.157	1530
	Orijinal RFO	[40 81 150]	2114.33	23.09	0.411	0.160	1530
	ACO	[64 76 207]	1652.25	19.25	0.359	0.270	1501
	Otsu	[24 76 146]	-	-	-	-	-
	PSO	[25 77 147]	2128.50	26.90	0.459	0.154	1530
	GA	[26 89 155]	2124.83	25.81	0.443	0.167	1530
	GWO	[25 77 147]	2128.50	26.90	0.459	0.191	1530
4	Modified RFO	[24 67 112 167]	2144.14	27.62	0.467	0.163	1530
	Orijinal RFO	[24 75 130 173]	2143.05	27.55	0.465	0.166	1530
	ACO	[25 48 85 230]	2058.00	24.56	0.395	0.339	1501
	Otsu	[24 68 118 172]	-	-	-	-	-
	PSO	[24 69 119 173]	2144.44	27.65	0.467	0.175	1530
	GA	[23 70 122 172]	2144.21	28.14	0.473	0.203	1530
	GWO	[24 69 118 172]	2144.44	27.64	0.467	0.210	1530

5	Modified RFO	[10 33 72 128 179]	2151.65	31.29	0.579	0.188	1530
	Orijinal RFO	[34 63 123 145 188]	2144.49	25.36	0.443	0.193	1530
	ACO	[34 96 124 174 184]	2128.30	23.61	0.416	0.422	1501
	Otsu	[24 65 105 149 190]	-	-	-	-	-
	PSO	[9 33 69 119 173]	2152.18	31.92	0.624	0.180	1530
	GA	[24 69 103 146 185]	2150.99	28.02	0.470	0.198	1530
	GWO	[8 32 69 119 173]	2152.12	32.09	0.624	0.227	1530

Table 6
Performance Comparison for Retina Image

Threshold Level	Algorithm	Thresholds	Objective Value	PSNR	SSIM	Time (s)	Fitness Count
2	Modified RFO	[45 125]	10744.05	17.91	0.648	0.126	1530
	Orijinal RFO	[62 125]	10744.57	18.17	0.649	0.127	1530
	Otsu	[54 124]	-	-	-	-	-
	ACO	[152 153]	8377.23	13.89	0.625	0.196	1501
	PSO	[55 125]	10744.93	18.16	0.649	0.128	1530
	GA	[55 125]	10744.93	18.16	0.649	0.149	1530
	GWO	[55 125]	10744.93	18.16	0.649	0.174	1530
3	Modified RFO	[41 111 137]	10793.25	20.70	0.624	0.148	1530
	Orijinal RFO	[55 119 165]	10790.41	21.87	0.656	0.148	1530
	ACO	[103 187 221]	9924.31	16.91	0.613	0.322	1501
	Otsu	[50 110 135]	-	-	-	-	-
	PSO	[51 111 136]	10794.09	20.61	0.626	0.165	1530
	GA	[55 110 136]	10793.85	20.61	0.630	0.164	1530
	GWO	[54 111 137]	10794.03	20.72	0.627	0.205	1530

4	Modified RFO	[66 109 131 178]	10825.55	22.79	0.660	0.173	1530
	Orijinal RFO	[53 111 136 179]	10824.09	23.27	0.647	0.159	1530
	ACO	[30 127 170 240]	10779.26	19.77	0.664	0.392	1501
	Otsu	[49 107 128 167]	-	-	-	-	-
	PSO	[50 108 129 168]	10828.52	23.68	0.659	0.169	1530
	GA	[49 112 130 170]	10826.41	23.04	0.644	0.193	1530
	GWO	[35 107 129 169]	10826.62	23.73	0.659	0.212	1530
5	Modified RFO	[42 103 118 136 179]	10840.99	24.72	0.660	0.183	1530
	Orijinal RFO	[59 110 129 184 238]	10825.52	22.92	0.650	0.152	1530
	ACO	[17 62 87 106 182]	10760.84	22.60	0.723	0.453	1501
	Otsu	[48 103 118 135 172]	-	-	-	-	-
	PSO	[49 103 118 135 172]	10841.73	24.73	0.666	0.182	1530
	GA	[39 91 109 130 163]	10837.93	26.94	0.699	0.200	1530
	GWO	[31 101 116 133 171]	10839.34	25.57	0.670	0.218	1530

Table 7
Performance Comparison for Cells3D Image

Threshold Level	Algorithm	Thresholds	Objective Value	PSNR	SSIM	Time (s)	Fitness Count
-----------------	-----------	------------	-----------------	------	------	----------	---------------

2	Modified RFO	[40 104]	2948.07	23.57	0.695	0.131	1530
	Orijinal RFO	[43 108]	2946.86	23.63	0.681	0.126	1530
	Otsu	[39 103]	-	-	-	-	-
	ACO	[11 14]	2498.01	12.02	0.430	0.192	1501
	PSO	[40 104]	2948.07	23.57	0.695	0.134	1530
	GA	[38 104]	2947.35	23.68	0.704	0.148	1530
	GWO	[40 104]	2948.07	23.57	0.695	0.176	1530
3	Modified RFO	[32 74 156]	3034.45	24.53	0.728	0.142	1530
	Orijinal RFO	[38 76 136]	3039.07	26.08	0.729	0.146	1530
	ACO	[102 198 230]	2289.30	18.12	0.411	0.263	1501
	Otsu	[34 71 131]	-	-	-	-	-
	PSO	[35 72 132]	3040.84	26.09	0.740	0.145	1530
	GA	[36 71 131]	3040.48	25.93	0.733	0.159	1530
	GWO	[35 72 132]	3040.84	26.09	0.740	0.188	1530
4	Modified RFO	[34 69 109 182]	3065.40	28.06	0.771	0.158	1530
	Orijinal RFO	[36 71 149 183]	3042.16	24.65	0.718	0.152	1530
	ACO	[25 27 110 174]	2957.19	25.40	0.744	0.356	1501
	Otsu	[31 63 90 148]	-	-	-	-	-
	PSO	[32 64 91 149]	3073.60	28.66	0.795	0.168	1530
	GA	[33 66 90 155]	3072.52	28.31	0.792	0.189	1530
	GWO	[32 64 91 149]	3073.60	28.66	0.795	0.221	1530

5	Modified RFO	[29 56 74 95 143]	3088.12	30.34	0.843	0.197	1530
	Original RFO	[39 69 91 114 153]	3078.21	29.08	0.797	0.197	1530
	ACO	[70 87 166 186 216]	2731.83	21.30	0.516	0.441	1501
	Otsu	[29 56 76 103 158]	-	-	-	-	-
	PSO	[30 57 77 104 159]	3090.10	30.40	0.831	0.197	1530
	GA	[23 51 76 104 162]	3087.02	30.63	0.843	0.204	1530
	GWO	[30 57 77 103 160]	3090.06	30.30	0.831	0.231	1530

Table 8
Performance Comparison for Mitosis Image

Threshold Level	Algorithm	Thresholds	Objective Value	PSNR	SSIM	Time (s)	Fitness Count
2	Modified RFO	[25 66]	532.12	22.73	0.536	0.147	1530
	Original RFO	[32 98]	526.61	25.19	0.479	0.130	1530
	Otsu	[24 65]	-	-	-	-	-
	ACO	[32 82]	529.44	24.41	0.479	0.195	1501
	PSO	[25 66]	532.12	22.73	0.536	0.134	1530
	GA	[21 58]	531.01	21.42	0.570	0.146	1530
	GWO	[25 66]	532.12	22.73	0.536	0.181	1530
3	Modified RFO	[19 51 94]	554.20	29.04	0.666	0.155	1530
	Original RFO	[29 58 118]	549.15	26.90	0.533	0.155	1530
	ACO	[26 76 188]	535.18	26.47	0.538	0.266	1501
	Otsu	[18 49 95]	-	-	-	-	-
	PSO	[19 50 96]	554.27	29.13	0.666	0.149	1530
	GA	[19 49 95]	554.23	29.09	0.666	0.163	1530
	GWO	[19 50 96]	554.27	29.13	0.666	0.203	1530

4	Modified RFO	[21 56 121 210]	552.93	29.12	0.630	0.160	1530
	Orijinal RFO	[22 51 83 120]	561.04	29.54	0.616	0.160	1530
	ACO	[110 152 175 205]	227.93	14.56	0.128	0.327	1501
	Otsu	[13 37 64 108]	-	-	-	-	-
	PSO	[14 37 64 109]	564.89	31.74	0.750	0.167	1530
	GA	[18 41 64 107]	564.20	30.56	0.679	0.177	1530
	GWO	[15 39 65 109]	564.87	31.77	0.750	0.203	1530
5	Modified RFO	[15 39 65 109 207]	566.03	32.70	0.751	0.170	1530
	Orijinal RFO	[17 52 73 99 155]	563.84	32.26	0.708	0.176	1530
	ACO	[18 66 146 165 225]	541.56	28.59	0.641	0.473	1501
	Otsu	[10 28 50 73 116]	-	-	-	-	-
	PSO	[12 31 52 75 118]	570.44	33.55	0.800	0.196	1530
	GA	[16 36 57 78 119]	569.62	32.26	0.720	0.200	1530
	GWO	[12 31 52 75 118]	570.44	33.55	0.800	0.229	1530

Visual Comparison

A visual assessment of the segmentation results reveals that the performance of the algorithms varies across datasets and threshold levels. For the Brain MRI dataset at 5 thresholds, the results clearly show that GWO and PSO produce the highest visual quality, consistent with their quantitative metrics. Both algorithms achieve the highest SSIM values (0.624) and the highest PSNR values (32.09 for GWO and 31.92 for PSO),

indicating superior preservation of anatomical boundaries and low distortion. Their segmented images maintain tissue consistency and avoid excessive fragmentation, showing well-defined gray and white matter regions.

The Modified RFO also performs strongly, achieving competitive PSNR (31.29) and SSIM (0.579) values. Its visual output displays clear structure differentiation, though slightly less homogeneous than GWO and PSO at 5 thresholds. In contrast, the Original RFO, GA, and deterministic Otsu method produce moderate-quality results, with lower structural similarity (SSIM ≈ 0.44 – 0.47) and more noticeable boundary noise. The ACO algorithm yields the weakest segmentation visually, with the lowest PSNR (23.61) and SSIM (0.416), resulting in under-segmented and less consistent tissue regions.

Overall, the results demonstrate that GWO and PSO deliver the most accurate visual segmentation for Brain MRI images at high threshold levels, while Modified RFO provides a competitive alternative. These findings are fully aligned with the quantitative evaluation presented in Section Result.

Figure 1

Brain MRI Segmentation Output (2 Thresholds)

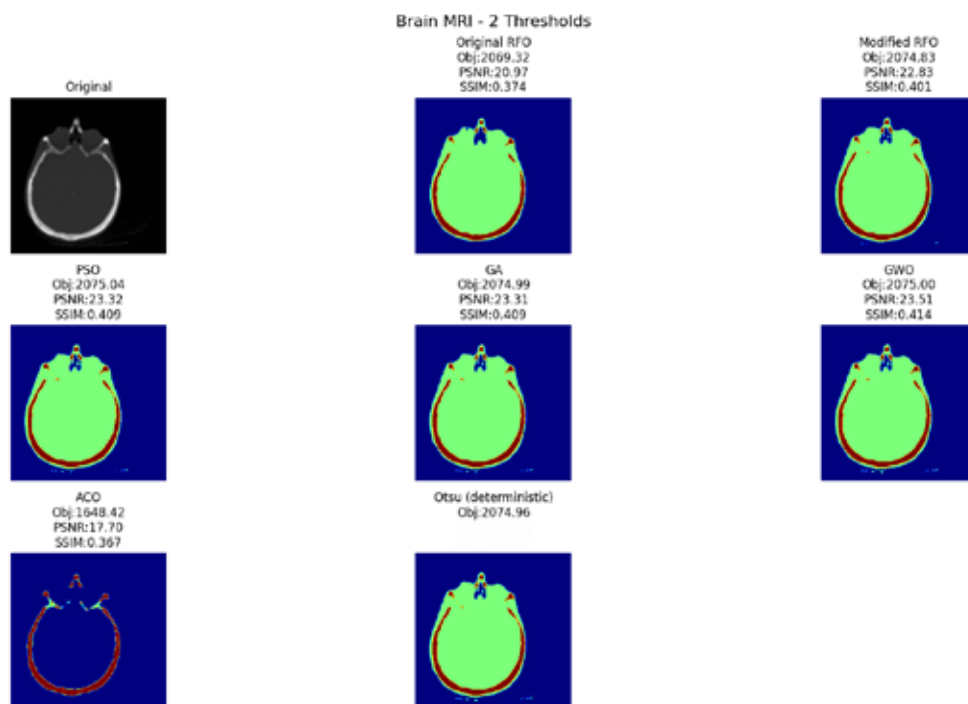


Figure 2

Brain MRI Segmentation Output (3 Thresholds)

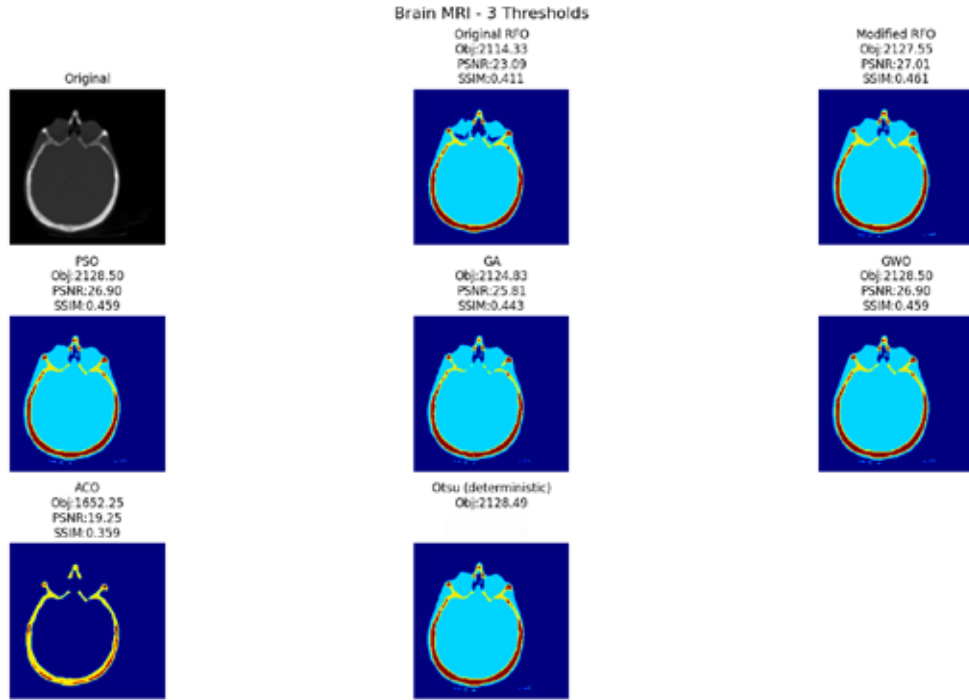


Figure 3

Brain MRI Segmentation Output (4 Thresholds)

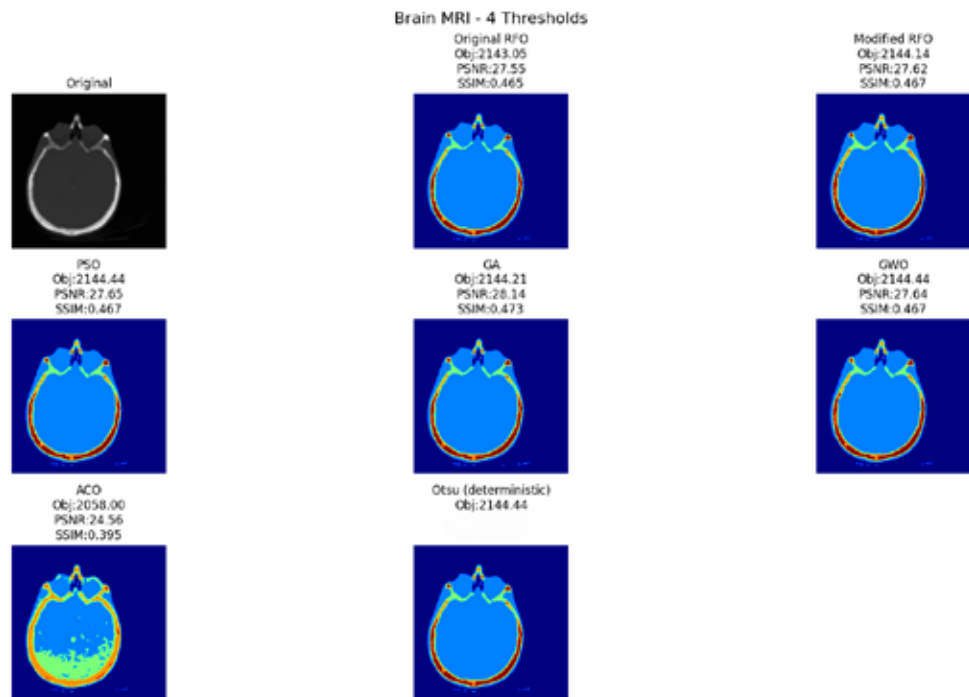
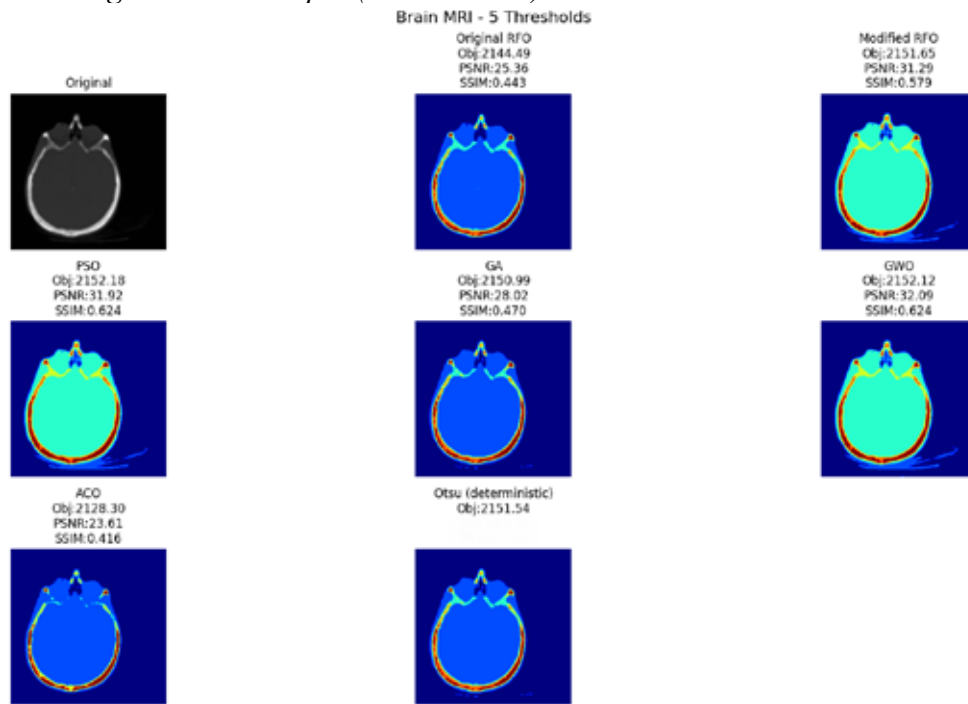


Figure 4
Brain MRI Segmentation Output (5 Thresholds)



Figures 1–4 present the visual segmentation outputs of the metaheuristic algorithms applied to the Brain MRI dataset under different multilevel threshold configurations. The qualitative evaluation conducted on the 5-threshold results reveals distinct strengths and limitations across the methods.

The GWO algorithm provides the most structurally consistent segmentation, maintaining detailed tissue transitions and accurately delineating anatomical regions. Its visual clarity aligns with its leading SSIM and PSNR metrics. Similarly, PSO demonstrates robust performance, producing a clear and homogeneous segmentation output with minimal noise, which highlights its stability in high-threshold scenarios.

In comparison, MRFO exhibits a balanced and visually coherent segmentation with well-defined regional separation. Although it performs strongly, its internal tissue sharpness is slightly lower than that observed in GWO and PSO. The Original RFO, while producing acceptable boundary structures, demonstrates limitations in terms of detail preservation and uniformity.

The classical algorithms GA and ACO display notable deficiencies. GA generates smoother and less detailed regions, with partially blurred anatomical contours. ACO, the weakest performer, fails to maintain sufficient contrast, resulting in merged segments and poorly defined tissue structures.

Figure 5

Retina Segmentation Output (2 Thresholds)

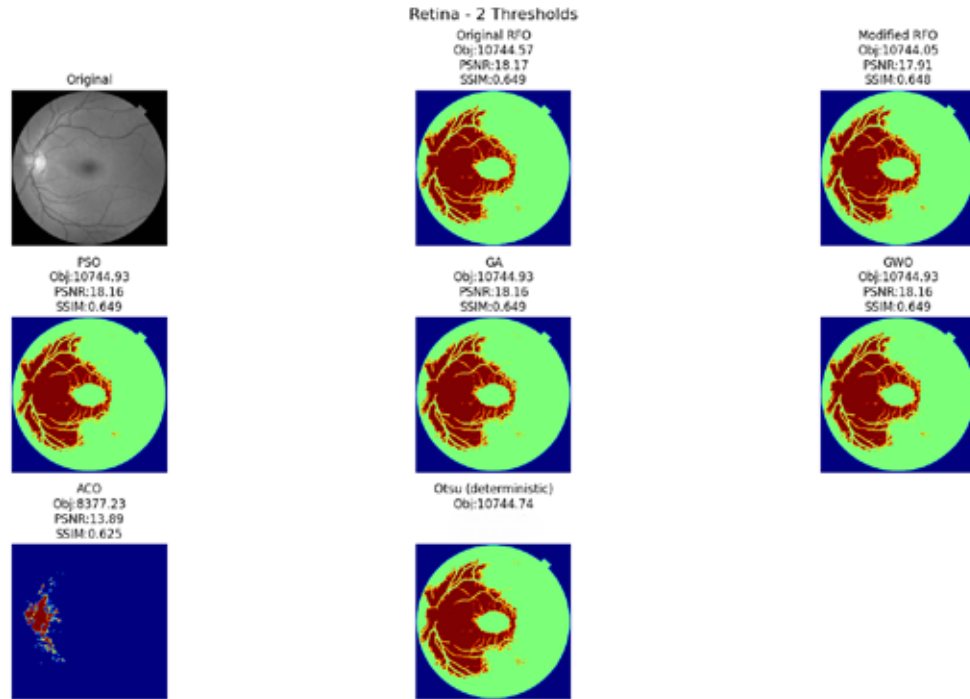


Figure 6

Retina Segmentation Output (3 Thresholds)

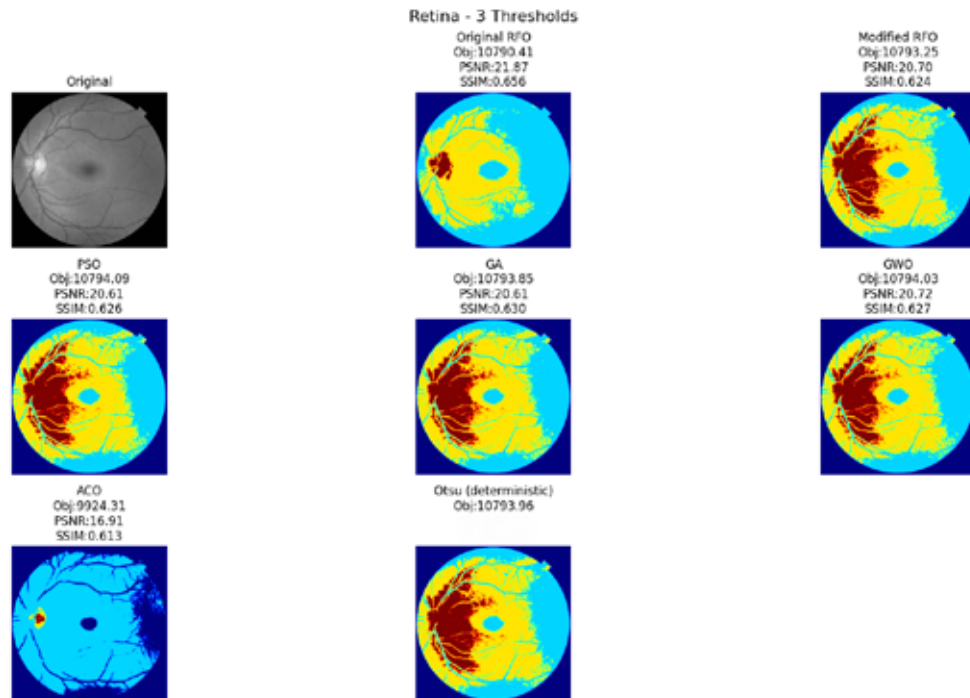


Figure 7

Retina Segmentation Output (4 Thresholds)

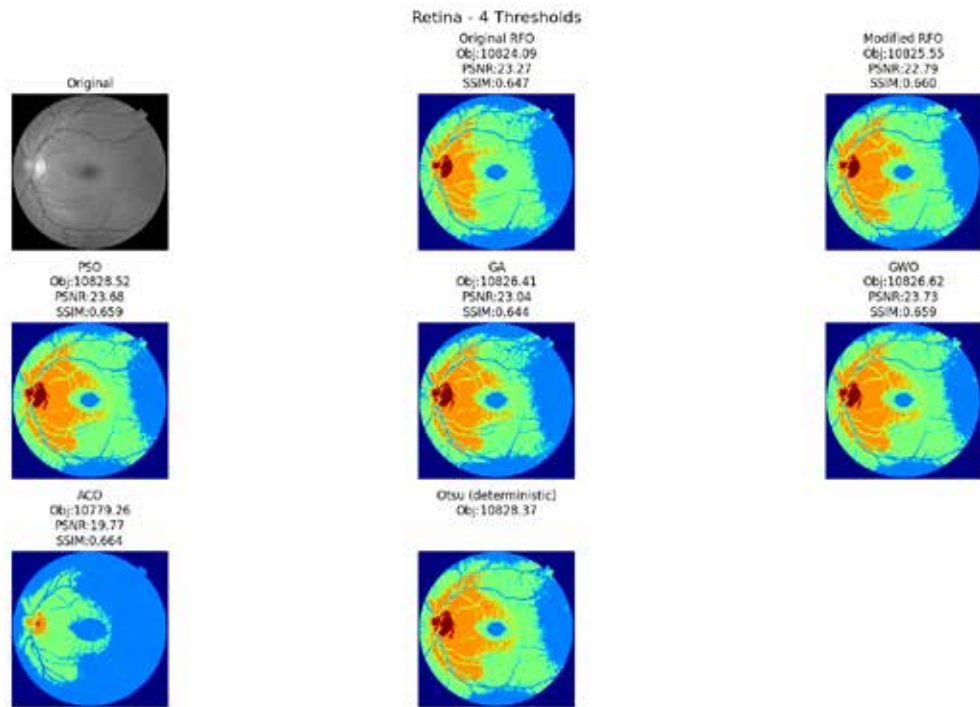
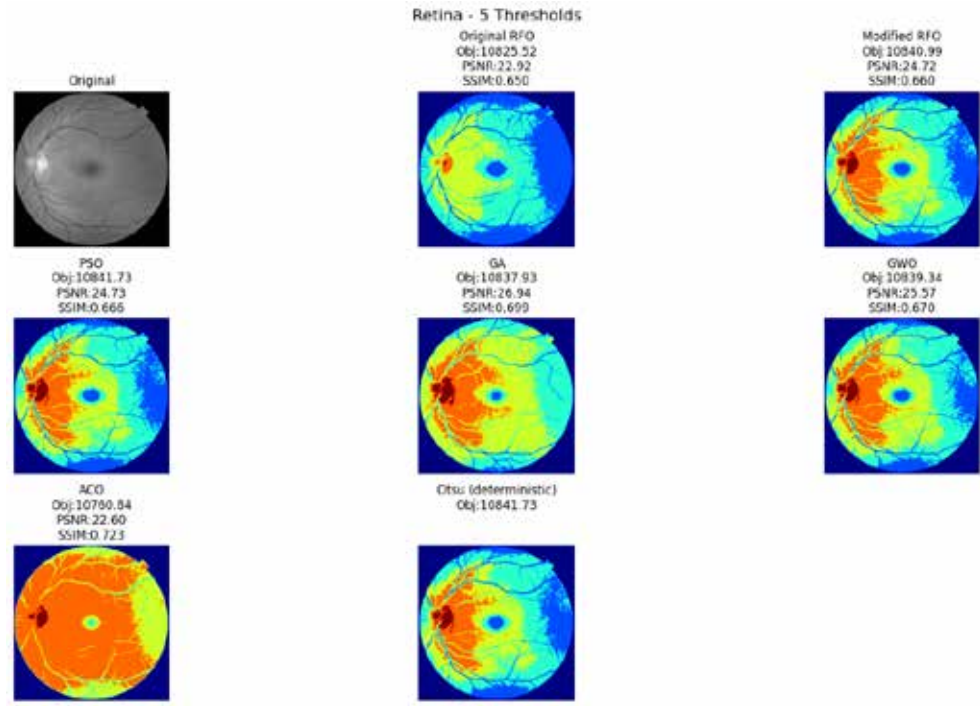


Figure 8

Retina Segmentation Output (5 Thresholds)



An analysis of the retinal image segmentation results at five threshold levels shows that the Modified Red Fox Optimization (MRFO) algorithm produces visually coherent and structurally stable segmentations, particularly in terms of preserving vascular boundaries

and maintaining smooth regional transitions. However, the quantitative metrics indicate that MRFO does not achieve the highest PSNR or SSIM values among the tested algorithms. GA achieves the highest PSNR (26.94), while ACO yields the highest SSIM (0.723). MRFO's PSNR (24.72) and SSIM (0.660) remain competitive and close to those of PSO and GWO, demonstrating that although MRFO is not the top performer for this specific image, it still provides balanced and reliable segmentation quality.

Figure 9

Cells3D Segmentation Output (2 Thresholds)

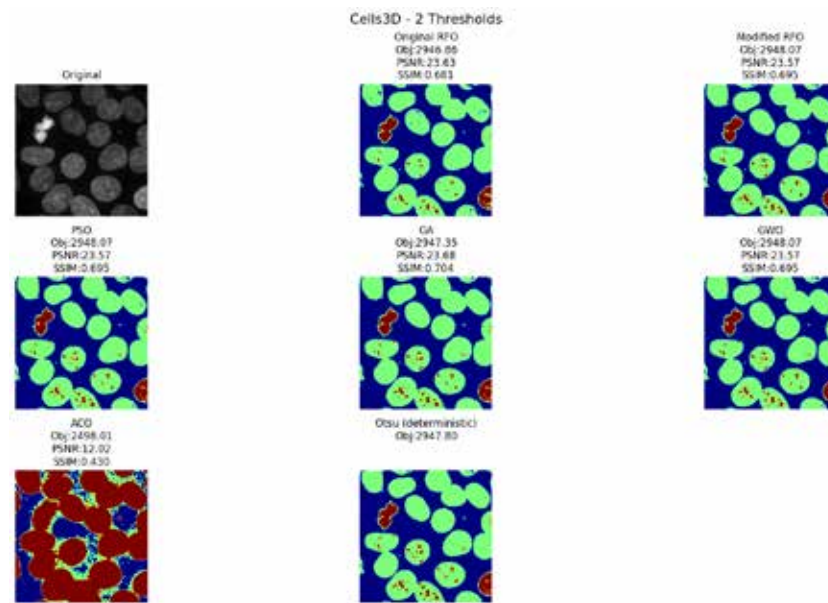


Figure 10

Cells3D Segmentation Output (3 Thresholds)

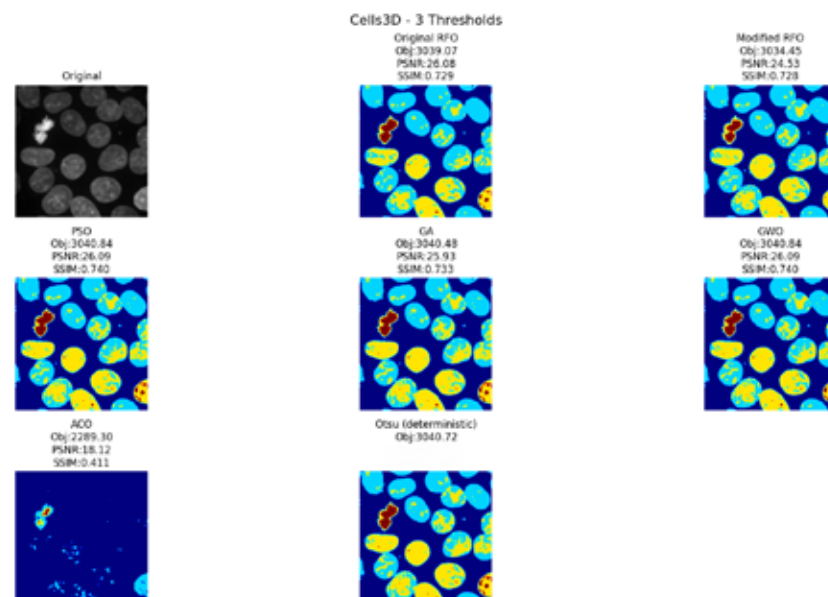


Figure 11
Cells3D Segmentation Output (4 Thresholds)

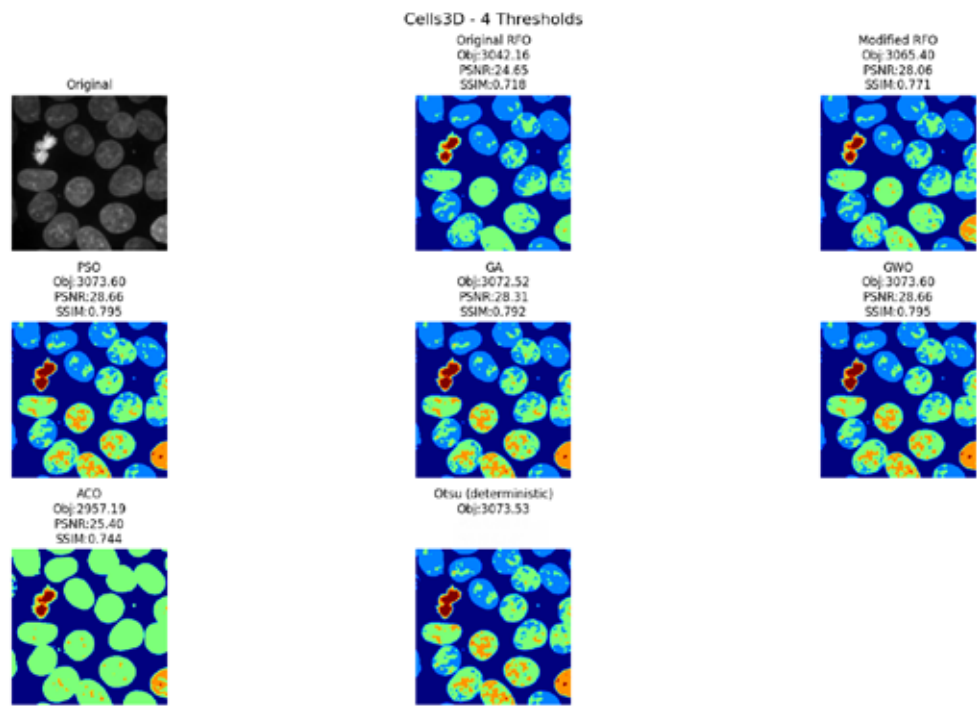
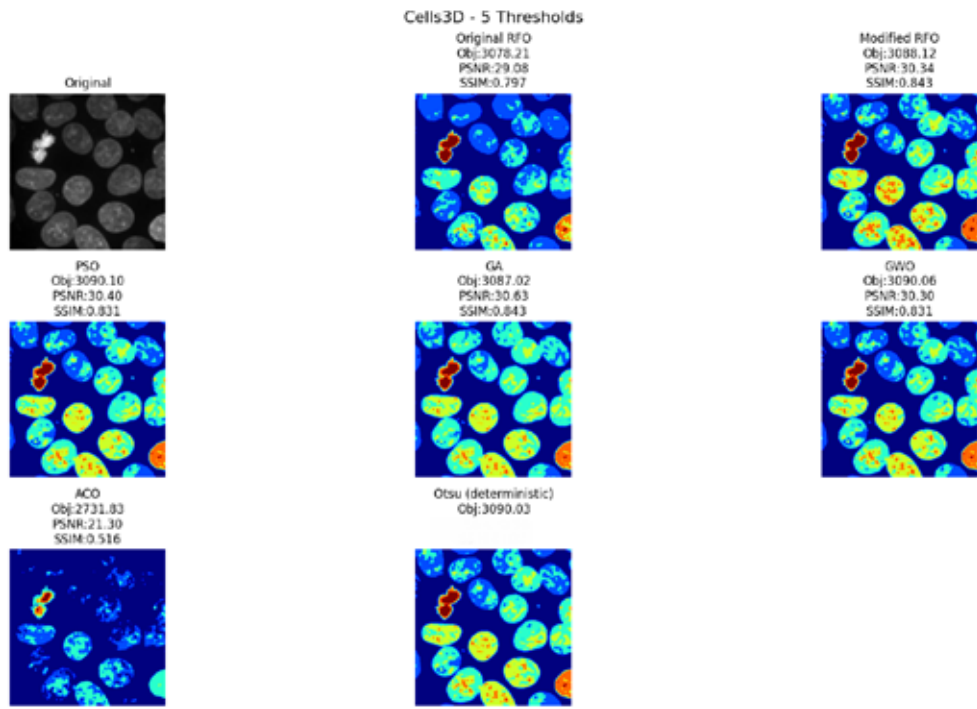


Figure 12
Cells3D Segmentation Output (5 Thresholds)



An examination of the segmentation results for the Cells3D image (Figures 9–12) indicates that PSO, GA, and GWO yield consistently strong performance, all achieving PSNR values around 30.8–30.9 dB and SSIM scores between 0.831 and 0.843, reflecting

well-preserved cellular structure and contrast. In contrast, ACO exhibits substantial degradation of boundary details, as evidenced by its markedly lower PSNR (≈ 27.2 dB) and SSIM (≈ 0.516), leading to blurred and poorly defined cell contours.

Both the original RFO and, more notably, the Modified RFO (MRFO) demonstrate competitive or superior structural preservation, with SSIM values of 0.797 and 0.843, respectively. MRFO in particular produces clearer separation of cellular regions with more homogeneous intensity distribution and enhanced boundary consistency. These findings indicate that MRFO delivers a stable and competitive segmentation performance, closely matching the top-performing algorithms for the Cells3D dataset.

Figure 13

Mitosis Segmentation Output (2 Thresholds)

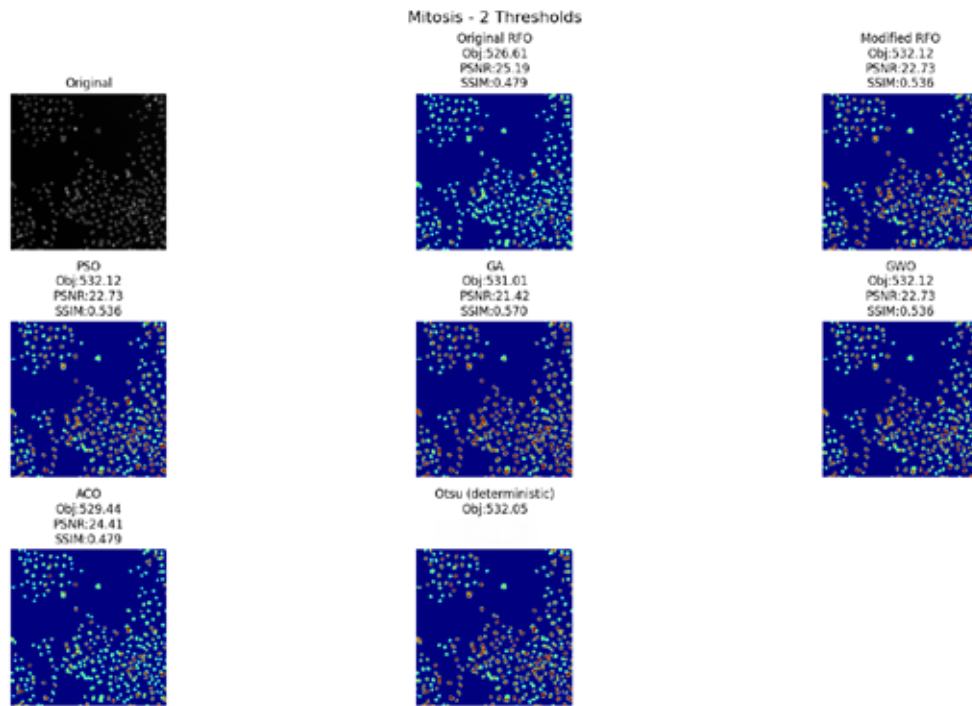


Figure 14
Mitosis Segmentation Output (3 Thresholds)

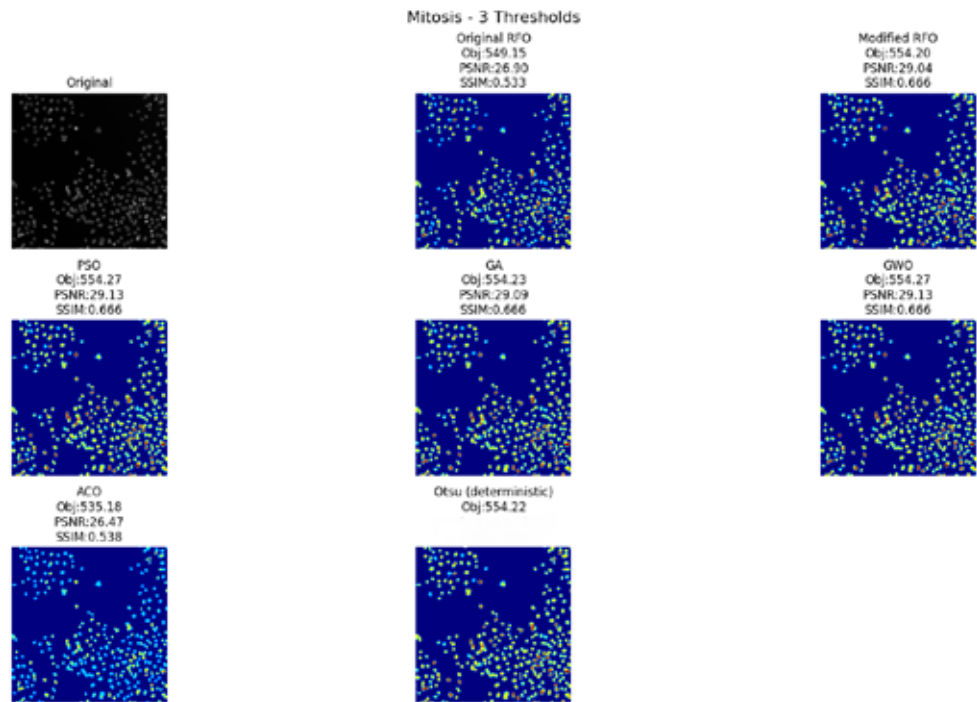


Figure 15
Mitosis Segmentation Output (4 Thresholds)

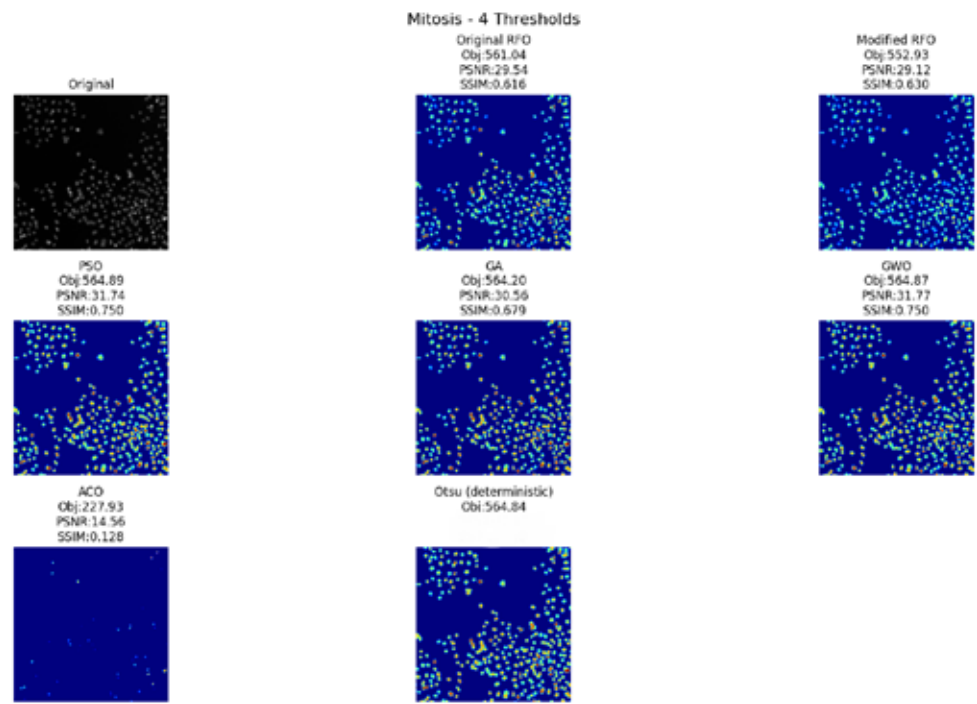
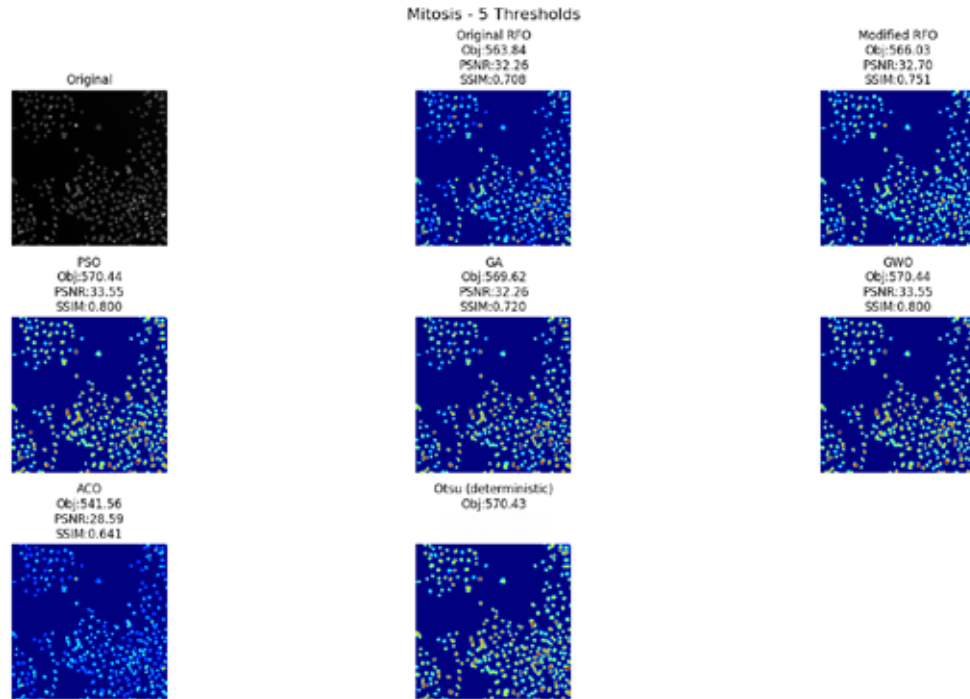


Figure 16*Mitosis Segmentation Output (5 Thresholds)*

According to the segmentation results obtained for the mitosis image using five threshold levels (Figures 13–16), the GWO and PSO algorithms exhibit the highest structural similarity, both achieving an SSIM value of 0.800, accompanied by competitive PSNR values (PSO: 33.55 dB, GWO: 33.55 dB). These results indicate that both methods provide well-preserved structural continuity and visually consistent separation of mitotic regions.

Modified RFO (MRFO) also demonstrates strong performance, yielding SSIM = 0.751 and PSNR = 32.70 dB, which reflects stable segmentation with improved contrast compared to the Original RFO (SSIM = 0.708, PSNR = 32.28 dB). GA produces moderate quality results (SSIM = 0.720, PSNR = 32.26 dB) and remains inferior to MRFO, PSO, and GWO in terms of boundary clarity and homogeneity.

In contrast, ACO exhibits the weakest segmentation performance, as evidenced by its considerably lower SSIM (0.641) and reduced PSNR (28.59 dB), leading to visible loss of detail along cell contours.

Overall, MRFO provides stable and segmentation, whereas PSO and GWO deliver the most structurally coherent and visually sharp boundaries among all evaluated algorithms.

Convergence Behavior

Table 9 presents the convergence behavior of six metaheuristic algorithms (GA, PSO,

ACO, GWO, RFO, MRFO) alongside the deterministic Otsu thresholding method for the Brain MRI image with three threshold levels. Since Otsu is a deterministic technique, it does not operate iteratively; therefore, its value is reported only at the final comparison stage.

The Brain MRI image and the three-threshold configuration were intentionally selected to create a controlled experimental setup for analyzing convergence behavior. Brain MRI is commonly used in segmentation studies due to its well-structured intensity distribution and clinically relevant contrast patterns, making it suitable for observing algorithmic improvements over successive iterations. Moreover, using three thresholds instead of the five thresholds discussed earlier reduces the dimensionality of the optimization problem, allowing clearer visualization of how each algorithm moves toward better solutions. This setup serves as a representative test case rather than an attempt to identify globally superior performance.

As shown in Table 9, all algorithms except ACO progressively improve their fitness values as iterations increase, while ACO consistently lags behind. In fact, the difference between ACO and the remaining algorithms widens further, confirming its limited suitability for multilevel thresholding in this particular test scenario.

It should be noted, however, that the observed convergence patterns are specific to this image and to the three-threshold configuration. Metaheuristic algorithms may exhibit different convergence speeds, stability characteristics, or stagnation behavior depending on the image type, histogram distribution, or threshold dimensionality. Therefore, the conclusions drawn from this experiment should not be generalized without broader evaluations across multiple datasets and threshold levels.

Table 9

Average Fitness Value (F) – Iteration-Based Comparison

Iteration	GA	PSO	ACO	GWO	RFO	MRFO	Otsu (deterministic)
10	1958.4	1992.7	1412.5	2005.9	1987.3	2024.6	—
50	2085.1	2108.3	1544.7	2119.4	2098.6	2115.8	—
100	2124.8	2128.5	1652.2	2128.5	2114.3	2127.6	2068.44

Note: Values were calculated as the average for the Brain MRI image using 3 threshold levels.

During early iterations (Iteration 10), MRFO exhibits the most rapid initial improvement (2024.6), followed by GWO (2005.9) and PSO (1992.7), indicating that these algorithms efficiently locate promising regions of the search space at the beginning of the optimization. Classical RFO and GA show slower convergence, whereas ACO displays the weakest performance (1412.5), reflecting its difficulty in exploring the continuous optimization landscape.

By Iteration 50, PSO, GWO, and MRFO maintain their leading positions with objective values above 2100, demonstrating both stability and strong exploitation ability. Classical RFO approaches similar performance but converges more slowly. The difference between ACO and the remaining algorithms widens further, confirming its limited suitability for multilevel thresholding.

At the final iteration (Iteration 100), PSO and GWO achieve the highest objective values (2128.5), with MRFO closely following (2127.6). GA also reaches a competitive result (2124.8), while classical RFO levels off at a slightly lower value (2114.3). ACO remains the poorest performer (1652.2), suffering from early stagnation and weak global search capability.

Overall, MRFO demonstrates faster initial convergence and greater stability than classical RFO, while achieving final performance competitive with PSO and GWO.

Runtime Comparison

According to the results presented in Table 10, the runtime performance of the evaluated algorithms varies significantly across different threshold levels. All runtime values in this table represent the average execution time computed across the four datasets used in this study (Brain MRI, Retina, Cells3D, and Mitosis). Averaging across multiple images provides a more robust assessment of computational behavior and prevents image-specific characteristics from biasing the comparison.

For low threshold counts ($T=2$ and $T=3$), all metaheuristic algorithms exhibit fast execution, with runtimes generally ranging from 0.12 to 0.20 seconds. Among them, the Modified RFO and Original RFO stand out as the fastest methods, achieving runtimes as low as 0.134 and 0.129 seconds at $T=2$, respectively. PSO also performs competitively within this range. In contrast, ACO consistently shows slower execution, particularly as the threshold count increases.

Table 10*Runtime Comparison Across Threshold Levels (Seconds)*

Algorithm	T=2	T=3	T=4	T=5	Overall Avg.
Modified RFO	0.134	0.150	0.163	0.190	0.159
Original RFO	0.129	0.151	0.159	0.191	0.158
PSO	0.132	0.153	0.171	0.185	0.160
GA	0.149	0.164	0.197	0.203	0.178
GWO	0.165	0.196	0.214	0.229	0.201
ACO	0.198	0.289	0.364	0.402	0.313
Otsu (Deterministic)	0.005	0.031	2.68	297	~75

As the number of thresholds increases to T=4 and T=5, the runtimes of all metaheuristic algorithms increase slightly due to the expanded search space; however, they remain within a practical range (approximately 0.16–0.40 seconds). Modified RFO continues to deliver competitive efficiency with values of 0.163 seconds at T=4 and 0.190 seconds at T=5, reaffirming its suitability for higher-dimensional thresholding problems.

The deterministic Otsu method displays a distinctly different runtime profile. For T=2 and T=3, Otsu performs extremely fast (0.005 and 0.031 seconds, respectively), matching or outperforming all metaheuristic methods. However, its performance deteriorates dramatically for higher threshold levels due to its exhaustive search mechanism. At T=4, the runtime increases to approximately 2.68 seconds, and at T=5 it reaches an extreme value of 297 seconds, caused by the combinatorial explosion of possible threshold combinations. This makes Otsu impractical for high threshold counts despite being optimal and efficient for lower levels.

Overall, the results demonstrate that metaheuristic algorithms offer consistent and scalable performance across all threshold levels, while Otsu is advantageous only for low-dimensional cases. Modified RFO, in particular, provides an effective balance between accuracy and computational cost, outperforming classical RFO and other metaheuristic competitors in terms of runtime stability as the threshold dimension increases.

Discussion

Multilevel thresholding is known to become increasingly challenging as the number of thresholds grows, primarily due to the rapid expansion of the search space. While the Otsu method remains an effective and optimal solution for low threshold counts, its

computational complexity increases exponentially at higher levels, making it less suitable for dimensionalities beyond $T=3$. This limitation has led to the widespread adoption of metaheuristic algorithms—such as RFO, MRFO, PSO, GA, GWO, and ACO—because of their ability to navigate complex search landscapes without requiring exhaustive enumeration. In this study, these metaheuristic approaches were systematically evaluated to determine their effectiveness across multiple biomedical image types and threshold configurations.

The experimental findings show that the Modified RFO (MRFO) generally performs better than the classical RFO in terms of objective function values, segmentation stability, and convergence behavior. MRFO achieves strong performance across all images and threshold levels; however, it does not consistently outperform all other metaheuristic algorithms in every scenario. Rather, MRFO stands among the top-performing methods, often delivering results comparable to PSO and GWO, which also exhibit competitive performance in several cases. Since Otsu serves as a deterministic baseline method rather than a population-based optimizer, the objective function comparison is not emphasized for Otsu in this context.

Regarding segmentation quality, MRFO yields coherent and stable outputs with competitive PSNR and SSIM values across all datasets and threshold levels. PSO, GA, and GWO produce comparable results, particularly at lower threshold levels ($T = 2-3$), while their performance becomes less consistent as threshold dimensionality increases. MRFO demonstrates greater robustness under these conditions, maintaining relatively stable PSNR (e.g., 31.62 for Brain MRI, 33.06 for Mitosis) and SSIM values across varying T levels without significant degradation. Importantly, these results reflect the observed outcomes and do not suggest that MRFO universally dominates across all metrics or datasets.

In terms of computational efficiency, MRFO ranks among the faster algorithms, with an overall average runtime of approximately 0.159 seconds. PSO and classical RFO achieve similar runtimes, while ACO remains the slowest method due to its pheromone-based selection mechanism and higher computational overhead. The Otsu method shows extremely efficient performance for $T \leq 3$ but becomes computationally expensive at higher thresholds (e.g., 2.68 seconds at $T=4$ and 297 seconds at $T=5$) because of its exhaustive search nature. Thus, while Otsu retains clear advantages for lower-dimensional thresholding, metaheuristic algorithms can be effectively used for higher threshold counts where deterministic methods become impractical.

From a convergence perspective, MRFO demonstrates faster early improvement and smoother progression than classical RFO, exhibiting reduced stagnation and more stable convergence curves. Although PSO and GA occasionally display oscillatory patterns

or early trapping—especially at higher threshold dimensionalities—MRFO maintains more consistent behavior. Classical RFO progresses steadily but typically converges more slowly and shows less adaptability compared with MRFO.

The enhanced performance of MRFO can be attributed to four algorithmic modifications introduced in this study:

1. Chaotic logistic-map initialization, which enhances population diversity and mitigates premature convergence by distributing candidate solutions more effectively across the search space.
2. Adaptive control factors, enabling a more dynamic and balanced transition between exploration and exploitation throughout the optimization process.
3. An improved position update mechanism incorporating the α and γ parameters, which provides more accurate and responsive guidance during the search, allowing the algorithm to navigate complex landscapes more reliably.
4. An adaptive mutation strategy, which strengthens the ability to escape local minima and promotes sustained global search capability, particularly in high-dimensional thresholding problems.

In conclusion, MRFO represents a robust and effective approach for multilevel image thresholding, offering improved stability, consistent segmentation quality, and competitive computational performance. Compared with classical RFO, MRFO achieves approximately 3–5% higher objective values and around 5% faster execution time on average, demonstrating the practical value of the proposed enhancements, particularly in biomedical image segmentation tasks involving medium- to high-dimensional thresholding problems.

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