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REVIEW ARTICLE

Firefly Algorithm for Medical Image Segmentation: A Systematic Review of Methods, Applications, and Future Directions

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Abstract

The firefly algorithm (FA) is a nature-inspired metaheuristic increasingly applied to medical image segmentation because of its flexible search mechanism and optimization capability. This paper systematically reviews FA-based approaches for medical image segmentation and related image-analysis tasks published between 2010 and 2026. A structured search of Scopus, PubMed, IEEE Xplore, Web of Science, and Google Scholar was conducted using predefined eligibility criteria. The included studies were categorized into multilevel thresholding, entropy-based segmentation, clustering-assisted methods, adaptive and chaotic FA variants, and hybrids with deep learning and other metaheuristics. Major applications included brain, lung, breast, and microscopic image analysis. The reviewed studies generally reported competitive performance and demonstrated FA's flexibility in optimizing thresholds, clustering centers, feature subsets, and model hyperparameters. However, direct quantitative comparisons remain difficult because of heterogeneity in datasets, imaging modalities, evaluation metrics, and experimental protocols. Major limitations include computational overhead, parameter sensitivity, inconsistent benchmarking, limited clinical validation, and insufficient investigation of three-dimensional and multimodal imaging. Future research should emphasize self-adaptive FA, GPU-accelerated and parallel implementations, integration with neural architecture search and explainable artificial intelligence, extension to three-dimensional and multimodal imaging, and validation on standardized multicenter datasets. Overall, FA represents a promising optimization framework for medical image segmentation, although methodological standardization, computational improvements, and rigorous clinical validation are required for broader practical deployment.

Keywords: firefly algorithm, medical image segmentation, metaheuristic optimization, multilevel thresholding, medical imaging, deep learning.

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1 Introduction

Digital image processing has become an essential tool across a wide range of scientific and engineering disciplines. The development of some branches of computer science, telecommunications, medical science and astronomy is dependent on the development of image processing [1, 2].

The importance and necessity of digital image processing is due to two main applications. Firstly, improving visual information for human interpretation and, secondly, processing of the scene data for self-perception of the device. Digital image processing has a wide range of applications such as remote sensing, image storage and data transfer for business applications, medical imaging, audio imaging, legal science and industrial automation. Images downloaded by satellites are useful in tracking land resources, geographic mapping and forecasting of crops, urban populations, weather forecasts, floods and fire control. Imaging spatial applications include identifying and analyzing objects in images taken from deep-space mission probes. There are also medical programs like X-ray processing, ultrasonic scanning, electron microscopy, magnetic resonance imaging, and so on [3–5].

Image segmentation is one of the most widely used approaches for extracting information from an image. Image segmentation is commonly regarded as an essential early stage of image analysis. In the segmentation procedure, an image splits into parts or components. The segmentation stops when the desired region of interest is isolated in a specific application. Generally, one of the most challenging tasks in digital image processing is the automatic segmentation technique [1, 2].

Various approaches have been developed for image segmentation, including mathematical methods, artificial-intelligence-based techniques, clustering, thresholding, and watershed transformation.

Firefly is an insect that produces mostly short and rhythmic flashes. These light signals are produced during a chemical process in the body of the firefly, and flashing behavior is the most distinctive characteristic of fireflies. These lights have two fundamental functions: attracting the opposite sex and warning the enemy. These flashing lights follow the rules of the physical world. The flashing behavior of the firefly varies according to the criteria of attractiveness, brightness and distance.

For meta-heuristic algorithms, exploration means the process of discovering various solutions within the search space. The firefly algorithm is a meta-heuristic algorithm belonging to the group of random algorithms; that is, a random search space is used to reach a set of solutions. The firefly algorithm at its lowest level focuses on generating solutions within a search space and chooses the best solution for survival. Randomization helps the algorithm escape local optima and reduces the risk of premature convergence [6].

In general, there are three ideal rules for the development of firefly-inspired algorithms:

I. All fireflies are considered of the same sex, so that a firefly will be absorbed into another firefly regardless of their gender.

II. The attractiveness decreases with distance and is proportional to the brightness of the emitting firefly. So, for each firefly, the one with lower brightness will move toward the one with higher luminosity. The attractiveness is proportional to the brightness, and as the distance between two fireflies increases, their mutual attraction decreases.

III. If none of the fireflies are brighter than the other, the firefly moves randomly [6].

1.1 Contributions of This Review

This paper presents a systematic review of firefly algorithm (FA)-based methods for medical image segmentation. The contributions are as follows:

1. *Domain specificity*: Unlike previous generic surveys of FA, this review focuses exclusively on medical image segmentation, covering brain, lung, breast, cardiovascular, tuberculosis, and retinal applications. No prior review has systematically mapped FA variants to specific disease domains.

2. *Comparative analysis framework*: This review provides direct quantitative comparisons between FA and other metaheuristics (PSO, DE, BA, cuckoo search, grey wolf) based on reported metrics (accuracy, Dice coefficient, PSNR, SSIM, convergence speed). Tables 1, 2, 3 explicitly list limitations alongside performance gains, offering a balanced view absent in prior literature.

3. *Chronological and methodological tracing*: The review traces the evolution of FA from foundational modifications (2010–2016)

through multilevel thresholding (2016–2021) to deep learning hybridization (2021–2026), revealing clear dependency pathways for future researchers.

4. *Clinical translation gap analysis*: Based on the authors' systematic analysis of the 78 included studies, 92% use public benchmarks (BraTS, ISIC, LIDC) and only 8% report prospective clinical validation, establishing a clear research priority.

5. *Future roadmap*: Specific, actionable directions are provided (GPU-accelerated FA, self-adaptive parameters, neural architecture search integration, 3D/multi-modal extension) that go beyond generic suggestions.

2 Systematic Literature Review

The firefly algorithm (FA), introduced by Yang [12], has emerged as a powerful meta-heuristic inspired by the bioluminescent communication of fireflies, and has been increasingly explored for biomedical and health care applications, including medical image analysis [13]. Due to its simplicity, adaptability, and strong global search capability, FA has been extensively applied to complex optimization problems, particularly in medical image segmentation. This section systematically reviews the evolution of FA-based methods for image segmentation, following the progression from classical thresholding techniques to hybrid deep learning models. The review is organized into thematic subsections that reflect the chronological and methodological dependencies among key studies.

2.1 Foundational Modifications of the Firefly Algorithm

The standard FA suffers from premature convergence and sensitivity to parameter settings. Early research focused on enhancing its performance through various modifications. Rahebi and Hardalaç [7] applied FA to optic disc detection in human retinal images, mapping pixel light intensities to firefly brightness and demonstrating that FA can effectively solve binary medical image segmentation tasks on standard fundus image databases (DRIVE, STARE, DIARETDB1, DRIONS), achieving detection accuracies of up to 100%. Fister et al. [8] introduced chaotic maps into FA (CFA) to improve population diversity and avoid local optima. Senthilnath et al. [9] evaluated FA as a clustering optimizer on thirteen benchmark datasets, comparing it with artificial bee colony (ABC) and PSO and demonstrating its competitive performance in population-based cluster search—a finding that directly informed subsequent FA applications to medical image clustering, while Fister Jr. et al. [10] presented a memetic FA (MFA) combining local search heuristics. Kora and Krishna [11] created a hybrid FA (HFA) with particle swarm optimization (PSO), demonstrating that hybridization mitigates premature convergence. These foundational works directly influenced subsequent image segmentation applications, where escaping local optima is critical for multilevel thresholding. Table 4 summarizes these foundational FA variants and their key modifications.

2.2 Firefly Algorithm for Multilevel Image Thresholding

Multilevel thresholding is a classic segmentation approach that becomes computationally expensive as the number of thresholds increases; comprehensive surveys of thresholding techniques and their quantitative evaluation provide the methodological foundation for these methods [14]. FA has been widely adopted to optimize threshold selection by maximizing or minimizing an objective function.

Early hybrid thresholding methods: He and Huang [15] proposed a modified FA (MFA) for color image multilevel thresholding, testing three objective functions on ten benchmark images. Their results confirmed MFA's superiority over standard FA. Naidu and Kumar [16] integrated FA with fuzzy entropy maximization, comparing it against differential evolution (DE), PSO, and bat algorithm (BA); FA achieved higher fitness values. Vennila and Thamizhmaran [17] applied FA to Otsu's method for gray-scale images, reporting improved peak-signal-to-noise ratio (PSNR) and CPU efficiency.

Entropy-based approaches: Manic et al. [18] combined FA with Kapur and Tsallis entropy for multilevel thresholding. They observed that Tsallis entropy yields better segmentation quality, while Kapur entropy converges faster. Sri Madhava Raja et al. [19] introduced Brownian distribution-guided FA to refine Otsu-based thresholding, outperforming Lévy flight and random operator variants in PSNR and structural similarity.

Avoiding premature convergence: Chen et al. [20] addressed the local optima trap by incorporating Cauchy mutation and a neighborhood search into FA. Their improved FA demonstrated better multilevel segmentation than PSO, DE, and standard FA. Similarly, Sharma et al. [21] proposed an

Table 1. Representative FA-based multilevel thresholding methods.

Authors	Objective Function	Entropy / Metric	Key Performance Finding	Limitations
He & Huang [15]	Three objective functions (Otsu, Kapur, minimum cross-entropy)	–	MFA outperforms standard FA on color images	High computational cost for >5 thresholds; parameter sensitivity
Naidu & Kumar [16]	Fuzzy entropy	Fuzzy entropy	FA achieves higher fitness than DE, PSO, BA	Limited validation on medical images; tested only on natural images
Vennila & Thamizhmaran [17]	Otsu's between-class variance	–	Better PSNR and CPU time for grayscale images	No comparison with modern metaheuristics (e.g., whale, grey wolf)
Manic et al. [18]	Kapur / Tsallis entropy	Entropy maximization	Tsallis = better quality; Kapur = faster	Tsallis entropy increases runtime significantly for >4 thresholds
Sri Madhava Raja et al. [19]	Otsu with Brownian distribution	–	Higher PSNR and structural similarity	Brownian motion parameters require manual tuning per image type
Chen et al. [20]	Otsu with Cauchy mutation & neighborhood search	–	Outperforms PSO, DE, standard FA	Neighborhood search radius is fixed; adaptive radius not explored
Pare et al. [24]	Modified fuzzy entropy + Lévy flight	Fuzzy entropy	Superior to Kapur entropy-based methods	Lévy flight increases randomness, causing inconsistent convergence
Wang & Li [25]	Fuzzy adaptive control	Fuzzy entropy	Best among heuristics on satellite images	Validated on satellite images only; applicability to medical imaging not demonstrated
Wang et al. [27]	2D reciprocal cross-entropy	Cross-entropy	Effective for COVID-19 CT lung segmentation	Requires pre-processing (Bezier curves); not fully automated

opposition-based improved FA incorporating Kapur entropy and variance modules for multilevel image segmentation, demonstrating superior ability to escape local optima and achieving improved segmentation quality on standard image segmentation benchmarks compared with standard FA variants.

Clustering integration: Yang et al. [22] combined FA with k-means for multi-threshold segmentation, using FA to determine initial cluster centers and overcoming k-means' sensitivity to initialization. Dhal et al. [23] proposed a randomly attracted rough FA for histogram-based fuzzy clustering, replacing pixel-based clustering with gray-level histogram analysis to reduce noise and computation time.

Fuzzy and adaptive control: Pare et al. [24] modified fuzzy entropy with Lévy flight FA for color image thresholding, showing superior performance over Kapur entropy. Wang and Li [25] designed a fuzzy adaptive FA where a fuzzy logic controller dynamically adjusts parameters; tests on satellite remote sensing images confirmed better optimization than other heuristics. Wang and Song [26] later used minimum cross-entropy with adaptive FA, further improving convergence speed.

COVID-19 lung segmentation: Wang et al. [27] applied two-dimensional reciprocal cross-entropy multithresholding combined with an improved FA to segment lung parenchyma from COVID-19 CT images, addressing ground-glass opacity challenges. Their method applied Freeman chain code for boundary tracing and Bezier curve fitting to smooth defective boundary segments. Table 1 provides a comparative overview of representative FA-based multilevel thresholding methods.

2.3 Firefly Algorithm for Medical Image Segmentation by Disease Domain

The direct application of FA to medical imaging, especially MRI, CT, and X-ray, has grown rapidly, driven by the need for accurate, automated diagnosis. This subsection is organized by disease domain, revealing the dependencies between methodological advances and clinical challenges.

2.3.1 Brain Tumor and Neurological Disorder Segmentation

MRI-based brain segmentation is challenging due to tissue heterogeneity, tumor variability, and anatomical complexity. Alomoush et al. [28] combined FA with fuzzy c-means (FCM) to find optimal clustering centers, outperforming random FCM. Kapoor and Agarwal [29] improved k-means using PSO and compared it with FA, showing FA's robustness. Ghosh et al. [57] introduced chaotic variables into FA-FCM to enhance global search for brain tissue segmentation, reducing over-segmentation and under-segmentation. Gudise et al. [30] proposed a chaotic enhanced FA integrated with FCM (CEFAFCM) to address intensity inhomogeneity and noise in brain tissue segmentation, achieving improved delineation of white matter, grey matter, and cerebrospinal fluid. Gupta and Meshram [31] used FA with a median filter for tumor/non-tumor classification, achieving high precision. Karnan [32] designed an intelligent hybrid of FA, bee colony optimization, and Markov random fields for MRI tumor segmentation.

Feature selection and registration: Jothi [33] developed a tolerance rough set–firefly-based quick reduct for supervised feature selection from MRI images, improving tumor classification accuracy. Narayana [34] optimized affine transformation parameters for CT-MRI registration using FA, enabling multimodal image alignment; in a similar vein, Xiaogang et al. [35] coupled FA with Powell's method for multi-resolution medical image registration. Fathi-Sanghari and Behzadfar [36] used an enclosing frame to locate brain tumors and FA to determine the starting point, increasing speed and accuracy in glioblastoma cases. Alsmadi [37] dynamically clustered multiple sclerosis lesions with FA-FCM, enhancing conventional FCM performance.

Semi-automatic detection: Deshpande and Honade [38] presented a semi-automatic tumor diagnosis system where only initial sample points require user interaction; subsequent processing uses FA for segmentation, reducing manual effort.

2.3.2 *Lung and COVID-19 Image Analysis*

Beyond the thresholding work of Wang et al. [27], other studies have focused on lung disease classification. Dhiman and Kumar [39] designed a PSO-firefly hybrid optimizer combined with a CNN for lung disease classification using chest X-ray images, demonstrating improved convergence. Kadry et al. [40] optimized both deep and handcrafted features with FA for chest X-ray investigation, showing that hybrid feature sets enhance generalization. Khan et al. [41] recognized COVID-19 cases from chest CT images by combining deep learning with entropy-controlled firefly optimization and parallel feature fusion, underscoring FA's role in pandemic-era diagnostic pipelines. Pearly and Karthik [42] proposed HybridNet-X, a hybrid deep learning network with a fuzzy-enhanced FA for lung disorder diagnosis, addressing class imbalance and noisy data.

2.3.3 *Breast Cancer Detection and Segmentation*

Early detection of breast cancer from mammography, ultrasound, and MRI is critical. Kaushal et al. [43] first proposed an FA-based segmentation technique for breast cancer medical images, achieving higher accuracy than conventional thresholding. Sasikala et al. [44] improved breast cancer detection by fusing bimodal sonographic features through a binary firefly algorithm, achieving enhanced sensitivity and specificity over single-modality approaches. Ogundokun et al. [45] introduced FIRE-Breast, an FA-driven EfficientNetB0 CNN model that balances computational efficiency and detection accuracy. Demir and Karci [46] applied FA with a golden ratio method for clustering on breast cancer data, demonstrating improved cluster quality over standard clustering approaches. Sadeghipour et al. [47] combined FA with an adaptive fuzzy neural network for breast cancer detection. Filipczuk et al. [48] applied FA to automatically detect nuclei in cytological images of biopsy materials. Mazen et al. [49] hybridized a genetic algorithm and FA to train neural networks for breast cancer diagnosis, achieving lower mean squared error.

2.3.4 *Cardiovascular Disease and Heart Rate Monitoring*

Mamun and Alouani [50] used FA to reduce feature dimensionality before applying a 1D CNN on ECG signals for heart attack diagnosis. Mülayim and Alaybeyoğlu [51] built an expert system for heart disease diagnosis based on FA, achieving high early detection rates. Long et al. [52] combined rough set attribute reduction with chaotic FA and interval fuzzy logic, noting limitations when attribute numbers are large. Deepika and Balaji [53] integrated grey wolf and FA with differential evolution for feature selection, followed by weighted ANN for heart disease prediction. Beyond traditional ECG analysis and structured clinical data, FA has been extended to dynamic physiological signal processing. Saini et al. [54] employed FA in conjunction with a deep neural network (DNN) for contactless heart rate measurement from facial videos, where FA optimized the selection of photoplethysmography (PPG) signal sub-bands to mitigate motion artifacts. The theoretical foundations underpinning these applications trace back to Yang's seminal work [12], which established the distance-based attraction and stochastic movement rules of FA that make it well suited to the multi-modal optimization landscapes encountered in cardiovascular signal processing. Building on this foundation, Srikanth et al. [55] demonstrated that an improved FA applied to multi-modal image fusion effectively integrates complementary information from different imaging sequences, a principle directly transferable to fusing cardiac MRI and CT data for comprehensive cardiovascular assessment. Rajinikanth et al. [56] further showed that FA combined with Tsallis entropy and Markov random fields achieves accurate lesion boundary delineation in brain MRI, illustrating the algorithm's capacity to handle complex intensity distributions analogous to those found in cardiac MRI segmentation. Ghosh et al. [57] demonstrated that chaotic FA integrated with fuzzy C-means effectively segments heterogeneous MRI brain tissues, underscoring the value of chaotic search strategies for avoiding local optima in multi-class segmentation tasks relevant to cardiovascular imaging. Additionally, Gadekallu et al. [58] showed that combining PCA-based feature reduction with an FA-optimized deep learning model enables early detection of diabetic retinopathy, exemplifying a lightweight hybrid strategy applicable to automated screening of cardiovascular comorbidities such as diabetic cardiomyopathy.

These FA-based approaches, spanning cardiovascular signal processing, brain MRI segmentation, and retinal screening, collectively affirm that FA's ability to balance exploration and exploitation is particularly beneficial for multi-modal medical imaging applications, which often involve multi-modal data (ECG, imaging, tabular clinical data) and conflicting optimization objectives (e.g., maximizing sensitivity while maintaining acceptable specificity). However, challenges remain in standardizing validation protocols across different patient populations and imaging modalities, and in developing real-time FA implementations suitable for wearable or point-of-care devices. Future research directions include federated FA frameworks for privacy-preserving multi-institutional CVD data analysis and the integration of FA with explainable AI to enhance clinical interpretability of cardiovascular risk predictions.

2.3.5 *Tuberculosis, Cholesterol, and Other Applications*

Automated tuberculosis screening has long relied on image-processing of Ziehl-Neelsen stained smears to identify *Mycobacterium tuberculosis* [60], and earlier work compared clustering and thresholding algorithms for bacilli segmentation [61], establishing the baseline against which metaheuristic methods are measured. Ayas et al. [59] performed bi-level segmentation of tuberculosis bacilli in microscopic images using FA optimized by single-level entropy, outperforming PSO and cuckoo search, and subsequently generalized this into a broader meta-heuristic bi-level segmentation framework for bacilli detection [62]. Anjarsari et al. [63] combined a radial basis function neural network with the firefly algorithm and simulated annealing to detect high cholesterol levels from iris images, achieving competitive classification accuracy. Kumar et al. [64] applied FA-FCM to segment lung tumors in CT scans, improving Dice and Jaccard indices. Table 2 summarizes key FA-based medical image segmentation studies by disease type, highlighting the hybrid approach and reported performance.

2.4 Hybridization with Deep Learning and Other Meta-heuristics

Recent trends show a shift from pure FA to hybrid models that leverage deep learning architectures and multi-algorithm synergy.

Deep learning integration: Bacanin et al. [65] optimized a CNN using FA for glioma brain tumor grade classification from MRI, outperforming standalone CNNs. Li et al. [66] employed parallel CNNs with firefly optimization for brain tumor type classification, reporting high accuracy across multiple categories. Nagarathinam et al. [67] proposed a multi-objective image fusion method using improved weighted quantum firefly optimization combined with StyleGAN-MAE-SwinViT for brain tumor detection, showcasing quantum-inspired variants. Gadde et al. [68] analyzed a GAN-driven convolutional model enhanced by FA for melanoma classification, reducing computational cost without sacrificing accuracy. Priyadarshini [69] designed an FA-optimized CNN–BiLSTM model for bone cancer and marrow cell abnormality detection. Garg and Jindal [70] integrated K-means clustering with an optimized firefly algorithm for skin lesion segmentation, demonstrating improved boundary delineation compared with standard K-means initialization.

Hybrid meta-heuristics: Rahkar Farshi and Ardabili [71] introduced a hybrid FA-PSO for multilevel image thresholding, achieving superior accuracy and speed over each algorithm alone. Tair et al. [72] developed a chaotic oppositional whale optimization algorithm with firefly search for medical diagnostics, leveraging chaotic maps for exploration. Bacanin et al. [79] modified FA to improve extreme learning machine for medical benchmark datasets. Özdaş et al. [73] applied FA to feature selection in optical coherence

Table 2. FA-based medical image segmentation by disease domain.

Disease / Application	Authors	Hybrid / Technique	Key Performance Metric	Limitations
Brain tumor (MRI)	Alomoush et al. [28]	FA + fuzzy c-means	More effective than random FCM	Tested only on synthetic MRI; real-clinical data missing
Brain tumor (MRI)	Kapoor & Agarwal [29]	FA + PSO + k-means	Robust segmentation	High computational overhead due to dual optimization
Brain tumor (MRI)	Gudise et al. [30]	Chaotic FA-FCM	Reduced noise and intensity inhomogeneity in brain tissue segmentation	Evaluated only on standard benchmarks; clinical validation absent
Brain tumor (MRI)	Gupta & Meshram [31]	FA + median filter	High precision tumor detection	Only binary tumor classification; no multi-class grading
Brain tumor (MRI)	Li et al. [66]	Parallel CNNs + FA	High accuracy across tumor types	Requires GPU cluster; not deployable on standard hardware
Brain tumor (MRI)	Nagarathinam et al. [67]	Quantum FA + StyleGAN	Multi-objective fusion	Quantum variant is theoretical; no physical quantum implementation
Lung disease (X-ray)	Dhiman & Kumar [39]	PSO-FA + CNN	Improved convergence	Requires tuning of multiple hyperparameters; tuning is non-trivial
Lung disorder (X-ray)	Pearly & Karthik [42]	Fuzzy-enhanced FA + CNN	Handles class imbalance	Fuzzy membership functions require expert knowledge
Breast cancer	Kaushal et al. [43]	FA-based segmentation	Higher accuracy than thresholding	Tested only on mammography; not validated on ultrasound or MRI
Breast cancer (US)	Sasikala et al. [44]	Binary FA + bimodal feature fusion	Improved sensitivity over single-modality detection	Validated on ultrasound only; MRI and mammography not included
Breast cancer	Ogundokun et al. [45]	FA + EfficientNetB0	Computational efficiency	Accuracy trade-off: 2% lower than larger CNNs
Heart disease	Mülayim & Alaybeyoğlu [51]	FA expert system	High early detection rate	Rule-based system fails on atypical patient presentations
Heart disease	Deepika & Balaji [53]	Grey wolf + FA + ANN	Effective feature selection	Three-algorithm ensemble suffers from slow convergence
Tuberculosis	Ayas et al. [59]	FA + entropy maximization	Outperforms PSO, cuckoo	Bi-level only; not extended to multi-class bacilli types
High cholesterol (iris)	Anjarsari et al. [63]	FA + RBF + simulated annealing	Competitive classification accuracy	Validated on iris images only; limited to cholesterol screening
Lung tumor (CT)	Kumar et al. [64]	FA-FCM	Improved Dice & Jaccard	Manual seed initialization required; not fully automatic

tomography (OCT) retinal images, using binary FA to identify discriminative feature subsets for classifying diabetic macular oedema, choroidal neovascularization, and drusen from healthy retinas. Their results demonstrated that FA-driven feature selection substantially reduces dimensionality while maintaining or improving classification accuracy, illustrating FA's natural suitability for channel and feature selection tasks in medical image segmentation networks.

Clustering and segmentation: Thomas and Kumar [74] coupled fuzzy c-means with FA for segmentation of neurodisorder MRIs, effectively handling noise and inhomogeneities. Bali and Singh [75] unified FA with density-based spatial clustering (DBSCAN) for medical image segmentation, accommodating arbitrary-shaped clusters.

Retinal disease detection: Prabhakar et al. [76] proposed an exponential gannet firefly optimization algorithm combined with deep learning for automated diabetic retinopathy detection, achieving high sensitivity in identifying retinal lesion severity grades. Table 3 categorizes hybrid FA models by their integration partner (deep learning / meta-heuristic / clustering) and highlights performance gains.

2.5 Systematic Reviews and Future Outlook

Recent review studies have examined the broader role of metaheuristic optimization in biomedical image processing. Kowdiki et al. [77] systematically reviewed the advantages and challenges of metaheuristic algorithms across a wide range

Table 3. Hybrid firefly algorithm models and their performance benefits.

Hybridization Type	Authors	Partner Method	Performance Gain	Limitations
FA + Deep Learning	Bacanin et al. [65]	CNN	Better glioma grade classification	Single MRI sequence used; multi-modal data not tested
FA + Deep Learning	Li et al. [66]	Parallel CNNs	High accuracy across tumor types	High memory requirements; unsuitable for edge devices
FA + Deep Learning	Ogundokun et al. [45]	EfficientNetB0	Reduced computational cost	Accuracy drop on small tumors (<5 mm)
FA + Deep Learning	Priyadarshini [69]	CNN-BiLSTM	Effective bone cancer detection	Increased inference time
FA + Deep Learning	Saini et al. [54]	DNN	Improved heart rate measurement	Subject motion causes performance degradation
FA + Meta-heuristic	Rahkar Farshi & Ardabili [71]	PSO	Superior thresholding speed & accuracy	Premature convergence remains for highly multimodal images
FA + Meta-heuristic	Tair et al. [72]	Whale optimization	Enhanced exploration via chaos	Increased computational complexity
FA + Meta-heuristic	Deepika & Balaji [53]	Grey wolf + DE	Effective feature selection	Three-algorithm hybrid is hard to reproduce
FA + Clustering	Thomas & Kumar [74]	Fuzzy c-means	Noise-robust MRI segmentation	FCM initialization still affects final segmentation
FA + Clustering	Bali & Singh [75]	DBSCAN	Handles arbitrary-shaped clusters	DBSCAN parameters (eps, minPts) require manual tuning

Table 4. Foundational modifications of the firefly algorithm.

Variant	Authors	Key Modification	Primary Advantage
FA[a]	Rahebi & Hardalaç [7]	Pixel-intensity-to-brightness mapping for retinal optic disc detection in fundus images	Demonstrates FA applicability to binary medical image segmentation
CFA	Fister et al. [8]	Chaotic maps for population initialization	Enhances diversity and avoids local optima
FA[b]	Senthilnath et al. [9]	Systematic clustering performance evaluation on UCI benchmark datasets	Establishes FA as a competitive population-based clustering optimizer
MFA	Fister Jr. et al. [10]	Memetic approach with local search	Improves exploitation and convergence speed
HFA	Kora & Krishna [11]	Hybridization with PSO	Balances exploration and exploitation

[a]Standard FA applied directly to medical image segmentation tasks.

[b]Standard FA evaluated as a clustering optimizer on benchmark datasets.

of biomedical image-processing applications, highlighting their potential for addressing complex optimization problems. However, existing reviews generally consider multiple metaheuristic algorithms and diverse biomedical imaging tasks rather than focusing specifically on FA and its development in medical image segmentation.

In contrast, the present review provides a focused synthesis of FA-based methods, tracing their progression from conventional thresholding and clustering approaches to adaptive variants and hybrid deep learning frameworks. It further examines their applications across medical imaging domains, compares reported strengths and limitations with other optimization approaches, and identifies remaining challenges related to computational efficiency, parameter adaptation, standardized evaluation, clinical validation, and three-dimensional and multimodal imaging. This focused perspective complements broader reviews of metaheuristic optimization and provides a more specific assessment of the current role and future potential of FA in medical image segmentation.

3 Review Methodology

To ensure transparency and reproducibility, this systematic review followed a structured search and selection process.

Search strategy: The following electronic databases were searched from January 2010 to June 2026:

Scopus, PubMed, IEEE Xplore, Web of Science, and Google Scholar. The search query combined the terms: ("firefly algorithm" OR "FA") AND ("image segmentation" OR "medical image segmentation" OR "multilevel thresholding") AND ("MRI" OR "CT" OR "X-ray" OR "breast cancer" OR "brain tumor" OR "lung" OR "COVID-19").

Inclusion criteria:

- Peer-reviewed journal articles or full-length conference papers.
- Studies applying the firefly algorithm (including hybrid variants) to medical image segmentation, thresholding, or classification.
- Papers written in English.
- Publication years 2010–2026, up to the search date.

Exclusion criteria:

- Theoretical FA developments without medical image application.
- Non-medical images (e.g., natural or satellite images only).
- Duplicate publications, editorials, or short abstracts.

Selection process: The initial search yielded 412 records. After removing duplicates (n=89), 323 titles and abstracts were screened. Full-text retrieval was performed for 112 articles, of which 78 met all inclusion criteria and are included in this review. A PRISMA-style flow diagram is available from the corresponding author upon request.

4 Discussion

This systematic review synthesizes evidence from 78 studies on FA-based medical image segmentation. The following subsections provide a detailed analysis of FA's benefits relative to compared studies, organized by algorithmic category.

4.1 Key Benefits of Firefly Algorithm Over Compared Methods

Benefit 1 – Parameter efficiency: FA requires only three main parameters (randomization parameter α, initial attractiveness β_0, and light absorption coefficient γ). In contrast, PSO requires inertia weight, two acceleration coefficients, and velocity clamping; DE requires scaling factor and crossover rate; and BA requires loudness, pulse rate, and frequency parameters. This simplicity makes FA easier to tune for medical practitioners without deep optimization expertise.

Benefit 2 – Natural multilevel capability: The attraction mechanism in FA directly supports multilevel thresholding. When segmenting a brain MRI into gray matter, white matter, CSF, and tumor, FA simultaneously optimizes multiple thresholds without additional encoding.

Benefit 3 – Hybrid readiness: As shown in Table 3, FA integrates seamlessly with fuzzy logic [25], clustering [28, 74], and deep learning [65, 66]. FA can serve as an external optimization mechanism for selecting hyperparameters or features; however, its ability to reduce overfitting depends on the specific optimization objective and validation strategy.

Benefit 4 – Escape from local optima: Chaotic FA variants [6, 57] and Lévy flight modifications [24] demonstrate superior ability to escape local optima compared to standard PSO. In segmenting heterogeneous tumors with multiple intensity peaks, this property has been reported to contribute to improved segmentation quality in the reviewed studies [57].

4.2 Comparison Against Standard Thresholding (Otsu, Kapur, Entropy)

Several reviewed studies report FA outperforming classical thresholding in segmentation accuracy [43] and Dice coefficient [78, 79], with the magnitude of improvement varying by imaging modality and threshold count. However, classical methods remain superior when speed is critical: Otsu thresholds a 512×512 image within milliseconds, while FA-based methods typically require seconds to converge, as reported in the reviewed studies [17, 19]. The trade-off is justified for offline diagnosis but not for real-time applications.

4.3 Comparison Against Other Metaheuristics (PSO, DE, BA, GWO)

As summarized in Table 5, the reviewed studies report that FA provides competitive exploration capability and a relatively straightforward parameter structure compared with PSO, DE, BA, GWO, and cuckoo search. FA frequently achieved comparable or superior segmentation performance in multilevel thresholding and clustering tasks [16, 20, 23, 28]. However, the relative advantage of FA over these algorithms is not universal: performance depends strongly on the dataset, objective function, parameter configuration,

Table 5. Reported comparative characteristics of FA and selected metaheuristics in the reviewed studies.

Compared Method	Reported FA Strengths	Reported FA Limitations	Evidence
Particle Swarm Optimization (PSO)	Competitive exploration ability and relatively simple position-update mechanism; favorable performance was reported in several multilevel thresholding tasks	Convergence speed and stability depend on parameter settings and problem characteristics	Naidu & Kumar [16]; Chen et al. [20]
Differential Evolution (DE)	Competitive global-search capability and effective exploration of complex threshold spaces in the reviewed applications	Stochastic behavior may lead to variability across independent runs, requiring repeated experiments for reliable evaluation	Naidu & Kumar [16]; Chen et al. [20]
Bat Algorithm (BA)	Competitive segmentation performance with a comparatively straightforward attraction-based search mechanism	Performance may deteriorate when exploration and exploitation are not appropriately balanced	Naidu & Kumar [16]
Grey Wolf Optimizer (GWO)	FA provides a flexible population-based search framework that can be readily combined with other optimization and learning methods	No consistent superiority of FA over GWO can be established because comparative results depend strongly on datasets, objectives, and parameter settings	Deepika & Balaji [53]
Cuckoo Search (CS)	Competitive optimization performance was reported for medical image segmentation and threshold-selection tasks	Computational efficiency and convergence behavior vary with population size, stopping criteria, and problem complexity	Ayas et al. [59]

and stopping criteria. No definitive ranking can therefore be established from the available evidence; FA should be regarded as one effective option within a broader portfolio of metaheuristic methods.

4.4 Comparison Against Pure Deep Learning (CNN, GAN, Transformer)

In the reviewed studies, FA-hybridized CNNs [65, 66] consistently outperformed standalone CNNs in both accuracy and Dice coefficient, with the primary benefit attributed to FA's ability to optimize hyperparameters more effectively than grid search or random search. However, FA-CNN hybrids generally require longer training time than pure CNNs due to the additional optimization loop, which may limit iterative experimentation in practice.

4.5 Why FA Performs Well Specifically for Medical Imaging

Medical images share three properties that align with FA's strengths:

1. *Multi-modal intensity distributions:* Tumors, lesions, and organs exhibit overlapping intensity ranges. FA's distance-based attraction naturally handles overlapping clusters without assuming Gaussian separability.
2. *High dimensionality with local structure:* A 3D MRI volume contains millions of voxels but strong local correlations. FA's population-based search explores the space efficiently without exhaustive enumeration.
3. *Small training datasets:* Medical image segmentation often relies on relatively small annotated datasets. FA can support feature selection and hyperparameter optimization in such settings, although its effectiveness in reducing overfitting depends on the specific model and validation strategy.

Overall, the reviewed studies indicate that FA-based methods can provide competitive segmentation and optimization performance compared with other metaheuristics, including PSO, DE, BA, GWO, and CS. However, the relative performance of these algorithms varies considerably with the dataset, objective function, dimensionality, parameter configuration, stopping criteria, and experimental protocol. Consequently, the available evidence is insufficient to establish a universal ranking of FA or to conclude that it consistently outperforms alternative metaheuristics. As summarized in Table 5, FA should instead be regarded as a flexible population-based optimization framework whose strengths and limitations are application-dependent. Algorithm selection should therefore consider the specific requirements of the medical imaging task, including segmentation accuracy, computational cost, convergence behavior, robustness, and scalability.

4.6 Other Domains Where FA Performs Significantly

Although this review focuses on medical imaging, the firefly algorithm has demonstrated strong performance in several non-medical domains. Based on comparative studies from the broader literature (not included in our 78 papers), FA excels in the following areas:

1. Wireless sensor network (WSN) localization: FA has been reported to reduce localization error compared with PSO and DE when optimizing anchor node placement, leveraging its ability to handle non-line-of-sight constraints, as discussed in the broader FA literature [6].

2. Retinal image analysis: FA has been applied to optic disc detection in fundus retinal images [7], demonstrating its effectiveness in binary medical image segmentation tasks and achieving high accuracy across multiple public retinal imaging databases.

3. Clustering and data analysis: FA has demonstrated strong performance as a clustering optimizer [9], outperforming or matching PSO and ABC across benchmark datasets; this clustering capability underpins FA-FCM and FA-K-means approaches widely used in medical image segmentation.

4. Image enhancement: FA has been applied to optimize contrast enhancement parameters for medical images, yielding improved PSNR compared with standard histogram equalization methods [80].

5. Feature selection in high-dimensional data: FA-based feature selection has demonstrated substantial dimensionality reduction while maintaining classification accuracy in high-dimensional medical imaging tasks [33]; similar principles are considered generalizable to genomic feature selection, though dedicated validation on microarray datasets is required.

6. Renewable energy forecasting: FA has been explored as an optimizer for neural network training in wind and solar power prediction tasks, with the potential for improved convergence over standard backpropagation discussed in the broader FA literature [6].

Key insight: FA is most effective when the optimization problem involves (a) multiple local optima, (b) expensive fitness evaluations, (c) small to medium dimensionality, and (d) the ability to parallelize fitness calculations. Medical image segmentation satisfies all four conditions.

5 Challenges and Future Directions

Despite the promising results, several challenges remain open for future research.

5.1 Computational Complexity for Real-Time Use

Most FA-based segmentations require seconds to minutes per image, which is not suitable for intraoperative or emergency settings. Future work should explore GPU-accelerated FA, parallel firefly swarms, and lightweight hybrid models (e.g., FA for feature selection + shallow CNN) to reduce latency.

5.2 Parameter Adaptation and Self-Tuning

Fixed parameters limit generalization across different imaging modalities. Adaptive FA variants such as fuzzy-controlled [25] or chaotic [8] have shown promise but require more extensive benchmarking. Self-adaptive FA that learns α, β, γ online using reinforcement learning is an underexplored direction.

5.3 Lack of Standardized Benchmarks

Many studies use private datasets or different evaluation metrics (accuracy, Dice, Jaccard, PSNR, SSIM), making direct comparisons difficult. The community would benefit from standardized medical image segmentation benchmarks (e.g., BraTS for brain tumors, LIDC for lung nodules, ISIC for skin lesions) with predefined training/test splits and evaluation protocols.

5.4 Deep Integration with Deep Learning

Current hybrid models often use FA only for threshold optimization or CNN hyperparameter tuning. More advanced integrations include:

- FA for neural architecture search (NAS) to design segmentation networks.
- FA-driven data augmentation to improve generalization.
- End-to-end differentiable FA layers for joint optimization.

5.5 Explainability for Clinical Adoption

Clinicians are reluctant to adopt "black-box" algorithms. Visualising why FA selects certain thresholds or cluster centres – e.g., through saliency maps or attention mechanisms – would increase trust and adoption.

5.6 Extension to 3D and Multi-Modal Images

Almost all reviewed studies operate on 2D slices. However, medical imaging is inherently 3D (CT, MRI volumes) or multi-modal (PET-CT, MRI-CT). Developing 3D FA with volumetric attraction rules and multi-modal FA that fuses information from different sequences is a high-impact research avenue.

6 Limitations of This Review

This review has several limitations that should be acknowledged:

- Language bias: Only English-language publications were included, potentially omitting relevant work in other languages.
- Publication bias: Studies reporting positive results (i.e., FA outperforms others) are more likely to be published, which may overstate FA's relative effectiveness.
- No quantitative meta-analysis: Due to heterogeneity in evaluation metrics, datasets, and experimental setups, we could not perform a formal meta-analysis to compute pooled effect sizes.
- Focus solely on FA: While FA is the main subject, the lack of systematic comparison with other state-of-the-art metaheuristics (e.g., grey wolf optimizer, whale algorithm) limits the generalisability of our conclusions.
- Time lag: Some recent preprints or 2026 publications may have been missed despite our comprehensive search.

7 Conclusion

This systematic review examined the development and application of the firefly algorithm (FA) in medical image segmentation and related image-analysis tasks from 2010 to 2026. The reviewed literature demonstrates the evolution of FA from conventional multilevel thresholding and entropy-based optimization to clustering-assisted, adaptive, chaotic, and deep-learning-based hybrid approaches. FA has been applied across multiple medical imaging modalities and clinical domains, including brain MRI, lung CT and chest X-ray imaging, breast imaging, and microscopic image analysis.

The available evidence indicates that FA provides a flexible population-based optimization framework for selecting segmentation thresholds, optimizing clustering centers, selecting informative features, and tuning model hyperparameters. In individual comparative studies, FA-based methods frequently achieved competitive performance relative to conventional thresholding techniques and other metaheuristic approaches. However, the substantial heterogeneity in datasets, imaging modalities, objective functions, evaluation metrics, parameter settings, and experimental protocols prevents a definitive conclusion that FA is universally superior to alternative optimization methods. Consequently, reported performance improvements should be interpreted within the specific experimental conditions of each study.

Several challenges continue to limit the broader application of FA in medical image segmentation. These include computational overhead, sensitivity to parameter configuration, inconsistent benchmarking practices, limited external and prospective clinical validation, and the predominance of two-dimensional and retrospectively evaluated datasets. Moreover, although recent studies increasingly combine FA with deep learning, the clinical benefit and computational efficiency of these hybrid approaches require more rigorous and standardized evaluation.

Future research should therefore emphasize self-adaptive FA variants, parallel and GPU-accelerated implementations, standardized evaluation on publicly available and multicenter datasets, and systematic comparisons with contemporary metaheuristic and learning-based optimization methods. Further investigation of FA for three-dimensional and multimodal medical imaging, neural architecture and hyperparameter optimization, and explainable artificial intelligence may also improve its practical relevance. Overall, FA remains a promising optimization framework for medical image segmentation, but its transition from experimental applications to clinically useful systems will require reproducible benchmarking, robust external validation, computational optimization, and closer integration between algorithm development and clinical requirements.

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