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Metaheuristics role in image processing and computer vision applications: a comprehensive review

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Abstract

Meta-Heuristic (MH) algorithms have gained prominence in computer vision and image processing due to their efficacy in solving complicated, high-dimensional optimization challenges. This review study thoroughly evaluates the effectiveness of MH approaches in classification, segmentation, and registration applications. The compilation consists of 84 studies: 39 in classification (47%), 23 in segmentation (27%), and 22 in registration (26%). The examination of these investigations reveals that the implementation of MH algorithms in hybrid models utilizing deep learning offers notable benefits in enhancing accuracy, circumventing local optima, and decreasing computational expenses. This research also examines limitations, including the substantial computing demands in real-time applications and the challenges related to data processing. The paper highlights the significant potential of MH algorithms in healthcare, agriculture, security, and remote sensing, along with their role in addressing current challenges. Renowned international publishers, such as Elsevier, Springer, IEEE, and MDPI, have disseminated relevant contemporary research. The acceptance percentages for these publications are 42%, 24%, 12%, and 11%, respectively. Publications from alternative publishers account for the remaining 11%. Also, the source codes and associated datasets of the 84 studies examined in this paper are available as open source at this link: https://github.com/mfaruk-sahin/Metaheuristics-in-Image-Processing-and-Computer-Vision.git

Keywords Meta-Heuristics · Image processing · Computer vision · Artificial intelligence

1 Introduction

The aim of image processing is to extract meaningful insights from the examination and/or manipulation of digital images. Conversely, the aim of computer vision is to develop devices capable of perceiving and understanding the environment via images [1–3]. Therefore, image processing is the process of transforming digital images through the use of stages such as normalization, feature extraction, and matching, which nevertheless generate either sensor or camera images [4]. In a variety of disciplines, including military, agriculture, remote sensing, and medicine, image processing is generally performed to enhance the meaning of the images or reduce computational consumption [5–7]. Computer vision deals with identifying features of color, shape, size, and texture of images [8]. Image processing techniques have been used to advance this process in image classification, object detection, semantic segmentation, and translating digital data into intelligible information [9–12]. Particularly, traditional image processing approaches have struggled to understand real-world images due to their complexity. So, employ deep learning approaches for image-based applications [13–15]. Consequently, substantial progress in image processing and computer vision has been realized through the application of Deep Neural Networks (DNNs), which are adept at modeling complex non-linear data patterns [16–20]. These advancements have significantly improved the efficiency of widely used methods such as image classification, segmentation, and registration within their sub-application domains through the integration of DNNs. Consequently, its application has proliferated across industries [21], including healthcare [22], security

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[23], autonomous systems [24], space [25], and numerous other domains [26–28]. Nonetheless, despite these advantages, DNNs encounter specific drawbacks, such as difficulties in hyperparameter optimization, vulnerability to local minima, challenges in feature selection, elevated computational expenses, and additional issues [29–31]. Meta-Heuristic (MH) approaches have been increasingly employed to address these issues and enhance performance in DNN and image-based applications [32, 33].

The MH methods are high-level strategies that direct underlying intuitive methods to robustly explore and efficiently exploit difficult search spaces [34]. These methods are valuable in solving optimization problems that classical mathematical methods struggle when faced with non-linearity, high dimensionality, or multiple local optima [35, 36]. While optimization methods based on gradients use information from derivatives and can get locked in local optima, the MH methods develop methods free of derivatives and are better suited for classification problems with complex, non-convex, or multimodal search spaces [37, 38]. The processes of these algorithms mimic adaptive processes that can be seen in nature, like survival of the fittest, collective intelligence, and energy minimizing, in order to adaptively change their search strategy based on the nature of the optimization problem [39]. Many algorithms have specific processes that assume mutation, reproduction and self-adaptive processes that improve exploration and the exploitation phase. MH algorithms substantially alter image processing and computer vision methodologies, offering resilient and adaptable answers to diverse optimization challenges [40, 41]. These algorithms offer efficient solutions in high-dimensional, non-linear, and multi-modal search spaces, as encountered in several visual data processing jobs. They emulate the processes of evolution, swarming, and physics [42–44]. The fundamental problems that one usually faces in image processing and computer vision arise due to the large and complex nature of data sets and data structures. Additional issues that may contribute to this include the inability to appropriately adjust hyperparameters, elevated computing expenses, and the incapacity to precisely track target objects in dynamic settings. This may also result from local optima issues, degradation in denoising, and the characteristics of the problem space. Such issues can be addressed via adaptable and robust MH algorithms. Due to its hybrid nature, MH algorithms broaden the scope of applicability [45]. Previous work shows that using MH algorithms with DNN models, as well as other conventional methods such as linear and nonlinear programming, helps achieve better accuracies and efficiencies [46]. With the advancement of technology, the systems are required to be more efficient due to increasing volume of data and complexity of tasks [47]. In this regard, the significance of MH algorithms is increasing, and they are anticipated to propel progress across various technological fields, such as medical imaging, autonomous systems, agriculture, and security, among others. This will transpire as current computational challenges are addressed and advancements in these domains are facilitated.

1.1 Motivation and contribution

In image processing and computer vision research, several domain-specific problems exist [48]. Although conventional approaches are employed to tackle some difficulties, their limits and deficiencies remain evident [49]. Consequently, to delineate domain-specific limits and promote enhancements, MH-based methodologies have gained significant traction in contemporary literature [50–52]. The research predominantly emphasizes image categorization, segmentation, and registration. In this context, we may succinctly delineate the functioning and purpose of MH algorithms in the domain as follows.

- MH algorithms serve as crucial tools and drivers of innovation in the development of image processing and computer vision. Their ability to explore vast and complex solution domains enables progress in optimization challenges that traditional approaches struggle to address.
- MH algorithms provide flexible and scalable solutions in domains marked by high-dimensional data and processing constraints. These algorithms effectively tackle issues like feature selection, parameter optimization, and multi-objective optimization, ensuring precision and efficiency.
- MH algorithms use intrinsic capabilities in image analysis by employing innovative strategies for segmentation, noise reduction, and multimodal data integration. Their heuristic traits foster resilience in scenarios with incomplete or ambiguous information. Thus, it may function as the essential component for enabling image analysis.
- MH algorithms substantially augment the functionalities of vision systems across several applications, including medical imaging and autonomous systems. By refining feature extraction techniques and calibrating machine learning models, these technologies proficiently convert raw data into actionable insights, enhancing accuracy and efficiency.
- MH approaches seamlessly adapt to many application domains defined by dynamic conditions in image processing and computer vision, including object identification and motion tracking. Their flexibility and effectiveness make them indispensable in both scholarly research and practical uses.

This study aims to carefully compile and assess current literature. This review will delineate the problems and constraints in these domains and will rigorously assess the advantages and disadvantages of MH-based methodologies in this context. Given these insights, this study is expected to help researchers in formulating more effective solutions from a broad perspective in image processing and computer vision. The distinctive contributions of our research might be encapsulated as follows:

- Applications in image processing and computer vision are broadly classified into three primary domains: classification, segmentation, and registration.
- This research emphasizes the significance of MH algorithms in overcoming challenges faced in various fields, including medicine, agriculture, security, hyperspectral imaging, and other related areas.
- The strengths and limits of MH-based methodologies in image processing and computer vision are examined with the prevailing issues in the field.
- The study provides essential insights to academics by pinpointing critical obstacles in the sector and examining the efficacy of MH algorithms in resolving these challenges.

The rest of this paper is organized as follows. Section 2 presents the statistics of MH-based studies for image processing and computer vision applications from various perspectives. Sections 3 and 4 review and discuss the role of MH algorithms in various image-based applications. Finally, Sect. 5 concludes the paper, highlighting key conclusions and potential directions for future research.

2 Statistics of MH-based studies in image processing and computer vision applications

This section provides statistical data on the aggregated studies in image processing and computer vision. Figure 1 presents a summary graphic of these data. This study employs a systematic review methodology to provide a comprehensive analysis of the role of MH algorithms within the domains of image processing and computer vision. The selection of studies for this evaluation was based on specific inclusion and exclusion criteria. The inclusion requirements were that each study utilize MH methods, exhibit direct applicability to image processing or computer vision, and be published in prestigious academic publications or conferences. Research was predominantly obtained from esteemed publishers including Springer, Elsevier, and IEEE, with a preference for those offering open-source datasets and code repositories. The exclusion criteria were to remove studies that did not provide MH algorithms, exhibited inadequate empirical validation, or lacked direct thematic relevance to the research subject. This stringent selection method was instituted to guarantee the review's rigor and augment its contribution to academic literature. The compilation comprises 84 studies: 39 in classification (47%), 23 in segmentation (27%), and 22 in registration (26%). The research in these areas is also categorized by their application fields,

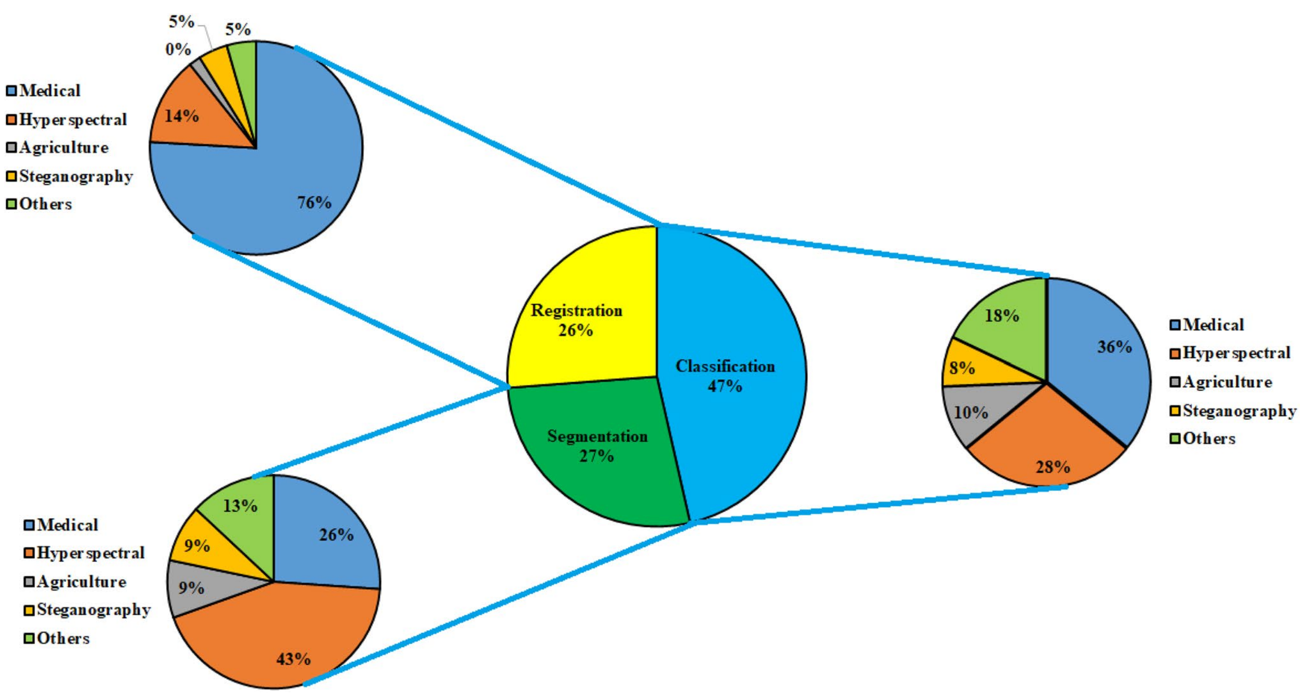

Fig. 1 Distribution of application areas of the reviewed studies

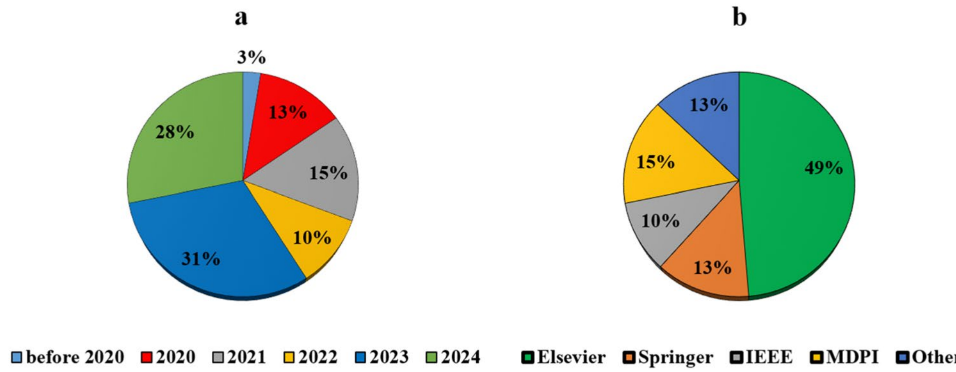

Fig. 2 Distribution of the reviewed studies in classification applications by (**a**) year and (**b**) publisher

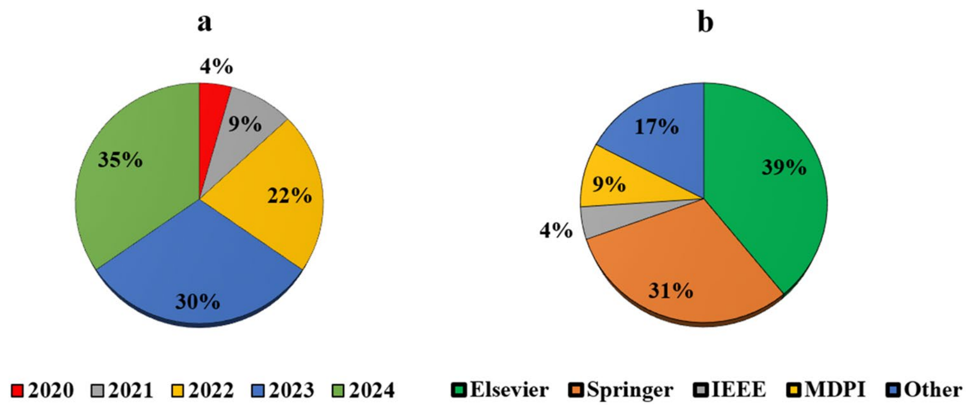

Fig. 3 Distribution of the reviewed studies in segmentation applications by (**a**) year and (**b**) publisher

such as medical, hyperspectral, agriculture, steganography, and others. The distribution of research among subfields within these application domains reveals that the classification domain is mostly utilized in medical imaging (36%), hyperspectral imaging (28%), agricultural (10%), steganography (8%), and other areas (18%). In the segmentation sector, hyperspectral imaging constitutes the largest share at 43%, succeeded by medical imaging at 26%, agricultural at 9%, steganography at 9%, and various other sectors at 13%. In registration applications, medical imaging comprises a significant 76%, whilst hyperspectral imaging accounts for 14%, steganography for 5%, and other domains for 5%. These distributions emphasize that the distinct demands and goals of various application areas influence the research focus within each category. Recent pertinent works have been disseminated by esteemed worldwide publications like Springer, Elsevier, IEEE, and MDPI. The study rates for these publications are 42%, 24%, 12%, and 11%, respectively. The remaining 11% comprises articles published by other publishers.

Figure 2 illustrates the distribution of the compiled research in classification applications by year and publisher. The allocation of studies by year is as follows: 13% in 2020, 15% in 2021, 10% in 2022, 31% in 2023, and 28% in 2024. Research published before 2020 comprises 3% of the compilation. Elsevier holds the largest distribution share among publishers at 49%, followed by Springer at 13%, IEEE at 10%, MDPI at 15%, and other publishers together at 13% with smaller percentages. Regarding the yearly publishing allocation by each publisher, Elsevier documented one publication before to 2020, three in 2020, two in 2021, none in 2022, five in 2023, and a maximum of eight publications in 2024. Springer had no publications before 2020, produced two articles in both 2021 and 2022, and one work in 2023. IEEE published one article in 2020 and two papers in 2021. MDPI had its highest output in 2023 with four publications, including one publication in each 2020 and 2024. MDPI published two publications each year in 2022 and 2023, with a single publication in 2024.

Figure 3 illustrates the distribution of the compiled papers on segmentation applications by year and publisher. Upon analyzing the annual distribution, the peak number of publications was recorded in 2024, comprising 35%, succeeded by 2023 at 30%, 2022 at 22%, 2021 at 9%, and 2020 at 4%. In terms of publisher distribution, Elsevier leads with 39%, followed by Springer with 31%, while IEEE and MDPI represent 9% and 4% of the articles, respectively. The"Other"group comprises 17%. Analysis of the yearly publishing output by publishers reveals that Elsevier produced one article in each of the years 2021, 2022, and 2023, with a high production of six publications in 2024. Springer published one article in 2021, 2022, and 2024, and three papers in 2023. In 2022 and 2023, both IEEE and MDPI published one article each, whereas the"Other"category,

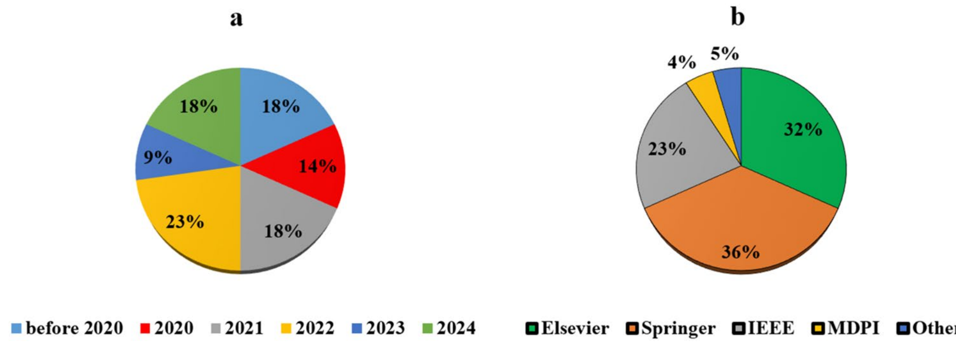

Fig. 4 Distribution of the reviewed studies in registration applications by (**a**) year and (**b**) publisher

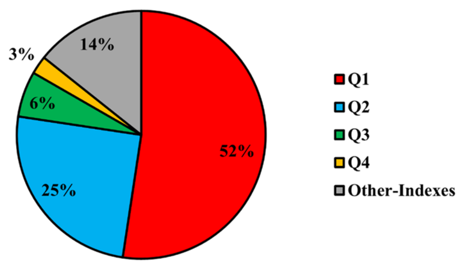

Fig. 5 Distribution of the studies across quartiles

which includes publishers such as Tech Science Press, King Saud bin Abdulaziz University, Frontiers, and ACM, jointly generated two publications each over the same timeframe.

Figure 4 illustrates the distribution of the aggregated research on image registration applications by year and publisher. Publications before 2020 constitute 18%, whilst those in 2020, 2021, 2022, 2023, and 2024 represent 14%, 18%, 23%, 9%, and 18%, respectively. Springer accounts for the largest share of published papers at 36%, followed by Elsevier at 32%, and IEEE at 23%. MDPI possesses a 4% market share, whilst other publishers collectively represent just 5%. Elsevier published one publication in each of the years prior to 2020, in 2020, and in 2023, and two papers in both 2021 and 2024. Nevertheless, no publications were identified in 2022. Springer published one article each before 2020, in 2021, 2023, and 2024, with one paper in 2023. Springer did not publish any papers in 2020. IEEE released one article before to 2020, one in 2020, one in 2021, and one in 2022. MDPI published a singular article in 2020. The"Other"category includes AIP Publishing, which released one article in 2024.

Figure 5 illustrates the quartile distribution of the analyzed studies. The Q1 category is 52% of the total, with 44 articles. The Q2 category has 21 journals (25%), Q3 consists of 5 journals (6%), and Q4 encompasses 2 journals (3%). Moreover, indexed journal publications in ESCI and Scopus, together with conference proceedings, are included under the Other-Indexes category. The Others category has 12 journals, or 14%. The assembled document illustrates that it was developed following an extensive literature review.

3 Role of meta-heuristic in image processing and computer vision applications

In recent years, the growth of Artificial Intelligence (AI) techniques has led to an increased utilization of image processing and computer vision technologies across different domains, including medicine [53], agriculture [54], IoT [55], satellite imaging [56], and others [57–59, 60]. Due to the specific challenges and limitations within these application domains, they continue to be a current research topic [61]. To improve these issues, MH algorithms have been preferred because they outperform traditional methods [62]. This section focuses on studies in image classification, segmentation, and registration, where MH techniques have been used to enhance traditional methods. Figure 6 provides a visual summary of the application areas where MH-based techniques are utilized in image processing and computer vision. These studies are categorized into three classifications. Furthermore, many MH algorithms employed in these investigations are illustrated in Fig. 7. In these papers, either classic MH algorithms have been applied, or hybrid MH algorithms have been proposed/used to tackle at least one problem in image processing and computer vision. Additionally, the source codes and pertinent datasets from the 84 papers examined in this work are compiled and made available as open-source resources for researchers. These resources are made accessible and available for examination by relevant researchers at the following repository: https://github.com/mfaruk-sahin/Metaheuristics-in-Image-Processing-and-Computer-Vision.git.

3.1 Overview of Meta-Heuristic algorithms

The MH algorithms are sophisticated optimization methods designed to address intricate, nonlinear, and high-dimensional challenges [63]. In contrast to conventional optimization techniques, they function independently of derivative information and can navigate an extensive solution space without becoming ensnared in local minima [64]. These algorithms aim to get the global best solution by successfully balancing exploration and exploitation processes. Owing to

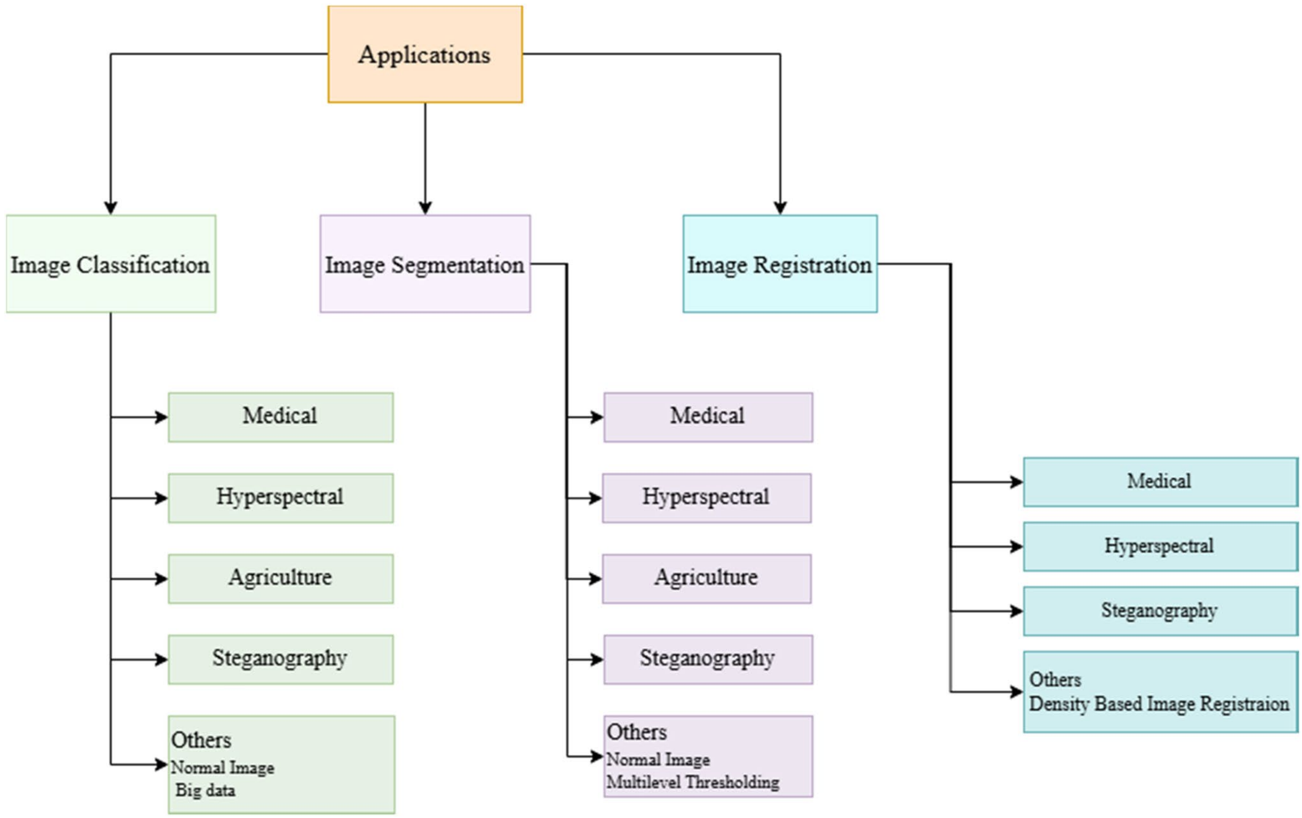

Fig. 6 MH Studies in image processing and computer vision applications

these attributes, they are extensively employed in diverse domains, such as image processing and computer vision [65]. Moreover, MH algorithms are categorized according to the scientific facts and principles that motivate them [66]. The first group consists of evolutionary algorithms, meaning that the expected solutions are produced or navigated by using general principles of biological evolution and natural selection [67]. Genetic Algorithm (GA), Differential Evolution (DE), and evolution strategies generate new solutions by creating a population of solutions; the best individuals are selected by fitness or quality, and the recommendations use crossover or mutation to create new solutions. This algorithm intends to maintain diversity in solutions to previously high-dimensional problems. Another group, swarm intelligence-based algorithms, are developed based on the natural producing behavior of social organisms [68]. Particle Swarm Optimization (PSO), which is an example of this group, is based on birds in flocking movement and fish schooling movement, each individual is directed by its best solution and the best global solution stagnant in the path. Artificial Bee Colony (ABC) algorithm generates solutions with bees foraging behavior, while Ant Colony Optimization (ACO) is based on ants laying down pheromone trails to guide each other to optimal paths. The third group is Physics based algorithms optimized by modeling physical processes in nature [69]. The Simulated Annealing (SA) algorithm is modeled after the annealing process in metallurgy, which explores a wide solution space initially at high temperatures before cooling down to refine the best solution. Based on Newton's law of gravity, the Gravitational Search Algorithm (GSA) improves solutions using the attraction principle between particles. The Electromagnetic Optimization algorithm suggests solutions through the forces of attraction and repulsion produced by magnetic fields. Also, nature-inspired algorithms imitate the phenomenon that exists in nature. The Artificial Rabbit Optimization (ARO) algorithm was developed based on the social intelligence and survival techniques of rabbits. Similarly, the Grey Wolf Optimization (GWO) algorithm is based on the hunting hierarchy of wolves. Moreover, the Cuckoo Search (CS) algorithm based on brood parasitism uses random mutation mechanisms to search for solutions. Recently, hybrid methods which are the 5th category have started being added to the literature. Hybrid MH techniques combine the best features of two or more algorithms to produce better solutions. The combination of GA and PSO maintains genetic diversity along with fast convergence. Using a combination method of ACO and DE during the search process provides a better solution set. Also, the integration of different MH algorithms with deep learning models leads to significant improvements in weight

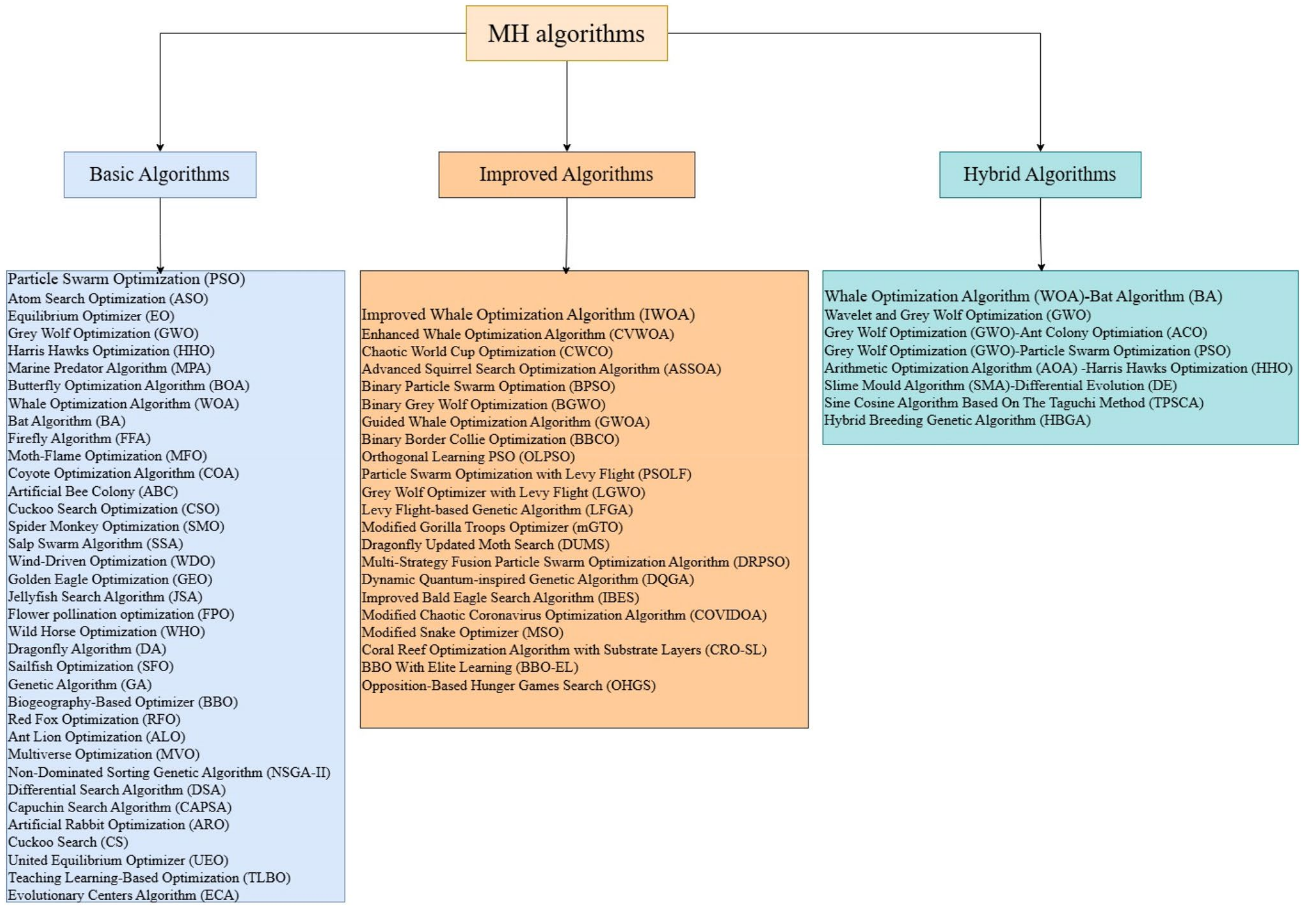

Fig. 7 Various MH algorithms used/proposed for image processing and computer vision applications

optimization, hyperparameter tuning, feature selection, etc. In short, the MH algorithms have been used successfully in different application areas and complex problems such as image processing and computer vision. They have the ability to search for large solution spaces and provide quick solutions to complex problems. While individual algorithms can solve certain problems, some face limits such as computational cost and need fine-tuning of parameters. Therefore, more efficient optimization results can be expected from selecting the most appropriate MH algorithm or developing hybrid ones.

3.2 Image classification based applications

Image classification facilitates the categorization of objects through the classification of an image's pixels [70, 71]. Due to this structure, it is frequently used in application areas that require object detection, such as medical [72], remote sensing [73], agriculture [74], encryption [75], and other fields [76–78]. This section focuses on studies that employ the MH approach for image classification and examines the identification of problems in different application areas. In this context, when reviewing the existing studies, as shown in Fig. 1, the application areas are evaluated under five main subheadings: medical, hyperspectral, agriculture, steganography, and others. An extensive literature review has been carried out to tackle the problems that arise in image classification through MH methods. Classification of images is often faced with issues of high computational power requirement, inappropriate feature selection, getting stuck in local optima and improvement of classification performance. Metaheuristic methods have flexibility and optimization abilities to resolve these issues. In the literature review, the words,"Feature selection, and extraction", “Reducing computational cost and training time", “Weight optimization”, “optimal points of the network for pruning”, “tumor detection accuracy” and “feature optimization.” were used. These keywords point towards the potential of MH techniques for enhancing efficiency of image classification techniques. Studies which do not use MHs are also excluded as they are not useful for the research objective. Thus, only the latest studies which use MH methods on image classification are used. Through a tight focus on the latest studies, this will give better clarity on how various MHs impact image classification.

3.2.1 Medical based applications

In medical studies, image classification is used to categorize diseases in a computer environment with faster and more accurate prediction success [79]. This allows for early diagnosis and treatment before the disease progresses [80]. In this context, image classification methods accelerate disease diagnosis in various diseases and imaging systems. However, due to the presence of different organs in these diseases, imaging systems vary [81, 82]. This requires different optimization methods for each case. This section includes studies related to breast cancer, skin diseases and cancer, brain tumors, COVID-19, and white blood cell disorders.

One of the key focus areas in the medical field is breast cancer. In detecting this disease, histopathological and X-ray imaging methods are used. Histopathological imaging presents challenges related to classification and the multidimensionality problem, particularly for large datasets. To address these issues, one of the preprocessing techniques used to select a subset of features that represent the data without losing information is feature extraction [83]. However, finding the best representative feature sets poses difficulties in terms of computational complexity, which has led researchers to use algorithms such as PSO, Atom Search Optimization (ASO), and Equilibrium Optimizer (EO) [84]. In the proposed approach, using EO, the F-Score reached 97.75%, and fewer features that best represented the dataset were extracted, resulting in improved classification performance. However, it has the disadvantage of increased computational cost. In another study, distinguishing abnormal breast tissues from normal tissues is considered a challenging process due to the structures and unclear boundaries of the tissues. Consequently, Convolutional Neural Networks (CNNs) encounter certain limitations, including slow convergence and prolonged training durations. To improve these limitations, a hybrid approach combining Wavelet and GWO has been proposed [85]. The proposed GWO-WNN method reduces computational cost and training time while achieving a classification accuracy of 98%, outperforming methods such as SOM-SVM (87.5%), LOFA-SVM (93.62%), MBA-RF (96.85%), and BAS-BPNN (96.3%). However, the disadvantage lies in the fact that only local features were used for classification, whereas global features are equally important in breast cancer diagnosis. In another detection method, X-ray imaging continues to face the critical issue of needing a sufficient amount of training data, and successful classification requires feature extraction [86]. Therefore, the Squirrel Search (SS) method has been improved, and an Advanced Squirrel Search Optimization Algorithm (ASSOA) has been proposed for classifying different cases in chest X-ray images [87]. The ASSOA method, with an average classification accuracy of 99.7%, improves classification performance within CNN compared to SS, GWO, and GA.

Skin diseases and cancer are among the most significant issues of the skin [88]. Skin cancer changes the color of the skin due to abnormal function or damage of pigment-producing cells [89]. When detecting skin cancer using AI architectures, MH methods often outperform traditional approaches [90]. To improve the success rate in skin cancer detection, a study suggested the use of Improved Whale Optimization Algorithm (IWOA) for DNN weight optimization, which enhanced performance [91]. However, like other MH algorithms, there are challenges such as early convergence, low speed, and complexity drawbacks. To address this issue, pruning techniques are applied in CNN and DNN network optimization [92, 93]. In this context, the Chaotic World Cup Optimization (CWCO) algorithm has been proposed for more efficient detection of optimal points in the pruning process of the neural network [94]. The proposed method achieves the best results with detection rates of 92.64% and 87.5% on the ACS and ISIC image datasets, respectively.

Mpox has been rapidly spreading globally since 2022, affecting 110 countries, including the US and Europe [95]. Image classification methods can be used for early detection of the disease, but there are limited studies due to data scarcity in this area [96]. To overcome this issue, a new method called the MH-based weighted average ensemble model (MO-WAE) has been developed [97]. This method combines the outputs of three core models DenseNet201, MobileNet, and DenseNet169 using a weighted average ensemble technique with transfer learning. The results on the Mpox dataset show an accuracy of 97.78%, improving upon previous studies in literature. However, due to its computational cost, it is challenging to use in real-time applications.

Another medical application area is brain tumor classification [98]. Various CNN and DNN-based applications have been developed to recognize tumor types [99, 100]. However, the accuracy of tumor detection in these applications is crucial for the patient's health. To address this issue, a Harris Hawks Optimized Convolutional Network (HHOCNN) has been developed [101]. The proposed method achieves an overall tumor detection accuracy of 98%. In another study, the Manta Ray Foraging Optimization (MRFO) algorithm was used for feature transfer in X-ray and Magnetic Resonance (MR) images via transfer learning [102]. The evaluation of the proposed architecture resulted in an accuracy of 99.96% for X-rays and 98.64% for T1-weighted contrast-enhanced MR images. However, there are limitations for real-time applications. Finally, to compare feature optimization in brain tumor tasks using MH algorithms, a study compared eight different optimization algorithms across 16 pretrained DNNs [103]. The algorithms used were Marine Predator Algorithm (MPA), ASO, Harris Hawks Optimization Algorithm (HHOA), Butterfly Optimization Algorithm (BOA), WOA, GWO, Bat Algorithm (BA), and Firefly Algorithm (FFA). GWO and ASO algorithms provided the best results with a classification accuracy of 95.7%.

During the Covid-19 pandemic, when a vaccine was not yet available, the focus shifted to detecting the virus through imaging [104]. Therefore, to improve the classification success of using images, a dataset consisting of normal and pneumonia chest X-ray images was created. Feature extraction from this dataset was performed using deep learning models like AlexNet, VGG19, GoogleNet, and ResNet. To select the best potential features, Binary PSO (BPSO) and Binary GWO (BGWO) algorithms were proposed, resulting in an overall accuracy of 99.38%. In another study, Guided WOA (GWOA) was proposed for feature selection [105]. However, both studies highlighted that adjusting the parameters of CNNs is necessary to further enhance classification performance.

Medical imaging tools are used to carry out the studies mentioned above. However, due to the complexity and limitations of the data, data-driven approaches are necessary for these tasks [106]. Therefore, MH methods are applied for database matching in medical imaging. During the training phase of CNN, features extracted are selected using hybrid Coyote-Moth Optimization Algorithm (CMOA), combining Moth-Flame Optimization (MFO) and Coyote Optimization Algorithm (COA) [107]. The proposed hybrid system outperforms existing methods with a precision value of 98%. However, transfer learning has not been used for feature transfer from trained CNN models. In medical imaging studies, applying MH methods to transfer learning approaches needs to be evaluated. To enable the learning of new features, GA is used, outperforming traditional feature extraction methods and improving performance [108]. However, the proposed method has the disadvantage of getting stuck in local optima.

Some diseases are associated with changes in the number and ratio of white blood cells (WBC), which can be linked to blood disorders [109]. Therefore, the detection and classification of each type is crucial for human health. To improve the performance of classification, an updated version of Border Collie Optimization (BCO), called Binary Border Collie Optimization (BBCO), has been introduced for feature reduction [110]. The proposed method demonstrates that the BBCO algorithm increases detection accuracy to 99.21% while also reducing classification time. However, a disadvantage of this approach is that it has been tested using only a single dataset.

3.2.2 Hyperspectral based applications

Remote sensing applications are among the techniques used in satellite and hyperspectral imaging [111]. Since remote sensing applications involve remote imaging, they come with various challenges. This section discusses how MH algorithms can be used to improve issues such as band selection, feature selection, feature extraction, iteration costs, and the problem of getting trapped in local optima in remote sensing applications.

The high number of hyperspectral bands in remote sensing images increases their utility but also leads to computational challenges [112]. This difficulty arises from the high correlation between adjacent bands and the presence of unnecessary information in images with numerous hyperspectral bands [113]. Due to the difficulties in accurately recognizing information and extracting relevant features, the selection of the most informative bands emerges as a crucial step [114]. Additionally, in classification tasks, insufficient training images for certain bands can negatively impact classification accuracy. To overcome this issue, MH algorithms are used to select appropriate bands [115]. However, due to the stochastic search nature of MH algorithms, the selected bands can yield different results depending on the application of the algorithm. As a result, the outcomes from classifying these different band subsets can also vary. To address this problem, a study tested 13 different MH algorithms using four different hyperspectral remote sensing datasets [116]. In this study, fusion-supported methods like ABC, CS, Firefly Algorithm (FFA), PSO, GWO, Spider Monkey Optimization (SMO), Salp Swarm Algorithm (SSA), Wind-Driven Optimization (WDO), Golden Eagle Optimization (GEO), Jellyfish Search Algorithm (JSA), PSO with Levy Flight (PSOLF), GWO With Levy Flight (LGWO), and Levy Flight-Based Genetic Algorithm (LFGA) were applied to hyperspectral datasets such as Indian Pine, Pavia University, Botswana, and Salinas. The proposed methods showed accurate improvements in determining the optimal number of bands, with improvements ranging from 0.4% to 15.7%, depending on the MH algorithm, objective function, and dataset. In another study, GWO was used to improve the objective function on the Indian Pine, Pavia University, and Salinas datasets [117]. However, these methods are considered simple as they do not require many parameters for basic applications. For more complex tasks, CNN/DNN-based architectures are used to select optimal bands. In this context, various works have been conducted on datasets like Indian Pine, Pavia University, Salinas, Botswana, and Washington Mall. Algorithms such as Flower Pollination

Optimization (FPO) [118], SSA [119],CSO [120], BGWO [121], and Wild Horse Optimization (WHO) have been proposed [122]. These methods compete with each other, yielding varying results. However, prediction success between classes is often imbalanced, and computational complexity remains a significant challenge.

For robustness in imbalanced and highly correlated classes, feature selection techniques are employed, and they work more efficiently when combined with MH algorithms [123]. Feature selection is particularly useful in hyperspectral image classification tasks, such as detecting plant leaf diseases. For such tasks, the Equilibrium Optimizer (EO) has been suggested [124] demonstrating an overall accuracy of 99.38% and an Area Under Curve (AUC) of 0.9985, yielding efficient performance. In another study focused on remote sensing image classification, the strengths of the Bat Algorithm (BA) and ABC algorithms were combined into a BA-ABC algorithm for feature selection [125]. This method was tested on five different datasets, achieving classification accuracy ranging from 94.6% to 99.9%. However, both studies suffer from iteration costs and local optimum trapping. These issues arise from reduced exploration capabilities in later iterations, insufficient population diversity, and slow convergence rates. To overcome these problems, MH algorithms are employed to enhance performance in image classification applications.

In satellite imagery, to improve the iteration cost of feature extraction while obtaining low-level semantic information, a hybrid WOA-BA approach has been proposed [126]. Tests performed on the UC-Merced land-use dataset showed that this method achieved up to 7.83% accuracy improvement over CNN-based similar approaches, with shorter iteration times. Another study proposed an advanced Dragonfly Algorithm (DA), which, despite its strong search capability, faced iteration cost and local optimum trapping issues. To address these, a guided differential operator, named BDA-DDO, was combined with DA [127]. This approach led to better classification accuracy in tests conducted on the UCI dataset. In a study focusing on the improvement of Bayesian optimization, four different MH algorithms PSO, ABC, HHO, and Sailfish Optimization (SFO) were applied [128]. This optimization helped the model improve its ability to recognize high-level features like edges, corners, textures, shapes, objects, and visual scenes. However, these studies have not been tested on more complex and larger datasets.

3.2.3 Agriculture based applications

Image classification also plays a pivotal role in agricultural applications. To increase agricultural productivity, health and types of plants can be detected using CNN/DNN algorithms with computer vision techniques. However, these applications face challenges, such as the detection of plant leaf health and identification, which vary depending on the specific issues.

Plant leaves can be affected by bacterial, fungal, and viral infectious diseases, which impair processes like transpiration and photosynthesis [129]. These diseases can significantly reduce agricultural production and pose a threat to plant growth. Early identification of these diseases can be achieved by analyzing the shape, color, and texture of leaf images using CNN/DNN methods[130]. However, due to the large size of the datasets, feature reduction is necessary. CNN architecture, due to their inherent structure, can handle this task. To improve detection performance, the optimization of weights with the use of Butterfly Optimization Algorithm (BOA) is suggested [131]. When compared to PSO and GA algorithms, the proposed method achieves an accuracy of 99%. However, the simplicity of the dataset used leads to very high success rates, and the method has not been validated with more complex datasets.

Another area is plant classification based on leaf images. Plant classification systems face challenges due to the high diversity and similarity between species, which results in time costs for feature extraction [132, 133]. To address this issue, algorithms like SMO, PSO, and GWO have been suggested [134]. The proposed framework reduces the burden of high-dimensional data by using MH algorithms to select the most relevant features. In another study, PSO algorithm was proposed to distinguish two types of weeds and rice plants accurately under different lighting conditions [135]. The proposed method resulted in higher accuracy compared to traditional methods. However, the datasets used in these studies were not complex and were imbalanced. In agriculture datasets, the imbalance problem often causes the model to get stuck in local optima. To address this issue, Orthogonal Learning PSO (OLPSO) was introduced [136]. The proposed method demonstrated improved performance with an accuracy of 98.2% on complex and large datasets.

3.2.4 Steganographic based applications

Steganography is a method of hidden communication that involves embedding secret information into images, videos, or text files [137]. Steganalysis, on the other hand, refers to the process of detecting whether a hidden message is embedded in an image, and it is often applied using image classification techniques [138]. To improve efficiency in these processes, there have been studies incorporating MH algorithms. For detecting the presence and location of hidden information in an image, the GWO algorithm has been proposed [139]. The suggested method achieves an average improvement of 1.87% to 2.32% in classification performance (per bit per channel) when detecting hidden and non-hidden parts of an image. Another study focuses on improving the security of hidden messages within an image. This work proposes a bidirectional asymmetric data embedding technique using the ACO [140], which makes it more difficult to detect the hidden data and enhances its security. In the context of Internet of Medical Things (IoMT) systems, a hybrid approach based on SSA and Arithmetic Optimization Algorithm (AOA) is suggested to secure the transmission of medical data and patient information by embedding it into medical images [141]. This method has been shown to be successful in providing security against common image processing attacks. There is still a need for more research in this field to address additional challenges.

3.2.5 Other fields based applications

In the context of computer vision, several methods have been proposed to improve the efficiency and performance of neural network models. One of the notable techniques is neural network pruning, which focuses on reducing unnecessary components within CNN and DNN models to enhance performance [142]. Pruning can lead to reduced model complexity and improved efficiency, but when done using traditional methods, it may result in a decrease in performance and require time-consuming fine-tuning processes [143]. To address this issue, GA has proposed for automatically searching the pruning rate and criteria within the network [144]. This approach allows the optimal pruning criterion and rate for each layer to be selected iteratively, improving the overall model performance. Additionally, to reduce the computational load of pruning, a new weight inheritance mechanism has been developed. This mechanism helps to reduce the training time of the model, making the pruning process more efficient and practical for real-world applications.

In another study, CNN models were optimized to reduce memory usage, energy consumption, and CO2 emissions through the pruning technique [145]. To efficiently navigate the search space and exploit these results, the PSO algorithm was proposed. This method led to a reduction in computational costs and CO2 emissions. However, there was a decrease in accuracy, ranging from 2.07% to 2.40%, compared to the original models. This demonstrates the trade-off between reducing environmental impact and maintaining classification accuracy, where minimizing the loss in accuracy is crucial. Beyond pruning, improvements have also been proposed for original MH algorithms. One such improvement is the Adaptive Habitat Biogeography-Based Optimization (AHBBO) algorithm, which addresses the early convergence and insufficient exploration issues of the Biogeography-Based Optimizer (BBO) [146]. AHBBO enhances the overall performance of the traditional BBO algorithm. However, due to its complexity, the practical use of this method in real-world problems is limited. Another MH optimization improvement is the Gorilla Troops Optimizer (GTO), which, due to its tendency to get stuck in local optima and early convergence in complex optimization tasks, led to the proposal of the Modified Gorilla Troops Optimizer (mGTO) [147]. This improved algorithm provides more consistent and better performance compared to the original GTO, but at the cost of higher computational complexity.

Another area of research using MH is related to big data, which involves large-scale, complex datasets with multiple autonomous sources [148]. In deep learning studies with big data, obtaining representations from large amounts of unsupervised data is crucial. Dimensionality reduction methods are used to eliminate unnecessary features, improving classification accuracy and speed. To select optimal features, the Sea Lions Algorithm (SLnO) has been employed for feature selection [149]. However, the study only evaluates the accuracy parameter. In classification applications, common evaluation parameters were considered in another study. In this study, to improve iteration costs and classification performance in big data images, the Dragonfly Updated Mothsearch (DAUMS) algorithm was proposed [150]. This research demonstrated that the DAUMS method reduces iteration costs and increases classification accuracy in big data classification tasks, enhancing the efficiency of existing optimization techniques.

In MH studies, preprocessing steps are essential to improve algorithm performance. One such preprocessing technique is cropping, which plays a critical role in identifying regions of interest for target object detection [151]. The Red Fox Optimization (RFO) algorithm is used to determine where the image should be cropped [152]. This approach enables the cropping of important areas, particularly where the object is located, thus reducing the size of the analyzed image and decreasing the time required for analysis. However, this technique comes with an increase in computational cost.

3.3 Image segmentation based applications

Image segmentation is one of the most popular research areas in computer vision and is used in various applications, such as autonomous vehicles [153], smart medical technologies [154, 155], image search engines [156], industrial inspections [157], augmented reality [158], and other fields [159, 160]. Image segmentation involves dividing an image into distinct regions with different characteristics, allowing objects to be separated from the background through meaningful and non-overlapping regions [161, 162]. This section discusses the detection of problems in different application areas of image segmentation and the improvements made to address them. A comprehensive literature review has been conducted to address the challenges encountered in the field of image segmentation through the application of metaheuristic methods. Common issues in image segmentation processes include entrapment in local optima, insufficient exploration, threshold selection, and high computational costs. To overcome these challenges, the optimization capabilities provided by metaheuristic methods play a crucial role. In the literature review, keywords such as"avoiding local optima and improving convergence,""enhancing early convergence and overcoming entrapment in local optima,""threshold selection,""reducing computational cost caused by an increased number of thresholds in threshold selection,""clustering optimization based on color information,""optimizing CNN parameters,"and"edge detection"were utilized. These terms highlight the potential of metaheuristic approaches to enhance efficiency in image segmentation processes. Furthermore, studies that do not incorporate metaheuristic methods are excluded, as they fall outside the scope of this research. This ensures a focus on relevant and up-to-date sources, facilitating a better understanding of the impact of metaheuristic methods on image segmentation.

3.3.1 Medical based applications

In medical image segmentation, common challenges such as tumor region segmentation, colon cancer, kidney disease, and multi-level thresholding are frequently addressed. Medical image segmentation aims to enhance the clarity of anatomical or pathological structures in images, thereby improving diagnostic efficiency and accuracy [163]. For this reason, research continues to focus on segmenting tumor tissues from healthy tissues in cancer studies within the field of medical image segmentation [164]. In these studies, two main problems that arise are convergence speed and local optima. To address these issues, research has been conducted on lung cancer pathological images. An improved method called WOA combined with a Random Mutation Strategy-Based (WDRIME) approach has been proposed for segmentation at three levels [165]. The proposed method improves convergence speed and prevents local optima compared to traditional methods. However, this hybrid approach increases the complexity of the model.

In colon cancer segmentation, the problem of early convergence and getting stuck in local optima in PSO has been addressed by proposing the Multi-Strategy Fusion PSO Algorithm (DRPSO) [166]. This method improves the performance of PSO. For breast cancer pathology images, a combination of SSA, Slime Mould Algorithm (SMA), and DE algorithms have been used to avoid local optima, resulting in the SDSSA method [167]. The proposed method outperforms other segmentation methods. In kidney disease segmentation, deep learning architecture suffers from sensitivity to local optima, insufficient exploration, and low solution accuracy. To address the limitations of WOA, the Enhanced WOA (CVWOA) has been proposed [168]. The proposed method improves the discovery and solution success compared to the classical WOA.

In medical segmentation, another challenge is the selection of threshold combinations in multilevel thresholding, which significantly impacts segmentation performance. Traditional optimization algorithms often require substantial time to solve multi threshold image segmentation problems, and the segmentation accuracy is frequently not satisfactory. Therefore, MH algorithms are used to optimize the determination of thresholds. However, some algorithms face issues such as insufficient exploration of the solution space and early convergence during threshold selection [169]. To address this issue, a hybrid Reptile Search Algorithm (RSA)-SSA method has been proposed [170]. This method, tested on Covid X-ray images, provides a better search space to find the optimal solution at each iteration. In another study, the computational cost of multilevel thresholding, which grows exponentially as the number of threshold values increases, has been tackled using Ant Lion Optimization (ALO) and Multiverse Optimization (MVO) [171]. The proposed method improved the computational cost in the context of brain tumor segmentation.

3.3.2 Hyperspectral based applications

Satellite imagery presents significant challenges for segmentation tasks due to its randomness, multiple regions of interest, weak correlations between pixels, and ambiguous areas. In hyperspectral applications, various studies focus on issues related to local optima, computational costs, and threshold selection in image thresholding. These studies address these problems using several algorithms such as Dynamic Quantum-Inspired Genetic Algorithm (DQGA) [172], CSO [173], Improved Bald Eagle Search Algorithm (IBES) [174], Modified Chaotic Coronavirus Optimization Algorithm (COVIDOA) [175], NSGA-II: Non-dominated Sorting Genetic Algorithm [176], Modified Snake Optimizer (MSO) [177], and WHO [178].

For the successful fusion of satellite images, traditional methods often encounter the local optima problem. To overcome this, the Differential Search Algorithm (DSA) is proposed [179]. The proposed multispectral fusion method improves convergence to a global minimum. In another study, remote sensing images are affected by solar radiation, atmospheric layers, radiation deviations, and other environmental factors, leading to significant noise. This causes challenges in high-precision remote sensing image segmentation. To enhance segmentation effectiveness, a Parallel Sine Cosine Algorithm Based on the Taguchi Method (TPSCA) was used to optimize CNN parameters, achieving a 40% improvement in performance [180]. In another study, satellite images, being crucial as a data repository, are used for land change detection monitoring. During this process, problems with edge sharpness in change detection are addressed, and the PSO algorithm is proposed to improve the detection. By using PSO, the quality of the detected edges and overall clarity is enhanced, resulting in better edge definition and sharper images [181].

3.3.3 Agriculture based applications

In agriculture, image segmentation plays a crucial role in the early detection and diagnosis of crop diseases. By helping identify disease regions and their features, segmentation lays the foundation for disease diagnosis and treatment. However, with the increase in the number of thresholds in color image thresholding methods, it becomes difficult to find the optimal threshold, which affects the quality of segmentation. To address this issue, methods such as the MSO [182] and Capuchin Search Algorithm (CAPSA) [183] have been proposed. These methods help to improve problems like irregular distribution in the initial population, low global search performance, and early convergence to local optima.

3.3.4 Steganographic based applications

The rapid advancements in Industrial Internet of Things (IIoT) and AI have led to serious security concerns due to the exposure of sensitive data. Ensuring privacy in real-time communication of security data has thus become a critical issue. To address this, AI techniques can be leveraged to design image steganographic methods in IIoT. Additionally, encryption techniques play an important role in preventing unauthorized access to the real data generated by IIoT devices. To ensure secure data transmission in the IIoT environment, a steganography-based data hiding technique called EIS-DHT has been proposed [184]. This method includes Quantum Black Widow Optimization (QBWO) to select pixel values that hide sensitive data in cover images, improving data hiding performance compared to traditional methods. Another study proposes the use of the PSO algorithm to enhance the quality of the hidden information [185], showing more successful results than conventional approaches.

3.3.5 Other fields based applications

In the field of image segmentation, there are studies focused on normal images such as face images, Lena, and various datasets that do not belong to a specific application area. The primary challenge in these studies is determining the optimal number of thresholds and their values for segmentation. To tackle this problem, several methods have been proposed using popular datasets, including the GWO [186], WGWO [187], and a hybrid approach combining the AOA and the HHO algorithm (AOA-HHO) [188]. These approaches aim to improve the segmentation process by optimizing threshold selection and addressing issues such as computational cost and segmentation accuracy.

3.4 Image registration based applications

Image registration is defined as the process of aligning two or more images taken from the same scene at different times or with different sensors [189]. This process aims to enrich the information content, reconstruct 3D models, and geometrically align the reference and perceived images for object detection and tracking [52]. This section discusses the improvement of image registration problems in various application domains using MH algorithms. In the field of Image Registration, the challenges encountered involve issues such as enhancing image quality, optimizing the search space, convergence speed, and entrapment in local optima. To improve these issues, the optimization capabilities provided by metaheuristic methods are of great importance. In the context of this literature review, keywords such as"improve image quality,""improve search space to enhance image quality,""convergence speed and local optima,""convergence is improved with optimal geometric space transformation parameters,""optimizing the search space to improve early convergence and avoid falling into local optima,""iteration cost,""enhancing exploration and exploitation capabilities,"and"defining the objective function"are utilized. Thus, this highlights how metaheuristic approaches can effectively contribute to image registration processes and their potential to enhance the efficiency of these processes.

3.4.1 Medical based applications

Medical image registration has become a popular research area due to the integration of various imaging modalities, such as X-ray, ultrasound, MRI, and CT scans [190]. However, obtaining reliable image registration is challenging due to irregularities in image orientation [191]. Traditional methods fail to capture complex spatial transformations and anatomical variations, leading to issues with image quality, convergence, and local optima. Therefore, MH algorithms are used to improve registration accuracy, focusing on these challenges.

In multimodal image registration, the Teaching Learning-Based Optimization (TLBO) algorithm has been proposed to create more successful image registrations [192]. The proposed method involves optimizing processes such as noise removal and normalization to improve image quality and ensure uniform scaling of the dataset. This approach reduces processing costs while providing better image quality and valuable information for medical diagnosis (especially for smart wireless medical systems [225]). However, it has the disadvantage of high computational cost. A similar problem is found in COVID-19 Computed Tomography (CT) images. To record CT images of the lungs of individuals infected with COVID-19, PSO and GWO algorithms have been applied [193]. In another study, the ISCA algorithm, formed by hybridizing SCA and PSO, is proposed [194]. These algorithms provide high-precision and robust registrations, demonstrating better performance in most cases compared to the latest methods. In another study, BA and GWO are proposed in a hybrid form for applying the similarity metric during the image registration process [195]. Additionally, PSO-based image registration is applied to the same sample sets, and the BA-GWO algorithm is compared with PSO. The proposed method competes with PSO. A method developed for medical image registration using BBO, Positron Emission Tomography (PET), and MR modalities has been proposed to demonstrate the success of various algorithms in multimodal medical images [196]. The proposed approach shows higher accuracy and robust registration success compared to the PSO algorithm. In addition to PET and MRI imaging, CT has been incorporated, and the Coral Reef Optimization Algorithm with Substrate Layers (CRO-SL) has been proposed [197]. The proposed method aligns with feature-based and density-based designs. Similar problems also exist in CT-MRI and retinal imaging in medical imaging. To address this, the ARO algorithm [224] has been proposed, leveraging reinforcement learning and new search strategies to enhance performance [198]. The proposed method outperforms traditional methods; however, it has limitations in exploration due to convergence and local optima. In monomodal imaging, the CSO algorithm has been proposed to improve the registration process in brain, breast, and kidney MRI scans [199]. The proposed method improves data quality by 2% and demonstrates efficient performance. However, exploration and exploitation parameters have not been investigated, and only time spent is discussed. Most optimization techniques provide correct results when the initial orientation is close to the transformation and provides the best registration. To address this issue, PSO-GA, which uses multiresolution techniques where images are registered at increasing resolutions starting from the previous low-resolution initial orientations, has been proposed. This way, the search space is used more efficiently [200].

In medical imaging, to address the issues of convergence and local optima during multimodal image registration, the United Equilibrium Optimizer (UEO) has been proposed [201]. The proposed algorithm enhances both the exploration and exploitation potentials of EO, achieving successful results by avoiding high local optima and improving the convergence of the algorithm. Additionally, UEO is compared with BA, GWO, BOA, WOA, and various other MH algorithms. To overcome shifting errors in image registration and avoid time complexity, a GWO-Based Non-Rigid Demons Registration method has been proposed for retinal images, making the method more efficient compared to existing techniques [202]. The proposed method achieves faster convergence than the basic GWO. However, the study has relatively low complexity since multimodal registration is not addressed. In another study, traditional approaches such as GA and PSO fail to find the global optimum on their own. To address this, the TLBO algorithm has been proposed [203]. The proposed method works more efficiently compared to existing techniques. Due to the limited number of MH studies in image registration, PSO, DA, and ABC algorithms have been tested [204]. The results show that PSO, DA, and ABC can successfully handle image registration. However, while DA provides higher-quality results, its convergence time is longer. PSO, on the other hand, has faster convergence but does not achieve the same high-quality images as ABC and DA. Additionally, as the population size increases, better fitness values are obtained, but this also leads to increased computational time. In multimodal medical image registration, there are studies focusing on improving early convergence and avoiding local optima by focusing on the search space and transformation parameters. In this context, the Opposition-Based Hunger Games Search (OHGS) algorithm [205] is proposed for optimal geometric space transformation parameters, while the Hybrid Breeding Genetic Algorithm (HBGA) [206], Biogeography-Based Optimization Algorithm with Elite Learning (BBO-EL) [207], and FPO-BOA [208] are suggested to improve the search space. This way, image registration in multimodal images is efficiently achieved by enhancing the search space.

3.4.2 Hyperspectral based applications

In remote sensing applications, image registration is used for 3D city modeling [209], land cover change detection [210], and various other applications [211, 212]. The geometric and radiometric differences in remote sensing images, their large sizes, and the presence of noise increase processing costs and complicate the creation of high-quality images. To address this issue, the Evolutionary Centers Algorithm (ECA) has been proposed [213]. With this method, iteration costs are improved compared to traditional methods, resulting in high-quality image registration. However, registration issues arise when the textures in the two images are homogeneous. To resolve this registration problem in images, SGD-DE is proposed [214]. This method improves registration quality by enhancing exploration and exploitation capabilities. However, there are limitations in parameter adaptation. In another study, point cloud image registration converges to suboptimal solutions due to the greedy search strategy. Therefore, the ABC algorithm is proposed for point cloud registration [215]. The proposed method shows more efficient performance when compared to GA and PSO. However, it needs to be tested with more parameters.

3.4.3 Steganography based applications

Digital watermarking technology is a content-based information hiding method and designing a high-performance system that meets criteria such as invisibility, robustness, embedding capacity, real-time performance, and security remains a challenging goal, particularly for color images. Therefore, in color multi-watermarking, identifying the most suitable embedding regions for copyright protection and determining embedding strengths with sufficient robustness are of critical importance [216]. In color multi-watermarking, determining the optimal embedding regions and embedding strengths with sufficient robustness for copyright protection is crucial. Therefore, PSO-GWO proposed to address this issuer [217]. The proposed method provides better embedding compared to traditional methods while ensuring higher security and invisibility against attacks. However, it has the disadvantage of high time complexity.

3.4.4 Others

In face detection and tracking applications, when visible light cameras are combined with thermal imaging, a more detailed representation of the person is obtained. However, this leads to the problem of intensity differences due to the integration of data from various modes, such as infrared (IR) and visible (VIS) images. To address this issue, a search strategy with the PSO algorithm is proposed to determine appropriate image registration parameters for the geometric transformation of the input image [218]. The proposed method improves image quality; however, it has the disadvantage of high computational cost.

4 Discussion

This comprehensive review study on MH-based algorithms in image processing and computer vision applications analyzes 84 papers. Tables 1, 2, and 3 give emphasis, optimization technique, role of MH, and a review of the benefits and disadvantages of the employed MH algorithms in each application area. These detailed tables examine the existing research in categorization, segmentation, and registration. The findings indicate that MH algorithms excel in offering answers to intricate optimization challenges within image processing and computer vision. The findings indicate that MH algorithms substantially enhance the resolution of intricate optimization challenges in image processing and computer vision, particularly by markedly improving the accuracy of hybrid models integrated with deep learning techniques, minimizing local optimum traps, and decreasing computational expenses. For example, although the HYDRO [219] method, which is one of the leading non-MH based methods in the field of image processing and computer vision, offers an innovative approach that provides optimization in interactive hybrid displays for digital signs, it is likely to get stuck in local minimums. Furthermore, when the quantity, dimensions, and placement possibilities of widgets on the screen expand, the solution space proliferates, hence constraining the method's performance. These issues can be addressed with metaheuristic algorithms like GA and PSO, or optimization of resolution settings across a broader parameter space can be achieved by techniques like ACO. Moreover, HYDRO possesses a static optimization framework and is unable to swiftly adjust to fluctuating environmental conditions. Separate research not focused on mental health [220] presents a novel approach based on complex brain tumor segmentation and Augmented Reality (AR)-based 3D visualization processes, but the active geometric contour models (level set method) used for segmentation are usually based on fixed parameter settings. This may limit the optimization flexibility for different image features and tumor sizes. Furthermore, low contrast and high noise levels in MRI data may degrade the performance of contour models and lead to inaccurate segmentations. Additionally, the methods used in 3D reconstruction may not guarantee accurate modeling of tumor boundaries. This may lead to errors during AR visualization. MH approaches, such GWO, can be employed to furnish starting parameters for active contour models or to enable these models to investigate a broader solution space, therefore decreasing potential mistakes and enhancing segmentation accuracy by mitigating excessive noise levels in MRI data. Distinct research aims to delineate highways using high-resolution satellite images, incorporating the Background Suppression Module and Strip-based Feature Alignment Module to

Table 1 Summary of MH algorithms in image classification applications

Ref	Application	Focus on	MH Algorithm	Role of MH	Advantage	Disadvantage	Accuracy
[84]	Medical	Breast Cancer	PSO, ASO, EO	Feature selection and extraction	The classification performance is improved by selecting a smaller number of features that best represent the dataset	Computational cost	97.73%
[85]	Medical	Breast Cancer	GWO- Wavelet	Reducing computational cost and training time	It reduces computational cost and training time while improving classification accuracy	The focus has been on local features. Global features are important for detection	98%
[87]	Medical	Chest Imaging	ASSOA	Feature extraction	Classification performance has improved	Computational cost	99.7%
[97]	Medical	Mpox	PSO	Weight optimization	Classification performance has improved	Due to computational cost, its use in real-time applications is disadvantageous	97.78%
[91]	Medical	Skin Cancer	IWOA	Weight optimization	Classification performance has improved	Early convergence, low speed, and complexity are disadvantages	85%
[94]	Medical	Skin Cancer	CWCO	Optimal points of the network for pruning	Performance has improved	Computational cost	ACS, ISIC: 92.6%/87.5%
[101]	Medical	Brain tumor	HHOCNN	Tumor detection accuracy	Improves the overall tumor recognition accuracy	Computational cost	98%
[102]	Medical	Brain tumor	MRFO	Tumor detection accuracy	Improves the overall tumor recognition accuracy	Its use in real-time applications is disadvantageous due to computational cost	98.64%
[103]	Medical	Brain tumor	MPA, ASO, HHO, BOA, WOA, GWOA, BOA, FFA,	Feature Optimization	Improves the overall tumor recognition accuracy	8 different MH algorithms were compared. There are no drawbacks	95.7%
[104]	Medical	Chest Imaging	BPSO and BGWO	Increasing the success of classification	Improves the overall tumor recognition accuracy	Adjusting CNN parameters is necessary to improve prediction accuracy	99.38%
[105]	Medical	Chest Imaging	Guided WOA	Increasing the success of classification	improves the overall tumor recognition accuracy	Adjusting CNN parameters is necessary to improve prediction accuracy	99%
[107]	Medical	Medical Imaging	CMOA	Database matching in medical imaging	It performs better than traditional methods	Transfer learning has not been attempted during CNN training	IMRA, MESSIDOR: 98%, 97%
[108]	Medical	Medical Imaging	GA	Ability to get new features in transfer learning	The performance of extracting new features has been improved	Convergence and local optima	95.98%
[110]	Medical	White blood cell detection	BCO	Increasing the success of classification	Improves the overall accuracy	Tested with a single dataset	99.21%

Table 1 (continued)

Ref	Application	Focus on	MH Algorithm	Role of MH	Advantage	Disadvantage	Accuracy
[116]	Hyperspectral	Remote Sensing	ABC, CSO, FFA, PSO, GWO, SMO, SSA, WDO, GEO, JSA, PSOLF, LGWO, and LFGA	Band Selection	The MH method is used to determine the optimal number of bands	It has been tested in simple applications that do not require many parameters	ABC: 67.4%, CSO:70.6%, FFA:67.5%, PSO:64.3%, GWO:68.5%, SMO:68.2%, SSA:70.1%, WDO:63.9%, GEO:69.1%, JSA:66%, PSOLF:81.1%, LGWO:79.7%
[117]	Hyperspectral	Remote Sensing	GWO	Band selection	High classification accuracy using a small number of samples	It is a method that does not require many parameters for simple applications. CNN/DNN-based architectures are used to select optimal bands in more complex applications	89%
[118]	Hyperspectral	Remote Sensing	FPO (CNN, Wavelet, and Gabor filter)	Band selection	Improved classification accuracy with optimal bands	Computational complexity	Indian Pines:98.06%, Pavia University: 98.94%, Salinas Scene: 98.92%
[119]	Hyperspectral	Remote Sensing	SSA	Band selection	Improved classification accuracy with optimal bands	Prediction successes across classes are unbalanced and computational complexity	97.14%
[121]	Hyperspectral	Agriculture	Binary GWO	Band selection	Improved classification accuracy with optimal bands	Prediction successes across classes are unbalanced and computational complexity	96.01%
[122]	Hyperspectral	Remote Sensing	IBSWHO	Local optima trapping in band selection	Avoiding local optima and improving performance	Computational complexity	Indian Pines: 82%, Pavia University: 92.73%, Salinas Scene: 97.34%
[124]	Hyperspectral	Apple leaves disease detection	EO	Band selection	Classification accuracy has been enhanced with optimal bands	Iteration cost and local optima trapping	99.38%
[125]	Hyperspectral	Remote sensing	BA-ABC	Feature selection	Classification performance has been improved on different datasets for remote sensing	Iteration cost and local optima trapping	94.6%
[126]	Hyperspectral	Satellite images	WOA-BA	Iteration cost and classification success	Achieved better results with shorter iterations	Computational cost	95%
[127]	Hyperspectral	Remote Sensing	BDA-DDO	Insufficient diversity of exploration and population in feature selection	It also provides higher classification accuracy	Tested on simple, non-complex datasets	89.8%

Table 1 (continued)

Ref	Application	Focus on	MH Algorithm	Role of MH	Advantage	Disadvantage	Accuracy
[128]	Hyperspectral	visual field (VF) images	PSO, ABC HHO, SFO	Improving performance in Bayesian optimization	Improved the ability to define visual fields	Tested on simple, non-complex datasets	PSO, ABC HHO, SFO
[134]	Agriculture	Plant Classification	SMO, GWO, PSO	Feature Extraction	Reduces the time cost of feature extraction	Tested on simple, non-complex datasets	VGG-16: 98.6%, VGG-19: 98.34%
[131]	Agriculture	Plant Classification	BOA	Increasing the success of classification	Classification performance has improved	Tested on simple, non-complex datasets	99%
[135]	Agriculture	Weed detection with stereoscopic camera	PSO	Increasing the success of classification	Classification performance has improved	Tested on simple, non-complex datasets	85.71%
[136]	Agriculture	classify healthy and unhealthy leaf images	OLPSO	Hyperparameter Optimization	Efficient on complex and large datasets	Time complexity	98.2%
[139]	Steganography	Steganalysis	GWO (levy-flight)	Regions in the image contain hidden information	Parts of the image that contain or do not contain hidden information	Computational cost	80.44%
[140]	Steganography	Steganography	ACO	Enhances the security of hidden messages	Makes the detection of hidden data more difficult and improves its security	Computational cost	*
[141]	Steganography	IOMT	SSA and AOA	Increase the security level during transmission over networks	It provides success against secure and common standard image processing attacks	Computational cost	*
[144]	Others	Normal Imaging	GA	DNN Pruning	The pruning process is provided automatically in a fast and effective way	Although the training time of the model is reduced, it is necessary to achieve a minimum decrease in classification success	*
[145]	Others	Normal Imaging	PSO	DNN Pruning	The pruning process has been automated quickly and effectively, reducing computational cost and CO2 emissions	A minimal decrease in classification performance is required	66.84%
[146]	Others	Normal Imaging	AHBBO	Hyperparameter optimization is applied in the original BBO to address early convergence and insufficient exploration	Classification performance has increased	Computational Complexity	92.33%
[147]	Others	Normal Imaging	mGTO	The traditional GTO faces issues of local optima and early convergence	mGTO has been improved compared to the traditional GTO	Computational cost	97.54%

Table 1 (continued)

Ref	Application	Focus on	MH Algorithm	Role of MH	Advantage	Disadvantage	Accuracy
[149]	Others	Big Data	SLnO	DNN optimization and feature selection are improved for big data with excessive information	More efficient feature selection is performed for big data	Time complexity	*
[150]	Others	Big Data	DAUMS	Iteration cost and classification success	Classification performance has increased	Computational Cost	80.6%
[152]	Others	Normal Imaging	RFO	Crop in image processing	It can reduce the size of the analyzed image and thus reduce the time it takes to analyze it	Computational cost	*

*Accuracy values for studies with multiple parameters are indicated, as full details cannot be accommodated within the table due to space limitations

improve the effectiveness of existing deep learning methodologies [221]. Despite their great contributions, they have some shortcomings that can be solved by MH approaches. For example, roads in satellite images cover a small part of the images. It is difficult to suppress the background effectively, and this may negatively affect road detection. Sand cat swarm optimization-based algorithms [222] can be useful in finding better global solutions in determining background pixels. In addition, misalignment of features in high-resolution images can reduce road detection accuracy. This problem can be solved by optimizing the strip convolution parameters with an algorithm such as PSO, and road detection accuracy can be increased. In another important study, a deep learning model called Transferred Multi-to-Mono-Modal Generation Networks (TMM-Nets) used in the diagnosis of rare diseases was developed [223]. However, this study can benefit from MH approaches in reducing speed and computational cost or tuning hyper-parameters. Therefore, the MH algorithms can be easily adapted to various tasks in different fields, proving effective in medical imaging, hyperspectral imaging, agriculture, steganography, and other applications due to their flexible structure of MH. However, alongside the advantages they provide, there are also various limitations.

This section examines the functions, benefits, and constraints of MH algorithms in classification, segmentation, and registration problems. In classification applications, the principal function of MH algorithms pertains to feature selection, feature extraction, DNN pruning, optimal band selection, enhancement of convergence and local optimum challenges, determination of image cropping points, DNN weight optimization, iteration costs, refinement of conventional MH algorithms, and ultimately the augmentation of classification accuracy. Nonetheless, classification algorithms continue to encounter difficulties associated with premature convergence, trapping in local optima, and the necessity to enhance computing efficiency. The substantial computational expenses, especially in real-time applications, constrain the scalability and usefulness of MH algorithms on a broader scale. With 59% of the research in the categorization category originating from 2023 and after, this underscores the escalating significance of MH-based methodologies in this domain, with anticipated future proliferation of their use.

In segmentation problems, MH algorithms have improved thresholding selection, convergence and local optimum issues, computational complexity, and edge detection performance in images. However, these methods are still constrained in real-time applications due to high computational costs. The development of hybrid systems and the combination of DNN methods with MH algorithms hold promise for overcoming these limitations. Additionally, 65% of the studies in this area are from 2023 and beyond, indicating that MH-based approaches have also become popular in segmentation tasks.

In registration tasks, the focus is on improving image quality, iteration costs, and addressing convergence and local optimum issues. However, when working with large datasets and high-resolution images, the long computation time and limited parameter adaptation constrain the applicability of these methods. In the future, accelerating the parameter optimization processes of MH algorithms presents a significant research area for overcoming these limitations. Unlike the other two application areas, only 27% of the studies in this domain are from 2023 and beyond. This is likely due to the fact that registration processes are more focused on improving alignment and shift problems in real-time images. Enhancing the efficiency of MH algorithms in real-time applications will contribute to the literature in this field as well.

Considering all elements, MH algorithms play a key role in boosting the performance of deep learning models.

Table 2 Summary of MH algorithms in image segmentation applications

Ref.	Application	Focus on	MH Algorithm	Role of MH	Advantage	Disadvantage	Accuracy
[165]	Medical	Lung Cancer	WDRIME	Avoiding local optima and improving convergence	Increases convergence speed and prevents local optima	Computational cost	83.09%
[166]	Medical	Colon Cancer	DRPSO	Enhancing early convergence and overcoming entrapment in local optima	Improves convergence and escape from local optima	Computational cost	92.2%
[167]	Medical	Breast Cancer	SDSSA	Avoiding local optima	Improves performance in escape from local optima	Computational cost	*
[168]	Medical	Kidney Disease	CVWOA	Traditional WOA suffers from insufficient exploration and low solution accuracy	Enhances exploration and solution accuracy compared to classic WOA	Requires additional parameter tuning for optimal performance	FSIM-30.51
[170]	Medical	Covid X-Ray	RSA-SSA	Threshold selection	Provides a better search space for finding the optimal solution.	Limited diversity in the tested datasets and computational cost	*
[171]	Medical	Brain Tumor	ALO, MVO	Reducing computational costs caused by an increased number of thresholds in threshold selection	Computational costs have been improved.	The lack of a hybrid system leads to different strengths between algorithms	94%
[172]	Hyperspectral	Thresholding	DQGA	Avoiding local optima in image thresholding	Improves the local optima issue	Parameter values are selected through trial and error	*
[173]	Hyperspectral	Thresholding	CSO	Convergence and early convergence issues.	Improves the local optima issue	Segmentation quality deteriorates at higher thresholding levels	97.2%
[174]	Hyperspectral	Thresholding	IBES	Improve model computational complexity and high computation time	Better threshold values are found within the same time	Needs tuning hyperparameter	SSIM: 93%
[175]	Hyperspectral	Thresholding	COVIDOA	Determining threshold values	Performs more efficiently compared to traditional methods	Needs testing with colored images for multi-level thresholding	*
[176]	Hyperspectral	Thresholding	Non-dominated Sorting Genetic Algorithm	Thresholding success	Performs more efficiently compared to traditional methods	Computational cost	98.47%
[177]	Hyperspectral	Thresholding	MSO-Otsu	Computational cost in threshold selection	Improved	Requires extensive testing for various threshold settings	*
[178]	Hyperspectral	Thresholding	WHO	Clustering optimization based on color information	Improves thresholding	Computational cost	*
[179]	Hyperspectral	Image Fusion	DSA	Avoiding from local optima	Improves the local optima issue	Computational cost	*
[180]	Hyperspectral	Segmentation in a noisy environment	TPSCA	Optimizing CNN parameters	Optimizes CNN parameters	Time complexity	88.25%
[181]	Hyperspectral	Land change detection	PSO	Edge detection	Provides better edges and clarity	Computational cost	*
[182]	Agriculture	Threshold selection	MSO	Improving global search performance and avoiding early entrapment in local optima	Improves the local optima issue and global search ability	Time complexity	76.21%

Table 2 (continued)

Ref.	Application	Focus on	MH Algorithm	Role of MH	Advantage	Disadvantage	Accuracy
[183]	Agriculture	Threshold selection	CAPSA	Improving global search performance and avoiding early entrapment in local optima	Improves the local optima issue and global search ability	Computational cost	72.29%
[185]	Steganography	Hiding information	PSO	Maximizing the capacity and improving the quality of the hidden image	Improve capacity and quality	Computational cost	*
[186]	Others	Threshold selection	GWO	Optimal threshold determination	Improves threshold	Computational cost	*
[187]	Others	Threshold selection	WGWO	Optimal threshold determination	Improves threshold	Computational cost	*
[188]	Others	Threshold selection	AOA-HHO	Optimal threshold determination	Improves threshold	Computational cost	*

*Accuracy values for studies with multiple parameters are indicated, as full details cannot be accommodated within the table due to space limitations

Traditional optimization methods are often insufficient in effectively addressing challenges such as hyperparameter optimization, feature selection, weight adjustment, and the avoidance of local minima. At this point, MH algorithms contribute to improving the efficiency of deep learning models through their strong search and exploration capabilities. In this context, algorithms such as ARO and PSO have been shown to enhance model accuracy while reducing computational costs in DNN weight optimization. Moreover, techniques such as CWCO for neural network pruning enhance model efficiency, rendering them especially appropriate for real-time applications. A thorough investigation reveals that the combined application of MH algorithms and deep learning models enhances accuracy rates while optimizing computing efficiency.

Finally, the geographical distribution in the reviewed studies is presented in Fig. 8. According to this, the majority of authors come from China (43.93%) and India (22.98%). However, notable contributions from African countries such as Algeria (5.41%) and Egypt (5.03%) demonstrate that research in this field is not limited to Asian countries alone, as other regions also play an active role in these studies. Türkiye (2.14%) and Iran (3.46%) represent relatively lower percentages, highlighting the need for further encouragement of local studies in this field. Among European countries, Germany (0.07%), France (0.25%), and Italy (0.12%) have even lower proportions. This indicates that Europe has relatively focused less on research in this area. In conclusion, while studies on machine learning algorithms have gained a global dimension under the leadership of Asia, conducting more research in other regions presents a significant opportunity to increase international contributions.

4.1 Challenges

MH algorithms have considerable promise in image processing and computer vision applications; yet, they face several hurdles. These problems restrict its effective implementation in real-time tasks such as image classification, segmentation, and registration due to substantial computational expenses and temporal complexity. Prolonged computation durations, vulnerability to entrapment in local optima, and challenges with premature convergence detrimentally impact the efficacy and adaptability of these algorithms. Numerous metaheuristic techniques grapple with achieving a balance between exploration and exploitation, resulting in either early convergence or protracted search durations. Moreover, improving the efficacy of these algorithms necessitates further parameter adjustment and hyperparameter optimization. Nonetheless, these procedures frequently require considerable time and inefficiently utilize hardware resources due to their dependence on trial-and-error techniques. Moreover, the propensity of algorithms to undergo evaluation predominantly on simplistic datasets limits their generalizability to more intricate and varied datasets, thereby diminishing their extensive application in real-world contexts. Despite their superior performance relative to non-MH legislation, these criteria remain inadequate in delivering a comprehensive solution. Therefore, MH-based methodologies require enhancement in several dimensions. Furthermore, the fundamentally stochastic characteristics of MH techniques need new methodologies to integrate them with the deterministic training processes of deep neural networks, with the objective of creating seamless and successful hybrid models.

The robustness of the algorithms is reduced, and the quality of the images is degraded as a consequence of the limited evaluation of multi-level thresholding and more

Table 3 Summary of MH algorithms in image registration applications

Ref	Application	Focus on	MH Algorithms	Role of MH	Advantage	Disadvantage	Accuracy
[192]	Medical	Image registration improvement	TLBO	Improve image quality	The image quality has been improved through enhancement	Computational cost	RMSE-45.39%
[193]	Medical	Image registration improvement for CT	PSO and GWO	Improve image quality	It achieves high precision and good registration	Computation takes relatively more extended time	SSIM-99.98%
[194]	Medical	Image registration improvement for CT	ISCA	Improve image quality	It achieves high precision and good registration	Computational cost	Dice Similarity-90.66%
[195]	Medical	Image registration improvement for CT	BA-GWO	Improve image quality	It achieves high precision and good registration	Computational cost	*
[196]	Medical	Image registration improvement for PET and MRI	BBO	Improve image quality	It achieves high precision and good registration	Computation takes relatively more extended time	*
[197]	Medical	Image registration improvement for PET, MRI, and CT	CRO-SL	Improve image quality	It achieves high precision and good registration	There are limitations on the exploration side due to convergence and local optima	*
[198]	Medical	Image registration improvement for CT, MRI, and Retinal	ARO	Improve image quality	It achieves high precision and good registration	There are limitations on the exploration side due to convergence and local optima	NMI-32.57%
[199]	Medical	MRI imaging of the brain, breast, and kidneys	CSO	Improve image quality	Improve image quality	Only time spent was calculated; exploration and exploitation parameters were not examined	*
[200]	Medical	CT and MRI multimodality imaging	PSO-GA	Improve search space to improve image quality	Improve image quality	Convergence and local optima	Correlation value-32.38%
[201]	Medical	Multimodal Imaging	UEO	Convergence speed and local optima	Improve accuracy	Time complexity	*
[202]	Medical	Multimodal Imaging	GWO-Based Non-Rigid Demons Registration	Convergence speed and local optima	Improve accuracy	Time complexity	99.7%
[203]	Medical	Multimodal Imaging	TLBO	Convergence speed	Improve image quality	Computational cost	RMSE-0.414
[204]	Medical	Multimodal Imaging	PSO, DA, ABC	Convergence speed and local optima	While DA provides higher quality results, its convergence time is longer. PSO, on the other hand, has faster convergence but does not provide high-quality images	In all three algorithms, the computation time is a disadvantage	*
[205]	Medical	Multimodal Imaging	OHGS	Convergence is improved with optimal geometric space transformation parameters	Improve accuracy	Limited performance in highly complex transformations	SSIM-73.29%

Table 3 (continued)

Ref	Application	Focus on	MH Algorithms	Role of MH	Advantage	Disadvantage	Accuracy
[206]	Medical	Multimodal Imaging	HBGA	Optimizing the search space to improve early convergence and avoid falling into local optima	Improve accuracy	Computational Cost	NMI-0.1811
[207]	Medical	Multimodal Imaging	BBO-EL	Optimizing the search space to improve early convergence and avoid falling into local optima	Improve image quality	Computational Cost	*
[208]	Medical	Multimodal Imaging	FPO-BOA	Optimizing the search space to improve early convergence and avoid falling into local optima	Improve accuracy	Computational Cost	MSE-0.002
[213]	Hyperspectral	Remote Sensing	ECA	Iteration cost	Improve image quality	Registration issues occur when textures in both images are homogeneous	RMSE-1.71
[214]	Hyperspectral	Remote Sensing	SGD-DE	Enhancing exploration and exploitation capabilities	Improve image quality	There are constraints on parameter adaptation	NMI-1.177
[215]	Hyperspectral	Point Cloud	ABC	Optimal solution in point cloud image registration	It performs more efficiently than traditional MH algorithms	Requires testing with more parameters and diverse datasets	*
[217]	Steganography	copyright protection for multi-watermarking	PSO-GWO	Defining the objective function	It is more secure and has higher invisibility against attacks	Time complexity	*
[218]	Others	Face Detection	PSO	image registration parameters for the geometric transformation of the input image	The image outputs are of higher quality	Computational cost	SSIM-0.3379

*Accuracy values for studies with multiple parameters are indicated, as full details cannot be accommodated within the table due to space limitations

complex processes in color images in segmentation tasks. In the same way, the absence of hybrid systems in classification applications precludes MH algorithms from utilizing the advantages of diverse methodologies, thereby reducing their overall efficiency. The adaptability of algorithms is limited in image registration tasks due to the challenges that arise during the alignment of images with homogeneous textures. The necessity for more resilient and adaptable methodologies in this field is emphasized by the decreased efficiency of algorithms in intricate tasks.

All of these challenges underscore the necessity of developing innovative and optimized solutions to enhance the potential of MH algorithms in the fields of image processing and computer vision. Lower computational costs, increased generalizability, and more flexible designs are critically important for expanding the application domains of these algorithms.

4.2 Current trends

Innovative methodologies in the formulation and utilization of MH algorithms have the capacity to produce more effective and efficient solutions. The creation of hybrid models can allow MH algorithms to achieve enhanced performance on intricate datasets when combined with CNN or DNN techniques. These hybrid applications integrate the solid framework of classical algorithms with the extensive learning capabilities of deep learning models, thereby providing

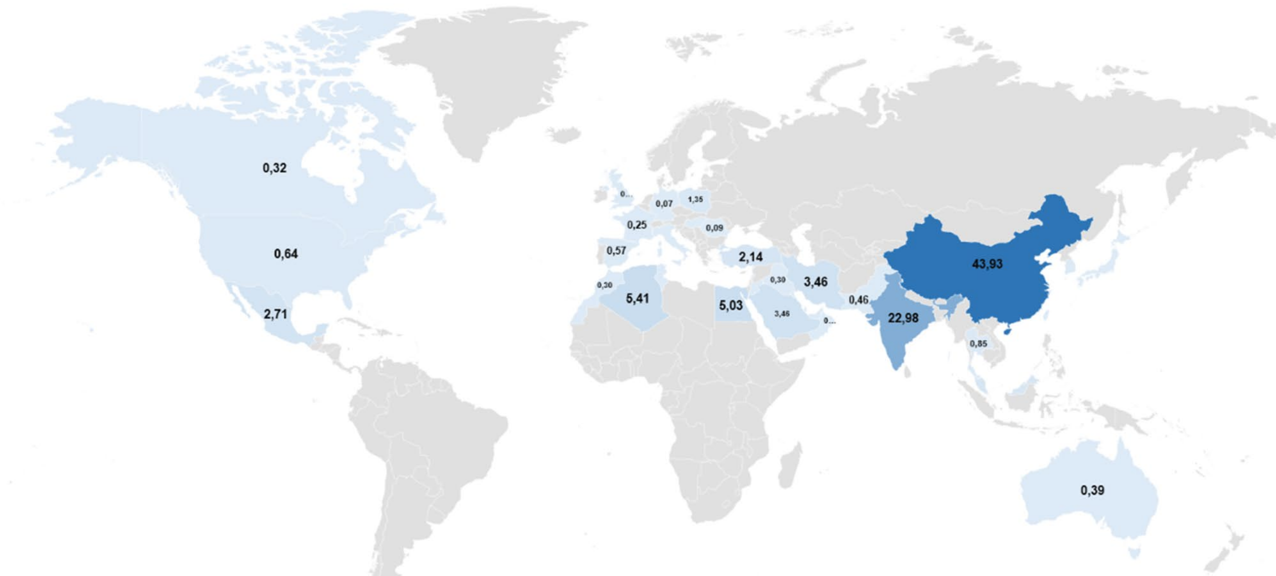

Fig. 8 Distribution of the countries of origin of the reviewed publications

potent solutions. The use of transfer learning in data-scarce domains is essential for addressing data deficiency challenges, especially in classification and segmentation tasks, by enabling the transfer of information from established datasets to novel ones. This enhances training expenses while also guaranteeing elevated accuracy rates.

The evaluation of MH algorithms in extensive and intricate datasets is crucial for assessing their generalizability and dependability. These assessments assess the viability of efficiently employing algorithms in large-scale systems, while minimizing computing complexity is particularly essential for real-time applications. Thus, the processing capabilities of MH algorithms may deliver superior performance even on resource-constrained devices, thereby improving the efficiency and processing speed of applications. The advancement of automated parameter optimization methods is crucial for enhancing the efficacy of MH algorithms. Dynamic and adaptive parameter tweaking techniques can significantly improve algorithm performance across many problem areas. This improvement will allow MH algorithms to attain a wider array of applications in both scientific and industry contexts.

5 Conclusion and future works

This study provides a comprehensive examination of the role of MH algorithms in classification, segmentation, and registration categories within image processing and computer vision applications. The versatility of MH algorithms, their capacity to adapt to many applications, and their efficacy in optimization challenges have demonstrated advantages, especially in areas such as medical imaging, hyperspectral imaging, agriculture, steganography, and additional sectors. Nonetheless, challenges like as premature convergence, trapping in local optima, elevated computing expenses, and suboptimal performance on intricate datasets restrict the efficacy of MH algorithms in large-scale and real-time applications. In classification problems, MH algorithms have effectively enhanced classification accuracy through procedures including feature selection and weight optimization. In segmentation, these methods, utilized in thresholding and edge detection, have improved accuracy rates; yet computational costs in complicated datasets persist as a challenge. In image registration tasks, MH algorithms attain elevated precision and accuracy, especially in complex domains like multimodal imaging.

As for future directions, the following areas should be focused on improving the effectiveness of MH algorithms:

Development of hybrid models: The hybrid application of MH algorithms with deep learning approaches (e.g., CNN, DNN) can provide more efficient performance on complex datasets.

Integration of transfer learning: The use of transfer learning, particularly in classification and segmentation tasks, can facilitate the transfer of knowledge obtained from existing datasets to new datasets.

Reduction of computational complexity: Lightweight algorithm designs and enhanced parallel processing capabilities will enable real-time applications.

Performance analysis on large and complex datasets: Testing and analyzing MH algorithms on large-scale and diverse datasets is crucial for large-scale applications.

Automatic parameter optimization: Dynamic and adaptive parameter tuning methods can be developed to enhance the effectiveness of MH algorithms.

In conclusion, the optimization capabilities of MH algorithms make them indispensable tools in the fields of image processing and computer vision. However, a continuous research and development process aimed at enhancing the efficiency of these algorithms is crucial for expanding their applications in both academic and industrial domains.

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