Grey wolf optimizer and other metaheuristic optimization techniques with image processing as their applications: a review

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Abstract. Image processing is an evolutionary field in the domain of computer vision that currently has a comprehensive spectrum of applications. It is being employed in image segmentation, image classification, medical imaging, image compression, etc. A lot of real-world prominent issues are tackling employed through these application techniques. These techniques can be employed by means of various algorithms; however, these offered immensely dominant outcomes with existing and modified optimization algorithms. Some of the metaheuristic optimization algorithms applied during the above techniques include Ant Colony Optimization (ACO), Genetic Algorithm (GA), Bat Algorithm (BA), Grey Wolf Optimizer (GWO), Evolutionary Strategy (ES), Particle Swarm Optimization (PSO), Genetic Programming (GP), and so forth. Hence, this manuscript's main objective is that the study of several applied optimization algorithms and their variants thus lead to the various domain of image processing concludes it work more efficiently and robustly.

Keywords: Grey Wolf Optimizer, Metaheuristic Algorithms, Support Vector Machine, Image Segmentation, Image Classification, Medical Imaging, Image Compression.

1. Introduction

Now days, Image processing is a very dominant research area from last two decades for the researcher. Image processing is a process by which operations are performed on the image to get intensified image and to extract useful information from the images. Digital image processing and analog image processing are two significant classifications of image processing. However, digital image processing being an efficient mechanism to visualize any image, restore the distorted image, eradicate noise, and image recognition. It is intensively employed in numerous areas such as face detection, remote sensing, moving object sensing, etc. Although analog image processing is a continuous process applied to analog signals and cannot be segmented into small components, it is eventually imposed as slow and costly. It is intensively employed in numerous areas such as remote sensing, Intelligent Vehicle and Highway System (abbreviated as IVHS) [1], etc.

Typically, the pixel is a fundamental component of an image. In other words, an image is a combination of rows and columns (matrix) of pixels stored in electronic form and can be modified, copied, or transferred by the computer. Significantly, an image is a two-dimensional visual
representation that contains color information. The various types of operations are employed on the image in image processing, whereas some of them are discussed in this section.

Image segmentation is an integral aspect of image processing that fundamentally segregates the image into distinct segments to extract valuable information that is more significant, subsequently; obtained isolated pixels are called super-pixels. In other words, image segmentation is a preprocessing strategy in order to analyze an image that segregates the foreground from a background of an image. The numerous applications to tackle diverse real-life problems are adopted by image segmentation such as machine vision, object detection, content-based image retrieval, etc.

Medical imaging is a technique employed to fabricate a visual portrayal of the interior body. This technique predominantly revealing the intramural structure of the skin to diagnose various diseases. This imaging technique is widely used to detect various diseases using image processing and is broadly employed in ultrasound, elastography, nuclear medicine, and so forth in the medical field.

Image compression is a process in which the data is compressed to minimize the expense of storage and transmission. Image compression is of two types, lossless and lossy compression. The image compression prohibits the redundancy of the image which occupies less storage. Lossless image compression (reversible image compression) does not slacken the size of an image, i.e., it can be reverted to its veritable form and less data-holding capacity. In contrast, lossy image compression (irreversible image compression) slackens the size of an image, i.e., it does not revert or reform toward its original form and contains immense data holding capacity than Lossless image compression.

The way toward classifying an object is based on its visual substance that is called image classification. Image classification can be divided into two categories, firstly supervised classification in which the training region is elected and subsequently generates signature files to classify it further. In contrast, in unsupervised classification, the image clusters are formed and further the classes are characterized for the image classification. The various applications of image classification are object recognition, image labeling, robotic vision, etc.

Over the most recent two decades, the metaheuristic algorithm frameworks are becoming more popular considering how to tackle broad range type problems, issues regarding design patterns, behave like a black-box function, the problem-independent high-level algorithmic paradigm, etc. In contrast, the heuristic algorithms are usually problem-dependent, such as choosing the random pivot element from a list of elements through quick sort. In the context of one word, Metaheuristic generally known as heuristics about heuristics i.e. it provides a set of guidelines or strategy to develop such optimization algorithms those are considered to be heuristic. The heuristic algorithms, moreover, formulating "good guess" function to provide 'good enough' solution in order to regarding problem. The Classification of Heuristic and Metaheuristic Optimization Algorithms are shown in figure 1. Although, the metaheuristic algorithms have been discussed in this research manuscript hence the key focus on it.
During the next section, a remarkable discussion about numerous fairly well-known meta-heuristic optimization algorithms assists in optimizing various real-world applications and several fields of study. Surprisingly, No free lunch theorem [2] state that a unique optimization algorithm cannot tackle all types of problems; however, all kinds of optimization algorithms cannot solve a single problem. As such it encourages constituting novel meta-heuristic optimization algorithms and renovating existing algorithms. The essential focal point of this section, a concise but lofty survey, is addressed about various striking meta-heuristic optimization algorithms that assist the various image processing domains to consider image segmentation, medical imaging, image compression, and image classification. Let’s discuss the following section to get various application domains employed by various meta-heuristics algorithms and their improved variants. The many abbreviated forms are utilized throughout this manuscript in sorted order (A to Z) tabulated in Table 1.

**Table 1. List of Abbreviation**

| Abbreviated Form | Expanded Form                        | Abbreviated Form | Expanded Form                        |
|------------------|--------------------------------------|------------------|--------------------------------------|
| ABC              | Artificial Bee Colony                | LBG              | Linde–Buzo–Gray                      |
| ACO              | Ant Colony Optimization              | LDA              | Linear Discriminant Analysis         |
| BA               | Bat Algorithm                        | MPL              | Multi-layer perceptron                |
| BFO              | Bacterial Foraging Optimization      | MSE              | Mean-Squared Error                   |
| CSA              | Cuckoo Search Algorithm              | OSMF             | Optimum Spectrum Mask Fusion         |
| CT Images        | Computed Tomography Images           | PCA              | Principle Component Analysis         |
| DE               | Differential Evolution               | PSNR             | Peak Signal-to-Noise Ratio           |
| ES               | Evolutionary Strategy                | PSO              | Particle Swarm Optimization           |
| FA               | Firefly Algorithm                    | QP               | Quadratic Programming                |
| FCM              | Fuzzy C-means Clustering             | SA               | Simulated Annealing                  |
In Section 1, the introduction has been discussed regarding image processing and the critical requirement of various metaheuristic optimization algorithms. The rest of this manuscript is organized as follows: the literature review has been discussed in section 2, whereas section 3 concerns results and discussion of this research article. Conclusively, the conclusion has been discussed in section 4 of this manuscript.

2. Literature Review
In this section, a comprehensive discussion regarding various metaheuristic optimization techniques and various applications of digital image processing. In addition, the advantages, disadvantages, limitations, and future scope have been discussed for respective strategies.

2.1 Genetic Algorithm
During 1960, a marvelous as well as prestigious optimization algorithm innovated by John Holland namely Genetic Algorithm (GA) [3, 4] in order to practically implements the principle of “Darwin’s theory of evolution”. This principle getting the direction toward survival of fitness i.e. dissolves such species from that environment whose cannot fit or survive in corresponding environment. The algorithm begins with a random population and incorporates three biological evolution operators: selection, crossover, and mutation have been executed respectively and recursively until getting the desired outcome or course of terminated conditions. To impose the optimization algorithm’s desired properties, i.e., exploration and exploitation, are mathematically obtained by crossover and mutation operators. Manifold research problems are optimized by means of GA; image segmentation and image classification are the most popular out of them whose described in the coming section of this article.

2.1.1. Application of Genetic Algorithm
Hung and Wu [5] inaugurated a novel clustering method known as FCM (fuzzy c-means) using genetic algorithm to overcome the disadvantages of FCM in form of cluster detection. The utilization of genetic algorithm improves the quality of recognizing the cluster center, identifying several diseases, and visualizing the anatomical structure. GFCM2G algorithm has been proposed in order to implement GAFCM (the fundamental thought behind this algorithm is to split the genetic population into multiple sub-populations) on the numerous embedded graphics processing units based gadgets. To implement algorithmically and computability, proposed algorithm executing two programming models parallel; the first one is Message-Passing Interface: MPI which is a broadcast mechanism that carries out the execution of the algorithm, and the other one is Compute Unified Device Architecture: CUDA that is used to enhance the computational features of the MRI segmentation.

2.2 Genetic Programming
During 1992, Genetic Programming (GP) [6-7] was inaugurated by JoneKoza. Reproduction, crossover, and mutation operators are implemented in the initial phase, architecture-altering operation applied during final phase in order of implementation of GP. This algorithm is a domain independent method and based on theory of evolution which comes under Evolutionary Algorithm. Many applications are very popular on which GP work well and provide satisfactory results as compare to other metaheuristic optimization algorithms. Image segmentation and image classification are more trending application areas for research work which is done by GP studying during this article.
2.2.1. Applications of Genetic Programming

Liang et al. [8] proposed three feature selection processes for image segmentation using genetic programming, first one abbreviated as PGP-FS (Parsimony Genetic Programming Feature Selection) that is implemented for single-objective applications, NSGP-FS (Non-dominated Sorting GPFS) and SPGP-FS (Strength Pareto GPFS) are second and third respectively which are multi-objective, however GP has not been looked into fairly in the field of feature selection. Single-objective as well as multi-objective are deployed together for the feature selection and compare the method capacity for searching effective feature subset which is to be tested on two benchmark datasets, the Weizmann and Pascal datasets which have high variation. The proposed method is able to produce lower feature set than the original set which contain 53 features. The goal of multi-objective in the consideration of reducing the number of features selected and grow up the performance of segmentation, on the other hand, the single-objective contains the ability to furnish potent feature subset on which bases the performance has to varying. However, the multi-objective employed more powerfully in order to generate the subset of effective feature. The diversity of the non-dominated solution is better maintained by the NSGP-FS.

Liang et al. [9] proposed a new approach for the problem of image segmentation employed using genetic programming. This algorithm does not require specifying the solution structure, it evolves the segmentors that conduct the figure ground segmentation instinctual and explicitly. The segmentation problem can be resolved more logically using top down approach and acquire the learning from object information. The testing of this approach is done on four different datasets (bitmap, Brodatz texture, Weizmannand, and Pascal databases) to validate the model and mature the segmentors. After the different testing and comparison, it has been found that the proposed model is more efficient for the purpose of image segmentation.

In order to deal with complex image classification problems, Iqbal et al. [10] proposed a novel method. The proposed methodology is centered on genetic programming and exchange of learning. The proposed technique explores genetic programming's ability to seek and extract valuable information from a straightforward errand to help become acquainted with an unpredictable assignment alongside the utilization of transfer learning. Kyllberg, Brodatz, and Outex standard data sets are being used here, whereas they have been used unrotated earlier and rotated later to perform the implementation. This technique involves extracting blocks of knowledge from simple images (without considering noise and rotation) in code fragments. The previous step's extracted knowledge is used to learn more intricate undertakings (various rotated and noisy renditions of the original images). The extracted knowledge is reused for learning concerning multiple domains and complex images as well. The aforesaid exchange learning technique considers GP has enhanced the classification performance over the traditional strategies such as completed local binary count (abbreviated as CLBC), dominant rotated LBP (DRLBP), and DeCAFs.

2.3. Differential Evolution

Storn and Price [11-14] proposed another evolutionary algorithm named Differential Evolution (DE) during 1990. The DE is a population-based algorithm and no need to evaluate differentiation or gradient to compute the candidate solution. The DE is also known as a metaheuristic optimization algorithm covering a large search space to evaluate more optimal solutions regarding candidate problems. While DE is not suitable for continuous problems, but it is provided a greater chance of obtaining optimal solutions despite incomplete information or no assumptions about the candidate problem.

2.3.1. Application of Differential Evolution

Sarkar et al. [15] proposed an unsupervised technique dependent on entropy and multi-level thresholding to image segmentation. In this regard, the entropies are named Renyi’s entropy as well as Cross entropy which are adopted for maximization and minimization problems respectively in order to optimal thresholding. Decomposition-based Multi-Objective Evolutionary Algorithms with DE
(shortened as MOEA/D-DE) are bestowed to assess Pareto optimal solution's set. Moreover, to bring out the approximated Pareto fronts, the MOEA/D algorithm alongside differential evolution operator is utilized. To automatically bring out the solutions which are most appropriate for the Pareto optimal set, the method is claimed that depends on the fuzzy membership function. Surprisingly, the remarkable performance of proposed algorithms had been compared with other highly developed MOEAs such as NSGA-II and MOPSO, conclude that MOEA/D-DE were dominated over them. A comprehensive evaluation alongside neoteric single-objective global optimizer methods is likewise carried out. Moreover, the proposed technique has been used to detect brain tumors and it worked proficiently.

2.4. **Ant Colony Optimization**

In his research work of Doctor of Philosophy, Marco Dorigo submits a marvelous proposal regarding the behavior of ants that found the food source and choose the optimal path toward their nest. The ants follow the behavior of swarm intelligence and such algorithms are known as swarm-based algorithms. To communicate with each other, ants disperse a special type of chemical which is known as a pheromone. In 1992, Ant Colony Optimization abbreviated as ACO [16-18] came into the picture that follows the intelligence behavior of ants which is discussed in his thesis article of doctor of philosophy. ACO is the very famous metaheuristic algorithm. ACO is applying in the enormous application of various domains. During this research article, the impressive performance of ACO arises in the application of image classification.

2.4.1. **Application of Ant Colony Optimization**

JayaBrindha and GopiSubbu [19] proposed a machine vision for varietal identification on the images. For the process of identifying other distinguishable variety in the seed testing laboratory, a machine vision technique is used instead of manual operation. The proposed approach conducted experiments on sunflower seeds for varietal identification. The data used here contains the sunflower seeds of ten varieties. The techniques used here for varietal identification are Kernel LDA (Linear Discriminant Analysis) based boundary features and Principle Component Analysis (PCA). LDA and PCA are dimensionality reduction techniques. In this proposed approach, ant colony optimization technique is used for obtaining the order of cascaded SVM by maximizing the total probability of correct decision. The above system contains the ability to distinguish other seed varieties.

2.5. **Bat algorithm**

Bat algorithm [20] is one more latest and trending metaheuristic optimization algorithm. It was developed by Xin-She Yang during 2010. Bat algorithm is a swarm based algorithm which applied social intelligence to compute global optimal solution from many feasible solutions. The echolocation behavior of microbats was the inspiration to propose this algorithm in which attempt the communication between bats based on echoes. Easy to design, simplicity and flexibility are the strength of this algorithm and it can be solved complex types of optimization problems. Performance of this algorithm is discussed in next section of this research article, in which image compression considered as the real-world application.

2.5.1. **Applications of Bat algorithm**

Karri and Jena [21] are enforcing Bat algorithm for image compression using fast vector quantification in present fabrication. The bat algorithm offers a comprehensive codebook alongside the minimum number of iterations including two parameters: loudness and pulse rate which are presumed as tuning parameters. Existing approaches for image compression are used, yet they have some deficiencies such as Linde–Buzo–Gray (LBG) originates lower peak signal-to-noise ratio value. PSO and Quantum PSO [22] goes beneath instability in convergence, Honey-Bees Mating Optimization (HBM) algorithm generates a near-optimum codebook in a limited time, firefly algorithm is shakiness when brighter fireflies do not exist, and the convergence is the volumetric challenge in continuation of particle
swarm optimization, whenever, the velocity of the particle becomes high. The proposed mechanism schemed uses BA on the underlying Solution of LBG. The PSNR value and quality of the reconstructed (compressed) image are preferable over LBG, PSO-LBG, QPSO-LBG, HBMO-LBG, and FA-LBG. Additionally, BA-LBG produces remarkable outcomes as compare to HBMO-LBG and FA-LBG.

To understand the unwavering quality of multispectral satellite images for examining the temporal variations, Senthilnath et al. [23] proposed a novel approach to deal with the classification process for assorted crop types utilizing bat algorithm (BA-based clustering). The proposed partitional clustering algorithm is utilized to inject information from training samples in the form of optimal cluster centers. Test samples are used to validate selected cluster centers. A real-time multispectral satellite image and one benchmark data set from the UCI repository have been obliged algorithm's reliability. The fruition of this approach is coordinated with several techniques such as BKM, GA, and PSO. Classification efficiency and time complexity are considered as evaluating parameters to figure out the outcomes. Compared to other metaheuristic techniques such as GA and PSO, BA is more computationally efficient. It is concluded that BA precisely converges optimal cluster centers and can be applied for tackling crop type classification problems.

2.6. Particle Swarm Optimization

During 1995, a prestigious research came into the picture to simulate social behavior firstly by Kennedy and Eberhart in the proposal of Particle Swarm Optimization (PSO) [24]. PSO is a swarm-based optimization algorithm and simulate social intelligence to compute optimal solution for complex optimization problems. There are two evaluating parameters to implement this algorithm, one is PBEST which is the personal best and other is GBEST which contains the global best or group best. PBEST is individual best and best out of PBEST considered as GBEST. The velocity and position vector (calculated by equation (1)) are mathematical model computing parameters on which PBEST got evaluate. A lot of real life optimization problems and applications are describing in literature, although, the performance of this algorithm is discussed in next section of this research article, out of those applications image segmentation as well as medical image is the discussing application.

\[ X_i(t + 1) = X_i(t) + v_i(t + 1) \] ....(1)

Where

\[ v_i(t + 1) = \underbrace{w(t)v_i(t)}_{\text{Inertia Weight}} + \underbrace{c_1r_1[p_i^{\text{best}}(t) - X_i(t)]}_{\text{Cognitive component or Individual Component}} + \underbrace{c_2r_2[g^{\text{best}}(t) - X_i(t)]}_{\text{Social Component}} \] ....(2)

The ‘w’ maintains the harmony between exploitation and exploration to ably performance of the algorithm. Although, it implies a constant value and is known as inertia weight. In comparison, ‘c_1’ and ‘c_2’ are also constant variables and well perform a balance among exploitation and exploration parameters. Hence, \( X_i(t+1) \) is the updated position for the next iteration. The above process is iteratively repeated till maximum number of iterations.

2.6.1. Applications of Particle Swarm Optimization

Mozafarri and Lee [25] proposed an algorithm for the image segmentation using image thresholding and for better optimization particle swarm optimization is used. The basic idea is to divide the particles into four sub-swarms for searching problem space. The method uses a new modified version of PSO which is Convergent Heterogeneous PSO algorithm; it gives better convergence, better
jumping to local position to global position. The Otsu’s and Kapur’s multilevel thresholding method have been used and the benchmark images is considered as dataset for the evaluation. All the experimental results show that CHPSO gives significantly remarkable accuracy and outstanding performances.

Zhang et al. [26] introduced the approach regarding real time segmentation that distinguish target image from the navigation image. To implement this approach, the Quantum Particle Swarm Optimization abbreviated as QPSO along with 2D fuzzy fisher are used to accomplish more accurate and quick segmentation in form of results corresponding to the input image. The 2D fuzzy fisher employed to make the adaptability between positioning target regions and retaining the boundaries of target fuzzy, based on criterion based integral image and the QPSO is used to encode current location of particles and mutative manipulation adds diversity to the particle swarm. The enhancements in its local searching capacity during the course of each iteration and to get the fast convergence, results is obtain by adding random orthogonal component along with quasi –optimum particle. The model is validated to check its competency of getting hasty segmentation and less valid signals simultaneously.

To determine the bone age maturity, Sabeti et al. [27] in this proposed work adopted three various versions of PSO. Various image processing methods are also owned. The dataset considered here contains left hand-wrist radiographs source of sixty-five referred children. The reason behind adopting three PSO versions is to magnify the segmentation accuracy. “The three versions of particle swarm optimization are standard PSO, Worst Behavior-based version of PSO abbreviated as WB-PSO and Adaptive Inertia Weight version of PSO abbreviated as AIW-PSO along with Otsu algorithm and an reiteratively statistical method are operated for segmentation of hand radiographs” [27]. The outcomes of Otsu algorithm along with above various versions of particle swarm optimization as well as iteratively statistical methods yielded 81.76, 82.49, 83.08, 84.27, and 69.04 percent classification accuracy respectively. White Gaussian noise along with various intensities was assembled to the compiled images to check vigorousness of schemed techniques. The fruition indicated that while increases the noise level the robustness against this white gaussian noise for the PSO variants also raised in more advertised manner as compared to Otsu as well as statistical methods. AIW-PSO image segmentation works efficiently for bone age estimation.

The other swarm-based algorithms such as ABC can be applied in other application areas such as wireless sensor network. Whereas, Karaboga [28] proposed a swarm-based metaheuristic optimization algorithm named artificial bee colony in 2005. The artificial bee colony is abbreviated as ABC and it has been inspired by the foraging behavior of honey bee swarm. The three group formation has been classified based on the intelligent foraging behavior of honey bees in order to the mathematical model. The author has proposed an approach namely SBHRA [29] to improving the stability, throughput, and lifetime of sensor node based on cluster network through ABC.

2.7. Cuckoo Search
In 2009, Yang and Deb [30] proposed a novel meta-heuristic optimization algorithm called Cuckoo Search (CS). The CS algorithm is an evolutionary population-based algorithm propelled by the lifestyle of the cuckoo bird family. The fascinating singing style and attractive voice are implied to be controlling paradigms that emphasize movement gradually to obtain the best solution from the previous solution. The cuckoo throws alien eggs from the current nest of host birds or searches the new nest to keep their egg that is considered the rule of thumb of this bird. The selection or locating the best nest to the cuckoo is considered as the main objective in the biological analogy. Similarly, explore the optimal solution concerning the real-world problem is the primary objective of the cuckoo search algorithm.

2.7.1. Application of Cuckoo Search
Bhandari et al. [31] proposed an advanced approach for image segmentation concerning color images using the Cuckoo Search algorithm utilized by Tsalis entropy for multilevel thresholding arranged by red, green, and NIR band. The fundamental objective of the applied algorithm is to pick the optimal
threshold value for the segmentation process. The algorithm is benchmarked upon ten different colored images that were captured by satellite. Additionally, SSIM, FSIM, PSNR, and MSE are considered as performance evaluation matrices. Furthermore, the performance has compared to DE, WDO, PSO, and ABC meta-heuristics algorithms and it has been found that implemented algorithm outperforms them. The accuracy of this algorithm is defined as far as the threshold's best objective value and computational cost in terms of CPU time. The limitation of this algorithm is in regard to color image multilevel thresholding, and the algorithm is found to be intricate. In contrast, this algorithm's profitability has meager control parameters, unlike DE, WDO, PSO, and ABC algorithms. This work's future scope can be utilized in real-time sophisticated image processing in which image classification, satellite image enhancement, various computer vision problems, etc. can be considered.

### 2.8. Firefly algorithm

Yang [32] introduced a meta-heuristic optimization algorithm that was inspired by flashing pattern of fireflies and mimic the characteristics of them, named Firefly algorithm (FA). The objective function is formed from brightness of firefly and the main objective has to consider the improvement in brightness of the fireflies. The light intensity is inversely square proportional to the distance. Consequently, low light intensity implies large distance and vice versa. Hence, every firefly is considered as solution and the objective is to minimize the distance between them. To achieve the above objective, the equation (3) is applied to movement of \( i \)th firefly (position \( x_i \)) toward \( j \)th firefly (position \( x_j \)) (\( j \)th firefly is more attractive than \( i \)th firefly):

\[
x_i = x_i + \beta (x_j - x_i)^2 - \alpha (\text{rand} - 0.5) \quad (3)
\]

Whereas, \( \alpha \) is randomization parameter \( \{\alpha \in [0, 1]\} \) and \( \text{rand} \) contains a random value \([0, 1]\). Although, the equation of \( \beta \) is derived from light intensity formula and calculated as:

\[
\beta = \beta_0 \left( e^{-r_{ij}^2} \right)
\]

\( \beta_0 \) is known as attractiveness coefficient \( \{\beta_0 = 1\} \). Whereas, \( r_{ij} \) is the Cartesian distance between position of \( i \)th firefly and \( j \)th firefly and calculated as:

\[
r_{ij} = \|x_i - x_j\| = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}
\]

The above equations are repeated till maximum iteration and produced an optimal solution for the optimization problem.

### 2.8.1. Application of Firefly algorithm

In image segmentation, conventional methods interpolate exceptionally high computational costs and breakdowns of their efficiency to accomplish the optimal threshold. This limitation motivates the application of meta-heuristics algorithms such as evolutionary algorithms or swarm intelligence algorithms. Naidu et al. [33] have proposed a multilevel thresholding algorithm utilized by the firefly algorithm to accomplish the above limitation. The objective is to maximize the Fuzzy entropy and Shannon entropy for the image segmentation. The algorithm is tested upon a natural and standard set of images (Lena, Goldhill, Pirate, and Starfish) to validate the performance and is additionally compared with other optimization techniques such as DE, BA, and PSO. PSNR, CPU Time, SSIM, Misclassification Error, Computational Complexity, and Stability Analysis are considered evaluation
metrics. The outcomes of the simulation clarify that the firefly algorithm outperforms the DE, BA, and PSO with respect to all evaluation matrices. In consideration of future work, the efficiency and convergence time will be enhanced by distinct optimization algorithms or an improved firefly algorithm.

2.9. Grey wolf optimizer
Grey wolf optimizer is a neoteric meta-heuristic optimization algorithm that is designed, formulated mathematically, and coded by Mirjalili et al. [34] during 2014. The grey wolf is non-domestic and found in North America as well as Eurasia and it is famous with a scientific name canis lupus subspecies. The hunting behaviour of grey wolves was the inspiration toward this meta-heuristics optimization algorithm. The grey wolves follow special type of strategy to attempt hunting their target in which a leadership hierarchy getting implements between pack of wolves. This leadership hierarchy (Figure (2)) contains top level i.e. leader of the pack known as alpha, wolf at the next level known to be beta, wolf at the next subsequent level known as delta, and omega types of wolves considered at the bottom level, out of which top three hierarchy are considered as best three solutions and calculated by equation (4) during this algorithm. GWO performs remarkable in many research applications and provide good results while solving complex types of problems. The performance of this algorithm is discussed in the next section of this research article in which image segmentation and medical image are considering as research domain.

![Leadership Social Hierarchy of Grey Wolf](image)

During the hunting process, the alpha, beta, and delta indicate the best position of prey and accordingly update the position of the remaining wolves (omega) of the pack. The hunting process is imposed as follows:

\[
\hat{X}(t + 1) = \frac{X_1 + X_2 + X_3}{3} \quad \ldots (4)
\]

Where \(X_1, X_2, \) and \(X_3\) are the positions of the prey according to alpha, beta, and delta grey wolf, respectively that is calculated as:

\[
X_1 = X_\alpha - A_1 \cdot (D_\alpha)
\]

\[
X_2 = X_\beta - A_2 \cdot (D_\beta)
\]

\[
X_3 = X_\delta - A_3 \cdot (D_\delta)
\]

\(D_\alpha, D_\beta, \) and \(D_\delta\) are distance between prey and alpha, beta, and delta grey wolf, respectively that is calculated as:
Where $\overrightarrow{X_{\alpha}}$, $\overrightarrow{X_{\beta}}$, and $\overrightarrow{X_{\delta}}$ are the position of alpha, beta, and delta grey wolf, respectively. However, $C_{\alpha}$, $C_{\beta}$, and $C_{\delta}$ are the constant parameters.

2.9.1. Applications of Grey wolf optimizer

With rise in the number of thresholds computational, complications also increase in multilevel thresholding. Understanding this hitch, Khairuzzaman and Chaudhury [35] adopted Grey wolf optimizer algorithm for multilevel thresholding in this proposed work. Here, in the consideration of GWO, Kapur’s entropy as well as Otsu’s between class variance functions are also owned. The validation of this proposed work is done on various standard test images sets which are showing in the summarizing table. To figure out the traits of segmented images, mean structural similarity is abbreviated as MSSIM exploited as an index. The outcome of testing phase shows that the above scheme provides high quality solutions as compared to particle swarm optimization as well as bacterial foraging optimization. When compared to bacterial foraging optimization, grey wolf optimizer is faster but slower than particle swarm optimization.

Li et al. [36] suggested and proposed a technique to extricate multi-level thresholding in the domain of image segmentation. In order to retrieve a bunch of thresholds, Modified Discrete GWO, abbreviated as MDGWO, is possessed to improve (optimize) the objective function adopted by Fuzzy Kapur’s entropy. MDGWO, however, is utilized as the apparatus, which infers pseudo-trapezoidal shape to form a fuzzy membership. Further, by owning local information aggregation image segmentation is done. When this applied with fuzzy it becomes FMDGWO. Improved PSNR and objective function values are ensured by FMDGWO while Electro-magnetism Optimization abbreviated as EMO, MDGWO, and Fuzzy entropy based Differential Evolution algorithm that is abbreviated as FDE are not as efficient as FMDGWO. FMDGWO performs high-level segmentation and has to ensure more stability.

Although, determining discrete wavelet transform based methods [37] yield a prominent degree of approximation yet the availability of edge features is less in medical image fusion for clinical disease identification. Daniel et al. [38] proposed a scheme of cascaded laplacian wavelet mask abbreviated as CLWM is reliant on fusion utilization of Hybrid variant in which Cuckoo search combined with Grey wolf optimizer, named as HCS-GWO to the fusion of the multimodal medical image in this proposed work. During the initial phase, several fusion evaluation indexes are considered, the introduced strategy is checked to Magnetic Resonance- Single Photon Emission Tomography (shortened as MR-SPECT), MR-Positron Emission Tomography, MR Computerized Tomography (shortened as MR-CT), and MR T1-T2 image fusion. GWA is combined with the CSA in the implementation of the final phase. CLWM is compared with other highly developed fusion techniques for validation and robustness that considers Entropy, MI, QAB/F, and standard deviation values as the appraisal of parameters. The developed framework is remarkably more effective than other highly developed enhancements techniques. The complementary feature fusions are acquired through using this proposed methodology, which offers the significance for medical diagnosis.

Finishing up the multi-modal image fusion scaling techniques taking into account static value selection reduces the quality of the fusion. To conquer the above limitation, Daniel et al. [39] developed an Optimal Spectrum Mask Fusion that is abbreviated as an OSMF for medical image fusion through a standard GWO algorithm to enhance clinical diagnosis. The GWO algorithm performs the fastest and selects dynamic scale; whereas the spectrum mask based fusion technique is adopted to enhance image contrast and edge quality. Plenty of information is gathered by the optimum mask in the multi-modality fusion. Brain’s images MR: T1-T2, MR-SPECT, MR-PET, and MR-CT
are being used for the validation of the proposed OSFM. This approach dominates other customary techniques involving fusion based on pixels and yields enhanced outcomes.

Ramakrishnan and Sankaragomathi [40] proposed a research work in order to classification and segmentation of Computed Tomography images (CT images) to assess the existence of tumor. The support vector machine classifier assists in the classification process to classify the images that involve tumor-containing and tumor-free images alongside certain kernel functions (such as Quadratic kernel function, Radial basis function, Linear kernel, Polynomial kernel, and MLP function) and various optimization techniques (such as Sequential Minimal Optimization, Least-Squares, and Quadratic Programming abbreviated as SMO, LS, and QP respectively). After the implementation of classification operation, segmentation is performed using Modified Region Growing (MRG) along with certain optimization algorithms (such as HS, GWO, and EP) are employed. The CT images data set is fetched from specialists (M/s Aarthi scans, Tirunelveli, India). The outcomes are validated using various parameters such as sensitivity, explicitness, and precision. The proposed tumor detection approach (MRG-GWO) is more precise than the other two techniques (HS and EP).

3. Results and Discussion

The problem-independent definition sparkle a significant milestone to meta-heuristic techniques. These techniques are becoming increasingly plausible day to day because of their versatility, simplicity, and flexibility. The meta-heuristic techniques are greatly ingenious to understand, readily adjustable, and utilized in various fields of analysis, real-world applications, and research areas. Conversely, low convergence rate and stuck in local optima are such limitations that constitute it more challenging. Introduce, produce, and innovate in order to novel meta-heuristics algorithms and their variants are utilized to overcome the aforementioned limitations and to conform with the no free lunch theorem [2].

Table 2. Applications and corresponding optimization techniques with references

| Applications        | Optimization Techniques [References]         |
|---------------------|---------------------------------------------|
| Image Segmentation  | Genetic Algorithm (GA) [5]                  |
|                     | Genetic Programming (GP) [8, 9]             |
|                     | Particle Swarm Optimization (PSO) [25, 26]  |
|                     | Cuckoo Search algorithm (CSA) [31]         |
|                     | Firefly Algorithm (FA) [33]                |
|                     | Grey Wolf Optimizer (GWO) [35, 36, 40]     |
| Image Classification| Genetic Programming (GP) [10]               |
|                     | Ant Colony Optimization (ACO) [19]         |
|                     | Bat Algorithm (BA) [23]                    |
| Medical Imaging     | Differential Evolution (DE) [15]           |
|                     | Particle Swarm Optimization (PSO) [27]     |
|                     | Grey Wolf Optimizer (GWO) [38, 39]         |
| Image Compression   | Bat Algorithm (BA) [21]                     |

The various optimization algorithms applied to various applications of image processing are tabulated in table 2 and depicted in figure 3. The final conclusion based on various parameters is eventually tabulated in table 3.
Figure 3. Various Image Processing Applications employed with various Optimization Algorithms

| References | Application | Utilized Optimization Algorithm | Data Set | Base Technique | Comparative Techniques | Performance Evaluating Parameters/ Comparative Parameters | Simulation Environment |
|------------|-------------|---------------------------------|----------|----------------|------------------------|----------------------------------------------------------|------------------------|
| [5]        | Magnetic Resonance Imaging [MRI] segmentation | Genetic Algorithm | Brain web dataset | Fuzzy c-means clustering | GFCM2G on different GPU devices | Speedup, Execution Time | NVIDIA Kepler based Tegra K1 (TK1) system |
| [8]        | Figure-ground segmentation | Genetic Programming | Weizmann and Pascal dataset | SVM | SPGP-FS, NSGP-FS | Accuracy, Fitness Function | Koza (1992) |
| [9]        | Figure-ground segmentation | Genetic Programming | Bitmap, Brodatz texture, Weimannand, Pascal dataset | Clustering | Conventional segmentation’s techniques (active contour model, region growing, K-means clustering, and thresholding) | Negative Rate Metric (NRM), F1-score, accuracy | MATLAB R2014b |
| [10]       | Image Classification | Genetic Programming | Kyberg, Brodatz, and Outex | TLGP-criptor | CLBC, DRLBPs and DeCAFs | Mean, Standard Deviation | EC Java-based software |
| [15]       | Medical Image | Differential Evolution | BRATS 2012, Cameraman, Gold Hill, I. Pepper House, etc. | SVM | NSGA-II and MOPSO | Misclassification Probability Error(MSE), Threshold values, Uniformity measures | MATLAB R2012a |
| [19]       | Image Classification | Ant Colony Optimization | Images that contain ten varieties of sunflower seeds | LDA, PCA | Manual operation of seed distinguishing | Boundary, Cosine, and Fourier descriptors | Montecarlo simulation |
| [21]       | Image Compression | Bat Algorithm | Goldhill, Barb, Peppers, Baboon, and Lena images | Vector Quantization | FA-LBG, LBG, QPSO-LBG, HBBMO-LBG, and PSO-LBG | PSNR, MSE | MATLAB version 7.9.0 (R2009b) |
| [23]       | Image Classification | Bat Algorithm | Real-time multispectral satellite image for | Clustering | GA, PSO, BKM | Efficiency, Accuracy | Matlab 7.12.0.635 |
Crop, image segmentation data set from UCI

[25] Image Segmentation Particle Swarm Optimization Benchmark images Thresholding HS, PSO, GA Standard deviation, PSNR MATLAB 2016

[26] Image Segmentation Particle Swarm Optimization Random test image 2D fuzzy fisher AGA, PSO, QPSO and RLQPSO Cost functions, Calculation Time PC with 2G memory and Intel(R) Core(TM)2CP U@2.40GHz

[27] Medical Image Particle Swarm Optimization Left hand X-ray images of 65 children referred to the Namazi hospital (Shiraz, Iran) for bone assessment PSNR, Uniformity Measure (UM), Structural Similarity Index Measure (SSIM), Accuracy An auxiliary diagnostic tool

[31] Image Segmentation Cuckoo Search algorithm 10 Satellite color images Tsallis entropy DE, WDO, PSO, ABC SSIM, FSIM, PSNR, and MSE #repetition: 10 Population Size: 25 Max iteration: 300

[33] Image Segmentation Firefly Algorithm Standard images or natural images (Lena, Goldhill, Pirate, Starfish) Shannon and Fuzzy entropy DE, BA, PSO PSNR, CPU Time, SSIM, Misclassification Error, Computational Complexity, Stability Analysis Intel Core i5 Preprocessor, 2GB RAM, Matlab 2009b

[35] Image Segmentation Grey Wolf Optimizer Zebra, Snake, Starfish, Airplane, Man, Baboon, Peppers, and Lena Multilevel thresholding BFO and PSO Mean Structural SIMilarity index (MSSIM), Average CPU time Matlab R2010a

[36] Image Segmentation Grey Wolf Optimizer Berkeley Segmentation Data Set Benchmarks 500 Fuzzy Multilevel Image Thresholding EMO, MDGWO, FDE Standard Deviation (STD), fuzzy entropy, PSNR, Lenovo Laptop configuration with 4GB memory and Intel Core i3 processor

[38] Medical Image Grey Wolf Optimizer Brain’s images MR: T1-T2, MR-PECT, MR-PET, and MR-CT Cascaded Laplacian Wavelet Mask Discrete wavelet transform (dB4) Entropy, Edge based similarity measure, Standard deviation MATLAB 2010a

[39] Medical Image Grey Wolf Optimizer Brain’s images MR: T1-T2, MR-PECT, MR-PET, and MR-CT Optimum Spectrum Mask Fusion Conventional pixel based fusion techniques Entropy, Edge based similarity measure, Standard deviation MATLAB 2012a

[40] Image Segmentation and Classification Grey Wolf Optimizer CT images dataset fetched from M/s Aarthi scans, Tirunelveli, India authorities SVM HS and EP False Discovery Rate (FDR), Random Index (RI) MATLAB 2012

4. Conclusion
Image processing is a vast area for researchers at the current time, gives rise to several new algorithms to implement and use image processing in efficient ways. The different application domains of image processing like image segmentation can be implemented more efficiently with GA, GP, FA, GWO, and PSO optimization algorithms which help obtain the results quickly and in a wide range. An optimization algorithm like BAT algorithm, when applied to the image compression it assists in increasing the compression ratio leaving no effect on the image quality. The algorithms like GP, BAT,
and ACO when applied to employ image classification then the techniques can easily trigger the complexity of the image variation providing fruitful results. The medical field also has various image processing applications like anatomical study, detection of tumors, and other disease prediction and treatment. The metaheuristic optimization algorithms such as PSO, GWO, and DE are used for more efficacious results to implement medical imaging more efficiently. These algorithms help obtain more specific information from the image, which is used to predict more precisely. Finally, in this manuscript, it has been discussed that optimization algorithms used in image processing and its applications eventually provide remarkable outcomes and these are less dependent on the input image acquired. It has been also found that GA, ACO, GWO, GP, etc., algorithms have provided superior results even in cluttered and high variation images compared to standard algorithms.

References
[1] Reinhart C, Johnson K, Cerreta B and Mathur BP 1995 January.Analog image processing for IVHS applications Intelligent Vehicle Highway Systems (Vol. 2344 pp. 54-60).International Society for Optics and Photonics.
[2] Wolpert DH and Macready WG 1997 No free lunch theorems for optimization IEEE transactions on evolutionary computation 1(1) pp. 67-82.
[3] Holland JH 1992 Genetic algorithms Scientificamerican 267(1) pp. 66-73.
[4] Davis L 1991 Handbook of genetic algorithms.
[5] Hung CL and Wu YH 2017 Parallel genetic-based algorithm on multiple embedded graphic processing units for brain magnetic resonance imaging segmentation Computers & Electrical Engineering 61 pp. 373-383.
[6] Koza JR 2010 Human-competitive results produced by genetic programming Genetic programming and evolvable machines 11(3-4) pp. 251-284.
[7] Kinnear KE, Langdon WB, Spector L, Angeline PJ and O'Reilly UM1994 Advances in genetic programming (Vol. 3). MIT press.
[8] Liang Y, Zhang M and Browne WN2017 Image feature selection using genetic programming for figure-ground segmentation Engineering Applications of Artificial Intelligence 62 pp. 96-108.
[9] Liang Y, Zhang Mand Browne WN2017 Genetic programming for evolving figure-ground segmentors from multiple features Applied Soft Computing 51 pp. 83-95.
[10] Iqbal M, Xue B, Al-Sahaf Hand Zhang M 2017 Cross-domain reuse of extracted knowledge in genetic programming for image classification IEEE Transactions on Evolutionary Computation 21(4) pp. 569-587.
[11] Storn R1996 June. On the usage of differential evolution for function optimization Proceedings of North American Fuzzy Information Processing (pp. 519-523). IEEE.
[12] Storn R and Price K 1997 Differential evolution--a simple and efficient heuristic for global optimization over continuous spaces Journal of global optimization 11(4) pp. 341-359.
[13] Price K, Storn RM andLampinen JA 2006 Differential evolution: a practical approach to global optimization Springer Science & Business Media.
[14] Rocca P, Oliveri G and Massa A 2011 Differential evolution as applied to electromagnetics IEEE Antennas and Propagation Magazine 53(1) pp. 38-49.
[15] Sarkar S, DasSandChaudhuri SS2017 Multi-level thresholding with a decomposition-based multi-objective evolutionary algorithm for segmenting natural and medical images Applied Soft Computing 50 pp. 142-157.
[16] Dorigo M, Maniezzo V andColorini A 1996 Ant system: optimization by a colony of cooperating agents IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 26(1) pp. 29-41.
[17] Parsons S 2005 Ant Colony Optimization by Marco Dorigo and Thomas Stützle, MIT Press, 305 pp. $40.00, ISBN 0-262-04219-3 The Knowledge Engineering Review 20(1) pp. 92.
[18] Colomi A, Dorigo M and Maniezzo V 1991 December. Distributed optimization by ant colonies Proceedings of the first European conference on artificial life (Vol. 142 pp. 134-142).

[19] JayaBrinda G and Subbu EG 2017 Ant colony technique for optimizing the order of cascaded SVM classifier for sunflower seed classification IEEE Transactions on Emerging Topics in Computational Intelligence 2(1) pp. 78-88.

[20] Yang XS 2010 A new metaheuristic bat-inspired algorithm Nature inspired cooperative strategies for optimization (NICSO 2010) (pp. 65-74). Springer, Berlin, Heidelberg.

[21] Karri C and Jena U2016 Fast vector quantization using a Bat algorithm for image compression Engineering Science and Technology, an International Journal 19(2) pp. 769-781.

[22] Wang Y, Feng XY, Huang YX, Pu DB, Zhou WG, Liang YC and Zhou CG2007 A novel quantum swarm evolutionary algorithm and its applications Neurocomputing 70(4-6) pp. 633-640.

[23] Senthilnath J, Kulkarni S, Benediktsson JAand Yang XS 2016 A novel approach for multispectral satellite image classification based on the bat algorithm IEEE Geoscience and Remote Sensing Letters 13(4) pp. 599-603.

[24] Kennedy J and Eberhart R 1995 November. Particle swarm optimization Proceedings of ICNN’95-international conference on neural networks (Vol. 4 pp. 1942-1948). IEEE.

[25] Mozaffari MHand Lee WS 2017 Convergent heterogeneous particle swarm optimisation algorithm for multilevel image thresholding segmentation IET Image Processing 11(8) pp. 605-619.

[26] Zhang C, Xie Y, Liu Dand Wang L 2016 Fast threshold image segmentation based on 2D fuzzy fisher and random local optimized QPSO IEEE Transactions on Image Processing 26(3) pp. 1355-1362.

[27] Sabeti M, Boostani R and Davoodi B 2017 Improved particle swarm optimisation to estimate bone age IET Image Processing 12(2) pp. 179-187.

[28] Karaboga D 2005 An idea based on honey bee swarm for numerical optimization (Vol. 200 pp. 1-10). Technical report-tr06, Erciyes University, engineering faculty, computer engineering department

[29] Yadav AS, Khushboo K, Singh V KangKushwaha DS 2020 Increasing Efficiency of Sensor Nodes by Clustering in Section Based Hybrid Routing Protocol with Artificial Bee Colony Procedia Computer Science 171 pp. 887-896.

[30] Yang XSand Deb S 2009 December. Cuckoo search via Lévy flights 2009 World congress on nature & biologically inspired computing (NaBIC) (pp. 210-214). Ieee.

[31] Bhandari AK, Kumar Aand Singh GK 2015Tsallis entropy based multilevel thresholding for colored satellite image segmentation using evolutionary algorithms Expert systems with applications 42(22) pp. 8707-8730.

[32] Yang X S 2010 Nature-inspired metaheuristic algorithms. Luniver press.

[33] Naidu M SR, Kumar PRandChiranjeevi K 2018 Shannon and fuzzy entropy based evolutionary image thresholding for image segmentation Alexandria engineering journal 57(3) pp. 1643-1655.

[34] Mirjalili S, Mirjalili S M and Lewis A 2014 Grey wolf optimizer Advances in engineering software 69 pp. 46-61.

[35] Khairuzzaman A K M andChaudhury S2017 Multilevel thresholding using grey wolf optimizer for image segmentation Expert Systems with Applications 86 pp. 64-76.

[36] Li L, Sun L, Kang W, Guo J, Han C and Li S 2016 Fuzzy multilevel image thresholding based on modified discrete grey wolf optimizer and local information aggregation IEEE Access 4 6438-6450.
[37] Vijayarajanand Muttan S 2015 Discrete wavelet transform based principal component averaging fusion for medical images \textit{AEU-International Journal of Electronics and Communications} \textbf{69}(6) pp. 896-902.

[38] Daniel E, Anitha J and Gnanaraj J 2017 Optimum laplacian wavelet mask based medical image using hybrid cuckoo search–grey wolf optimization algorithm \textit{Knowledge-Based Systems} \textbf{131} pp. 58-69.

[39] Daniel E, Anitha J, Kamaleshwaran K K and Rani I 2017 Optimum spectrum mask based medical image fusion using Gray Wolf Optimization \textit{Biomedical Signal Processing and Control} \textbf{34} pp. 36-43.

[40] Ramakrishnan T and Sankaragomathi B 2017 A professional estimate on the computed tomography brain tumor images using SVM-SMO for classification and MRG-GWO for segmentation \textit{Pattern Recognition Letters} \textbf{94} pp. 163-171.

[41] Russell SJ and Norvig P 2003 Artificial Intelligence: A Modern Approach (2nd ed.), Upper Saddle River, New Jersey: Prentice Hall, pp. 111–114, ISBN 0-13-790395-2.

[42] Geem Z W, Kim J HandLoganathan G V 2001 A new heuristic optimization algorithm: harmony search \textit{Simulation} \textbf{76}(2) pp. 60-68.

[43] Rashedi E, Nezamabadi-Pour H and Saryazdi S 2009 GSA: a gravitational search algorithm \textit{Information sciences} \textbf{179}(13) pp. 2232-2248.

[44] Van Laarhoven P J and Aarts E H 1987 Simulated annealing \textit{Simulated annealing: Theory and applications} (pp. 7-15), Springer, Dordrecht.

[45] Hofmeyr S A and Forrest S 2000 Architecture for an artificial immune system \textit{Evolutionary computation} \textbf{8}(4) pp. 443-473.