Aswan University Journal of Science and Technology Volume 2, issue 1, June 2022

Image segmentation-based optimization algorithms: A Review

Amal Yassen Mohamed, Mountasser Mohamed Mohamed[1], Ashraf M Hemeida[2]
[1]Electrical Engineering Deparmtment, Faculty of Engineering, Aswan University
[2]Electrical Engineering Department, Faculty of Energy Engineering, Aswan University

ABSTRACT

Image segmentation is the division of a digital image into multiple subgroups of pixels known as Image Objects. This procedure can minimize the complexity of the image, making image analysis easier. Image Segmentation is one of the most crucial areas in computer vision and one of the oldest research questions. There are many useful applications of image processing such as image sharpening, blurring, grayscale conversion, and edges detection that can be utilized in different domains. Digital image processing employing neural networks has gained popularity recently because of the expansion of artificial intelligence algorithms and its ecosystem. It can be used in a wide range of industries, including security, banks, the military, agriculture, law enforcement, manufacturing, and medicine.

Keywords: Image Segmentation, Particle Swarm Optimization (PSO); K-means; ant colony optimization (ACO); Artificial bee colonies (ABC), Poplar Optimization Algorithm (POA); Neutral Network.

1- INTRODUCTION

Image segmentation is the most important phase in image processing, and multi-level image segmentation is one of the most efficient and simple ways. Image segmentation in computer vision is used to accomplish most of the judging or evaluating tasks in image processing and analysis. The partition of a digital image into several areas and separating the region of interest, which is a significant region is known as picture segmentation. Either the similarity principle or the discontinuity principle is the foundation for image segmentation algorithms. The discontinuity concept seeks to identify regions that differ in attributes like intensity, color, texture, or any other aspect of an image's statistics. The similarity principle seeks to classify pixels according to their shared characteristics. The processing of medical images, driverless vehicles, and face recognition all make extensive use of picture segmentation. Automatic segmentation techniques are a significant development in image analysis. They can distinguish between structures in a variety of imaging modalities, including magnetic resonance imaging (MRI), computed tomography (CT), aerospace technology, face recognition, intelligent transportation, and ultrasound. Remote sensing, astronomy, material science, forensic medical and medical diagnosis are just a few of the domains where digital image processing is being used. Automatic fingerprint, iris, and biometric identification technologies are now often used by even regular people [1,2,3].

When researchers used bio-inspired methodologies, they took a variety of approaches. Traditional approaches had various disadvantages, such as lowering image quality from a visual perspective. One way was to change the objective functions, search methods, or updating strategies of these

Corresponding author E-mail: ashraf@aswu.edu.eg

Received September, 20, 2022, received in revised form, September 27, 2022, accepted September 27, 2022.

(ASWJST 2021/ printed ISSN: 2735-3087 and on-line ISSN: 2735-3095) https://journals.aswu.edu.eg/stjournal

methods, which has proved to increase the performance of the original methods. Another strategy was to integrate these approaches with other algorithms to improve performance and overcome the constraints of the individual methods. The first used bio-inspired algorithms in conjunction with other segmentation techniques like thresholding, edge detection, Neutral Network, and determining the right threshold value and clustering. PSO was used to initialize the population of ABC, for example. These methods improved the quality and accuracy of the results while also cutting down on the computation time. Even though there have been hundreds of segmentation strategies documented in the literature and with the volume of image segmentation research growing, it might be challenging to choose the optimum segmented output measurement strategy for a certain type of image [4,5,6,7].

2- THEORIES OF SEGMENTATION

Multitargeted segmentation is frequently used in the field of real-world image segmentation because different thresholds must be used to segment the local features of the image in practical image segmentation because the contrast between the target and the background varies at different points in the image. The number of thresholds grows as the spatial complexity of the picture segmentation calculation grows, making it harder to find the optimal solution and costing more to compute. Numerous modern heuristic techniques have been developed to solve combinatorial and numerical optimization problems. These algorithms can be categorized into a wide range of classifications depending on the criteria being used, including population-based, iterative-based, stochastic, deterministic, etc. These algorithms are still well because only a few parameters are needed to fine-tune them [8,9,10].
a few examples of intelligent optimization algorithms that have surfaced recently because of how quickly artificial intelligence is developing. When compared to the direct application of the maximum variance between classes or clustering technique, the accuracy, operation time, and convergence speed of image segmentation have all risen somewhat [11].

2.1 Algorithms for image segmentation go through several stages

The first step is picture acquisition, which entails gathering the input images. The input image is then preprocessed to prepare it for the segmentation method, such as converting colored images to grayscale images, image scaling, noise removal, or color quantization. The image segmentation process begins once the image is complete. However, there may be some erroneous boundaries or minor sections that have not been properly segmented. Image post-processing is used to correct these flaws and generate the final segmented image. There are a variety of segmentation strategies available, each with its own set of outcomes [12] Fig [1].

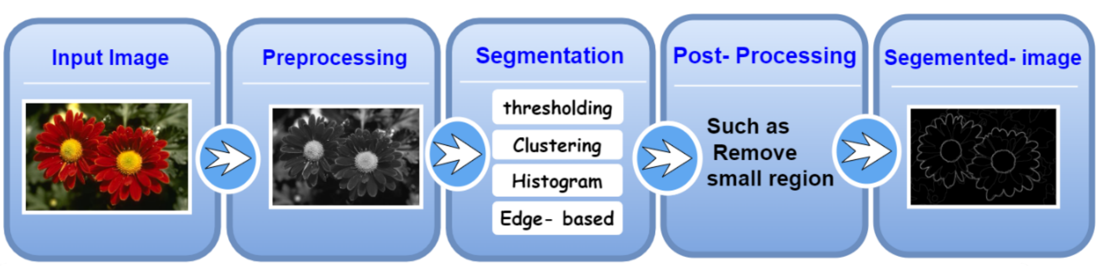

Image Segmentation Pipeline.
The flower image in pipeline is taken from the Berkeley image dataset

Fig [1] Image Segmentation pipeline

3- TYPES OF SEGMENTATION

3.1 Thresholding based segmentation

Thresholding-based segmentation is one of the most straightforward ways to image segmentation and one of the most effective and noticeable approaches among the different segmentation techniques that are available in the literature. Since the segmented image produced by thresholding benefits from less storage space, quick processing. The last few years have seen a lot of interest in thresholding strategies. Effective segmentation is to distinguish pixels with neighboring values to improve the contrast and to separate objects from the background.

Depending on the quantity of image segments, thresholding techniques fall into the bi-level and multi-level categories. Image segmentation into two distinct sections is done using bi-level thresholding. According to a particular value T, object pixels are defined as having grey values greater than T, while background pixels are defined as having grey values lower than T [13]. If there is very little noise in the image, you can consider the threshold value (T) to be a constant (unnecessary information and data). Depending on your needs, you can maintain a constant threshold value or make it dynamic [14]. There are five steps in the area thresholding classification system. Excess Green Gray transformation, segmentation, labelling the image, erasing the undesirable information, and area thresholding-based categorization are among them [15,16]. The system's block diagram is shown in Fig [2].

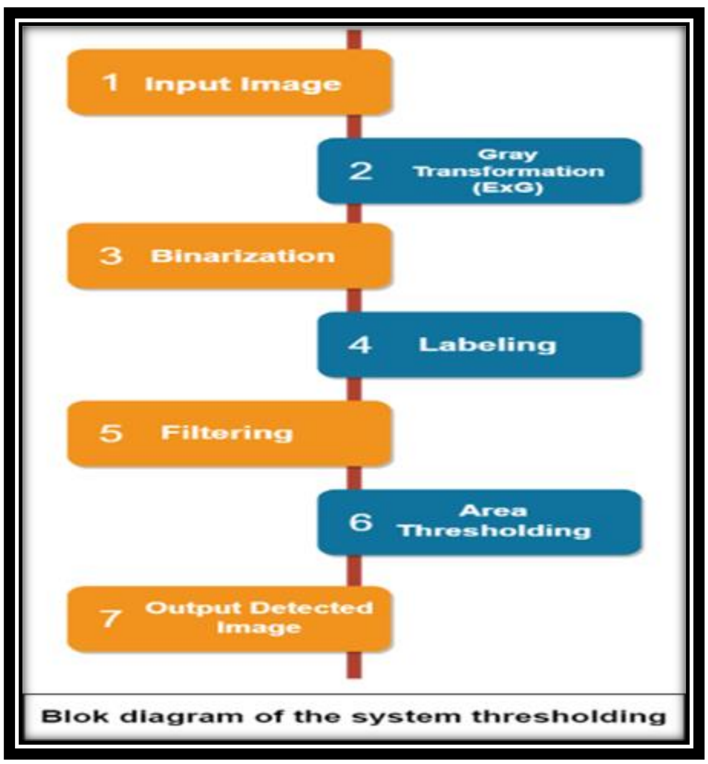

Fig [2] Block diagram of the system thresholding

3.2 Edge Based Image Segmentation

One of the most used types of segmentation in image processing is edge-based segmentation. By observing the change in intensity of pixels in a picture, edge detection separates the image into an object and its background. Two popular techniques for detecting edges in images are the grey histogram and gradient. It focuses on recognizing the borders of various objects in a picture because doing so enables you to remove unused and superfluous information from the image. The size of the image is drastically reduced, which facilitates image analysis. According to variations in texture, contrast, grey level, color, saturation, and other attributes, algorithms employed in edge-based segmentation locate edges in a picture [17].

3.3 Region-Based Segmentation

Instead of selecting seed locations, a user can split an image into a variety of randomly spaced, unconnected sections, which they can subsequently combine. These areas consist merely of a collection of pixels. Following the discovery of the seed points, a region-based segmentation algorithm would either increase their pixel count or decrease it to combine them with other seed points. The theory based on quadtree data is typically used to implement region splitting and merging [17].

The distinctions between segmentations based on regions and those based on edges are outlined in table [1] below. At this stage, even though the edge detection method does not significantly increase the quality of multi-spectral images, we would want to infer that it has the advantage of not always requiring closed borders. As opposed to the segmentation method that is region-based, this one bases its computation on difference rather than similarity.

Tab1e [1] Summary difference between Region Based and Edge detection

Region-Based Segmentation	Edge Based Image Segmentation
Closed boundaries	**Boundaries formed not necessarily closed**
Multi-spectral images improve segmentation	**No significant improvement for multi-spectral images**
Computation based on similarity	**Computation based on difference**

3.4 Watershed Segmentation

A real-world flood event serves as the analogy for the watershed model, a mathematical morphological method. Images are changed into gradient images. The image is then interpreted as a topographical surface, with the values of the grey scale representing the elevation of the surface at that place. Water then effuses out of the minimal grey value to begin the flooding process [18].

3.5 Bio- Inspired Algorithms

Bio-inspired algorithms are methods for solving complex problems that are based on the biological systems of particular species [19]. Numerous bio-inspired algorithms are employed to enhance image segmentation, and they have shown to be successful. The bio-inspired algorithms were divided by Binitha and Sathya into three groups: algorithms based on evolution, algorithms based on smarm, and algorithms based on ecology. Although the majority of the currently used bio-inspired algorithms fall into one of these three categories, some new algorithms go outside of those three categories [20]. Four groups have been created out of the bio-inspired algorithms. The algorithms in question are multi-objective algorithms, swarm intelligence algorithms, ecology-based algorithms, and evolutionary-based algorithms. Despite having considerable differences from other evolutionary algorithms, artificial neural networks are included in evolutionary algorithms as the closest related category. This paper divides algorithms into different categories based on how they were biologically inspired Fig [3].

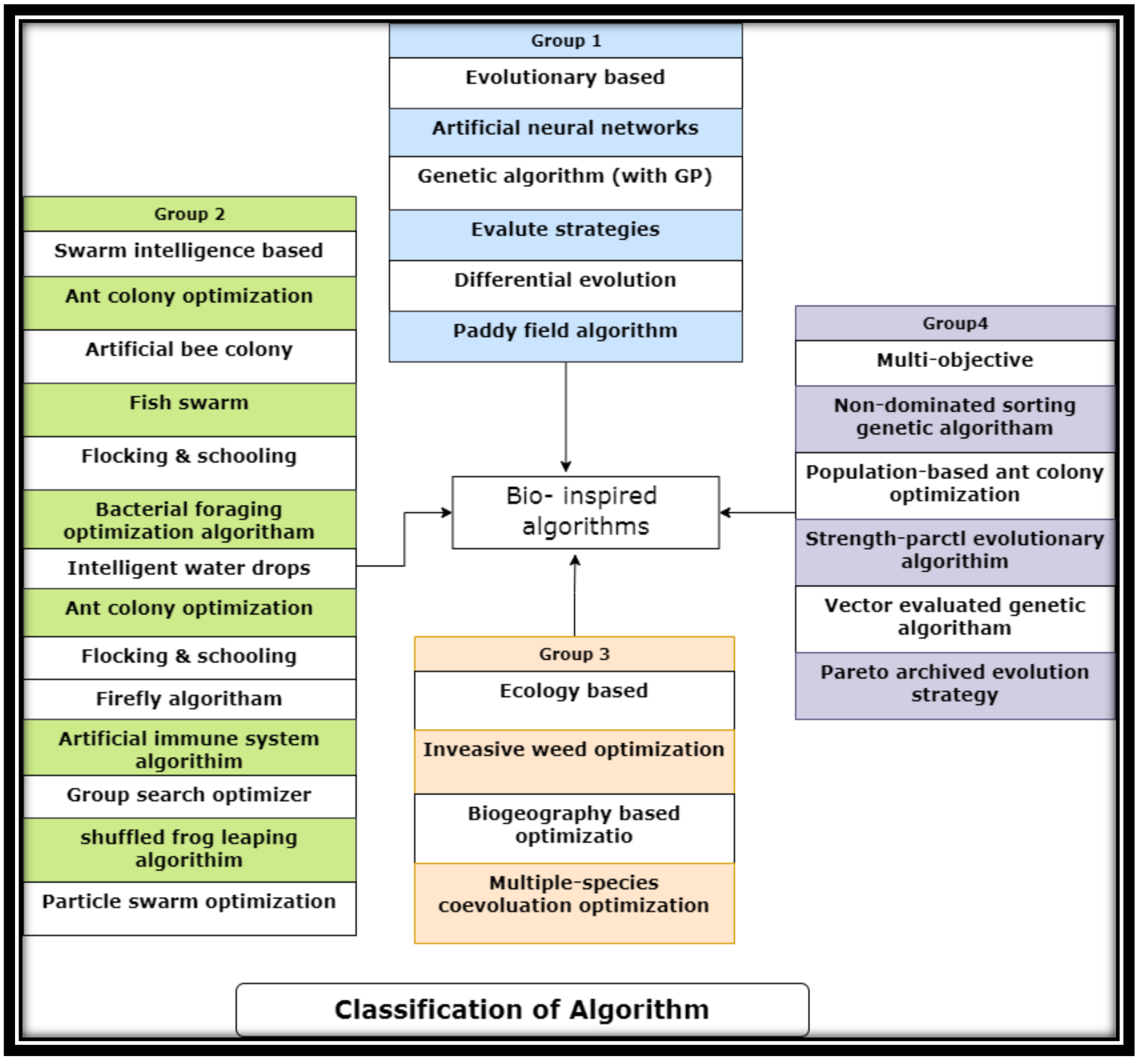

Fig [3] classification Bioinspired algorithm

3.6 Artificial neural network (ANN)

In early artificial neural networks research, there was a focus on simple networks with a single hidden layer, for more modern applications specialized layers have been developed and increasingly deeper networks are being utilized. It is now common for neural networks to have several layers, depending on the intended application.

While basic networks with a single hidden layer were the focus of early research on artificial neural networks, more advanced applications now make use of layers that are more specialized and deeper networks are being used. Depending on the desired application, it is currently typical for neural networks to contain multiple layers.

Artificial neural networks are extremely versatile and may be used to solve a wide variety of problems. Recently, image recognition and processing as well as time-series analysis have seen great success [20].

3.7 Genetic Algorithm (GA)

Genetic algorithms (GA) have been used in image processing [19] and segmentation Fig [4]. GA are well suited to achieve this purpose since segmentation may be considered as a process that identifies the optimal areas partition of an image according to a criterion. Indeed, GAs are especially useful when the search space is limited and the criterion to optimize is mathematically challenging, as is the situation in image processing. The primary benefits of employing GA for segmentation are their capacity to find the best number of areas in a segmentation result or to choose certain features such as the size of the analysis window or heuristic thresholds.

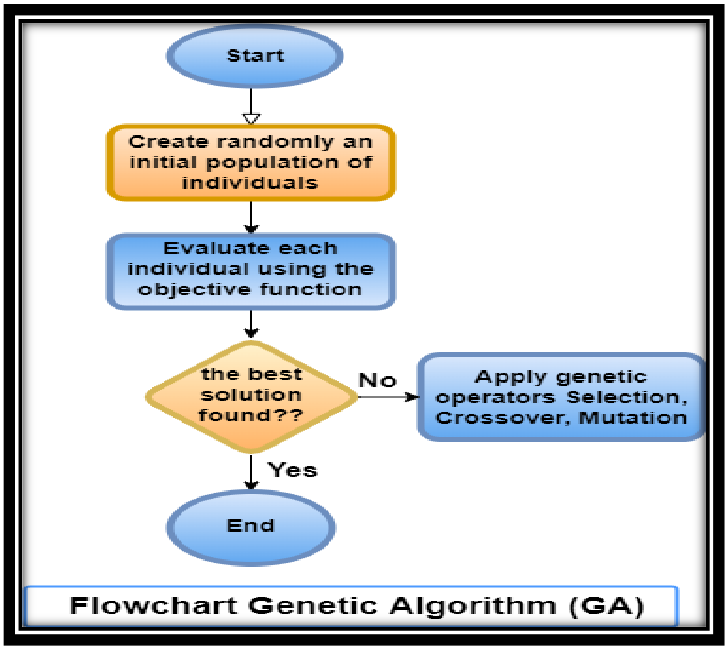

Fig [4] Flowchart GA

3.8 Ant Colony Optimization (ACO)

ACO is a population-based technique that employs a swarm of artificial ants to find a rough solution to a given optimization problem. To employ the idea of pheromones, the researched problem is transformed into a shortest-path optimization problem depicted in a weighted graph. Each ant begins by randomly selecting a node (a vertex) and moving to another node (also randomly picked) by allowing pheromones to develop a trail behind it. Other ants are drawn to this trail. The more times the trail is used, the more pheromone is deposited, and the more ants are drawn to it. Because it is not frequently visited, the longer trail has less pheromones, and the few implanted pheromones quickly dissipate [19,21,22] Fig [5].

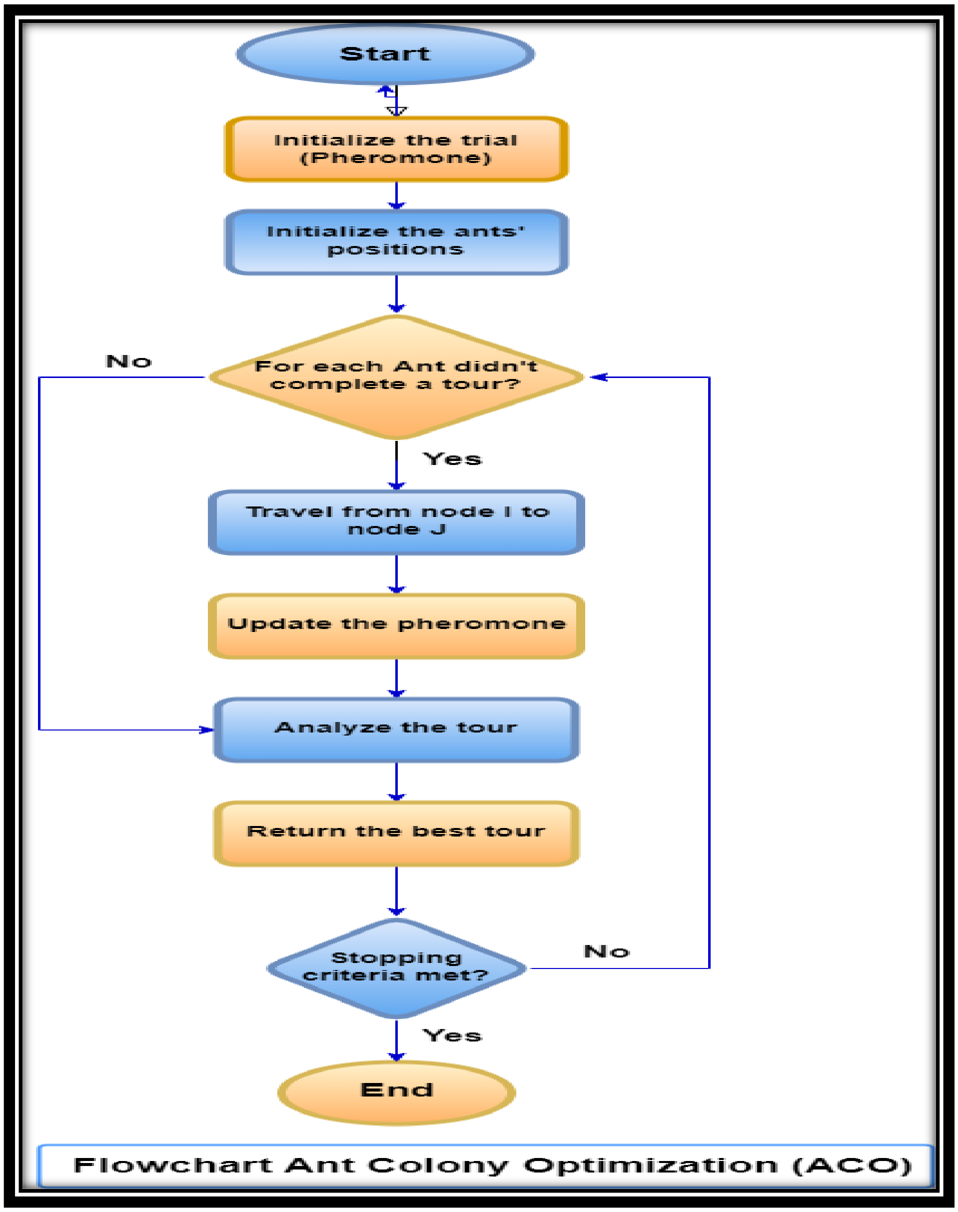

Fig [5] Flowchart ACO

3.9 Particle Swarm Optimization (PSO)

PSO is a population-based stochastic approach for solving continuous and discrete optimization problems. In particle swarm optimization, simple software agents, called particles, move in the search space of an optimization problem. PSO is one of the latest and emerging digital image segmentation techniques inspired from the nature. It was developed by Dr Kenney and Dr Eberhart in 1995, and it has been widely used as an optimization tool in areas including telecommunications, computer graphics, biological or medical science, signal processing, data mining, robotics, neural networks etc. [5]. The movement of the particles is influenced by two factors, the particle's best solution (pbest) and the global best solution found by all the particles (gbest), which influence the particle's velocity through the search space by creating an attractive force [23]. As a result, the particle interacts with all neighbors and store's optimal location information in its memory. After each iteration the pbest and gbest are updated respectively if a more optimal solution is found by the particle or population Figure [6] This process is continued iteratively until the desired result is achieved.

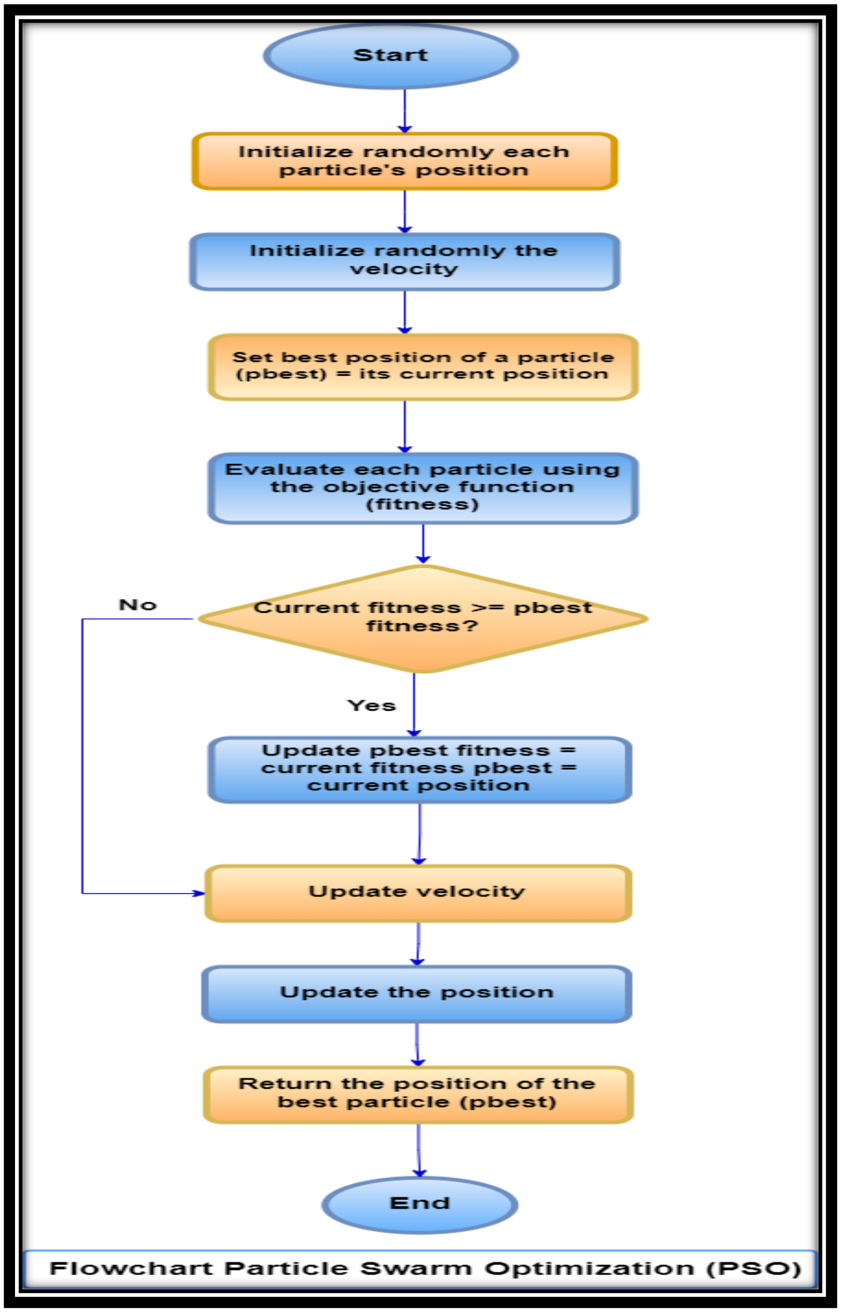

Fig [6] Flowchart PSO

3.10 Artificial Bee Colony (ABC)

ABC imitates the attitude of honey-bee colonies. The bees move randomly in the search space to find food resources. In this artificial technique [19], the colony of artificial bees contains three groups of bees: employed bees, onlookers, and scouts. A bee waiting on the dance area for making decision to choose a food source, is called an onlooker and a bee going to the food source visited by itself previously is named an employed bee. A bee carrying out random search is called a scout. In the ABC algorithm, first half of the colony consists of employed artificial bees and the second half constitutes the onlookers. For every food source, there is only one employed bee. In other words, the number of employed bees is equal to the number of food sources around the hive [24,25]. The employed bee whose food source is exhausted by the employed and onlooker bees becomes a scout Figure [7].

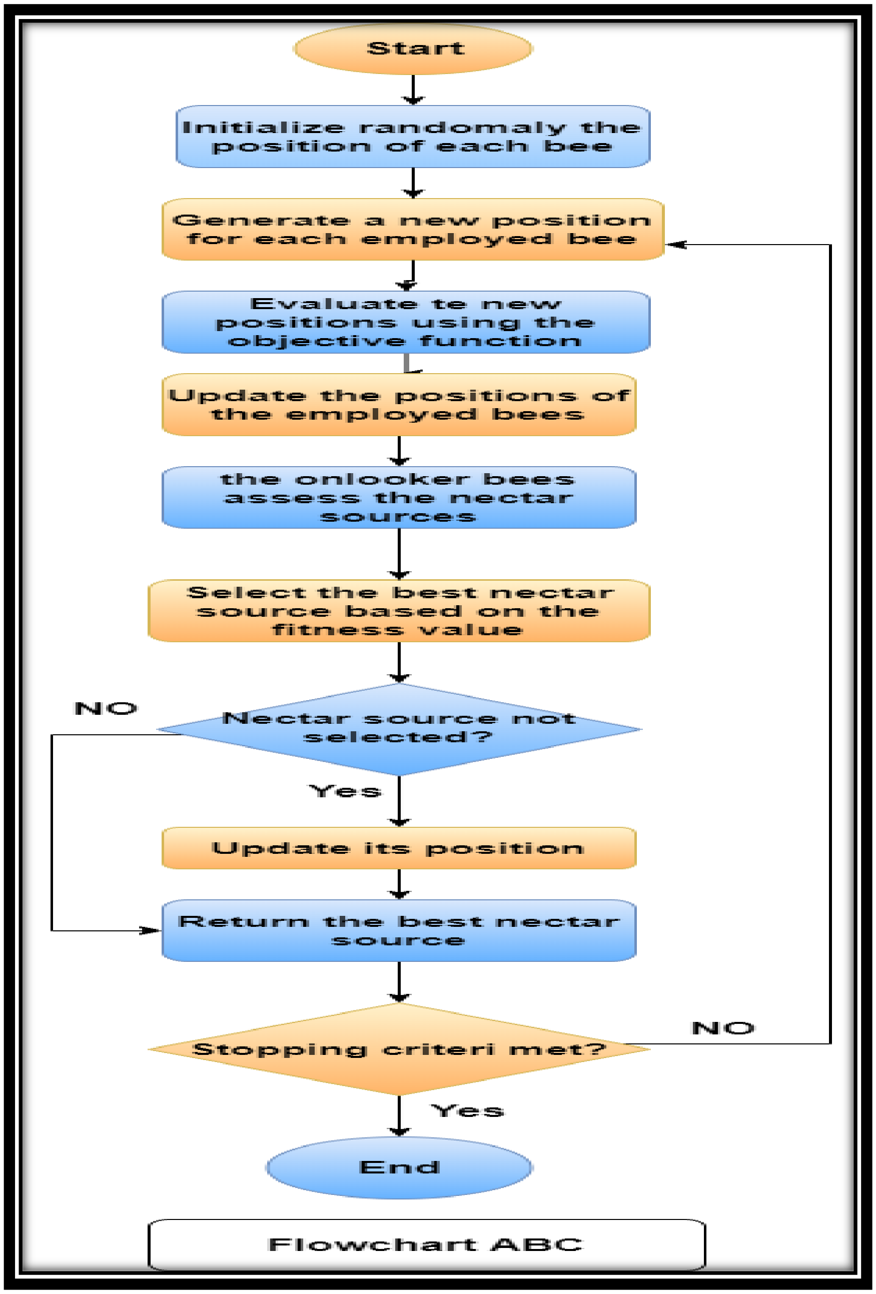

Fig [7] Flowchart ABC

3.11 Whale Optimization Algorithm

The whole optimization algorithm, which was proposed by Mir Jalili and Lewis in 2016, is inspired by the foraging behavior of humpback whales in nature [26]. Humpback whales tend to create spiral bubbles, and then swim to the prey along the trajectory of bubbles. The encircling prey and bubble-net attacking behaviors represent the exploitation phase of optimization. The other phase of optimization namely exploration is represented by the search for prey behavior. It is worth noting that the position vector of search agent is defined in a d-dimensional space, where d denotes the number of decision variables of an optimization problem [27,28].

3.12 Multi threshold segmentation method

The thresholding technique is frequently used to separate various sections of the image. A set of appropriate thresholds should be chosen to segment the image if it has many regions with various grey levels to get better segmentation results [29].

3.13 Clustering Based Image Segmentation

The greyscale image is divided into clusters (disjoint groups) of pixels with similar characteristics using a clustering technique. It would group the data items into clusters based on how much more similar the pieces in one cluster are to those in another. Additionally, applicable to color and multispectral photos is clustering [30,31,32].

3.14 K-means clustering algorithm:

The idea behind the k-means clustering algorithms is to minimize the sum of squared distances between every point in each cluster domain and the cluster center. Contrary to the between cluster distance, which is the sum of the distances between each cluster center and the overall global mean of the entire data set, referred to as the within cluster distance [30,33,34].

3.15 Fuzzy C-means algorithm for image segmentation

The pixels in the image may be grouped into more than one cluster when using the fuzzy c-means clustering algorithm. A pixel can thus be a part of several clusters, according to this. However, the degree of similarity between each pixel and each cluster would vary. The effectiveness of FCM significantly depends on the first cluster canters, which are challenging to identify [5,35,36].

3.16 The Otsu approaches

The Otsu approach is straightforward to use and offers a quick processing time for choosing thresholds that automatically determine which classes have the greatest variance [37,38].

4- Uses Segmentation

4.1 Segmentation of medical images

Medical images are crucial in helping doctors and other healthcare professionals diagnose and treat patients.

Medical image analysis mostly relies on visual perception and because of the growing number of medical imaging modalities and the overwhelming number of medical images that need to be evaluated, manually segmenting medical images by radiologist is not only a difficult and time-consuming process, but it is also not particularly accurate. As a result, it becomes vital to assess current approaches to image segmentation using automated algorithms that are precise and call for the least amount of user intervention. The value of artificial intelligence techniques like machine learning, fuzzy logic, and pattern recognition in digital image processing Image techniques can be categorized into the following categories: Image Engineering (IE). As depicted in Fig. 1, this is made up of three layers: image processing (lower layer), picture analysis (middle layer), and image

understanding (high layer). It has been shown that the initial and most important step in image analysis is image segmentation. Its goal is to extract information (represented by data) from an image using object representation, feature measurement, and picture segmentation. thus, in medical imaging applications, the computerization of medical picture segmentation is crucial. It is widely used in many different fields [39].
Medical image processing and analysis have become widely used in fundamental clinical research and therapy in nowadays, which enhances the standard of care by supplying diagnostic opinions and identifying lesions. The diagnosis of diseases, surgical planning, postoperative analysis, and the creation of chemotherapy and radiotherapy programs all depend on the precise segmentation of tissue and lesions from medical pictures. Analysis aids the doctor in a variety of clinical problems as well as the researcher's in-depth study of the target diseases. In 2012, Hinton et al. initially suggested CNN for the job of classifying images. Convolutional layers, pooling layers, activation layers, and full connection layers are the typical segmentation methods for medical pictures based on CNN, which may be loosely split into four categories according to their structure [40,41,42].

4.2 The segmentation of hyperspectral images

There are two categories of spectrum imaging: multispectral and hyperspectral. When compared to multispectral images, hyperspectral imagery (HSI) has more bands, and a greater spectral resolution. Imaging spectrometers like HYDICE (Hyperspectral Digital Imagery Collection Experiment) and AVIRIS, which produce hyperspectral images, are common in this field (Airborne Visible InfraRed Imaging Spectrometer).
Each spectral vector is a reflection value of a specific pixel at each spectral wavelength. Numerous spectral bands provide high dimensional data, which makes segmentation, classification, and picture processing difficult. Most techniques are intended for color or multispectral images, not hyperspectral images, or gray-level analysis of images. The method of feature reduction, which creates fewer features by combining a variety of already-existing channels, involves looking for a vector set that represents the reduction dimensions of the observation data. A hyperspectral image's pixels are vectors that each contain the spectral data obtained through various spectral channels at various wave lengths. The integration of the segmentation and classification processes in the hyperspectral image processing process has been done as an example to enhance the classification results Fig [8]. Multispectral and hyperspectral picture segmentation approaches have been introduced in some literature. Several of these methods rely primarily on region-merging methods, in which the homogeneity of the adjacent picture segments determines how they are merged [43,44,45,46,47].

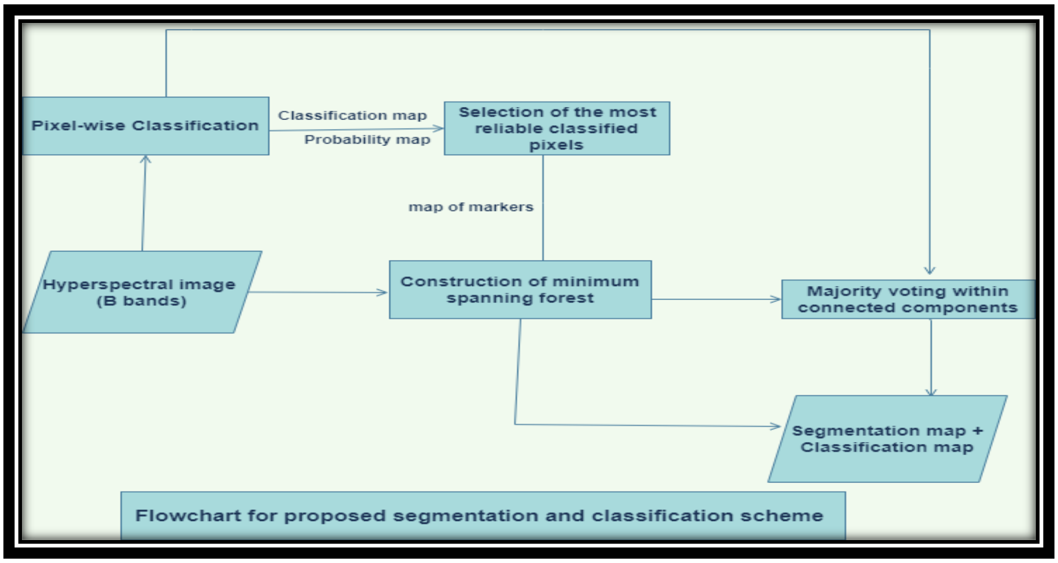

Fig [8] Segmentation and Classification hyperspectral

4.3 Image segmentation based on particle swarm optimization is used to detect illnesses on sunflower leaves

Using image processing and the Particle Swarm Optimization Algorithm, presents a novel way for detecting and classifying Sunflower leaf illnesses. Experts have been identifying diseases in plants with their naked eyes since ancient times, based on their extensive experience. This strategy is not viable for vast fields and has shown to be a time-consuming, exhausting, expensive, and time-consuming procedure. Automatic detection of disease symptoms developing on sunflower plant leaves using modern accessible techniques such as image processing, pattern recognition, and some automatic classification tools can be used to accurately identify and control disease in sunflower plants. Farmers can utilize them to improve the quality and quantity of their crop products. One of the best strategies for controlling and precisely identifying the illness of sunflower leaf (Di et al., 2015) in the field is to use computer image processing technologies. One of the most popular strategies employed by researchers is texture feature extraction. While reviewing the literature on leaf image segmentation, it was discovered that the proposed approaches only perform well on leaf photos recorded in a controlled environment. To improve the clustering accuracy, the proposed techniques can be combined with additional evolutionary algorithms [48,49,50].

Photographs of various types of leaves are taken with a digital camera or similar equipment, and the photos are then utilized to determine the damaged area in the leaves. Following picture acquisition, several image-processing techniques are applied to them to extract various and useful properties for further analysis. The stages in processing segmentation of leaf photos using Particle Swarm Optimization are illustrated in the flow chart below in Figure [9].

The following Sunflower plant samples were used as input:

(a) White rust disease on a sunflower leaf

(b) Bacterial leaf spot disease on a sunflower leaf

(c) Downy mildew disease on a sunflower leaf

(d) Powdery mildew disease on a sunflower leaf

(e) Septoria leaf blight on a sunflower leaf

(f) Sun rust disease on a sunflower leaf.

Figure [10,11] shows the original photos with their segmented output images.

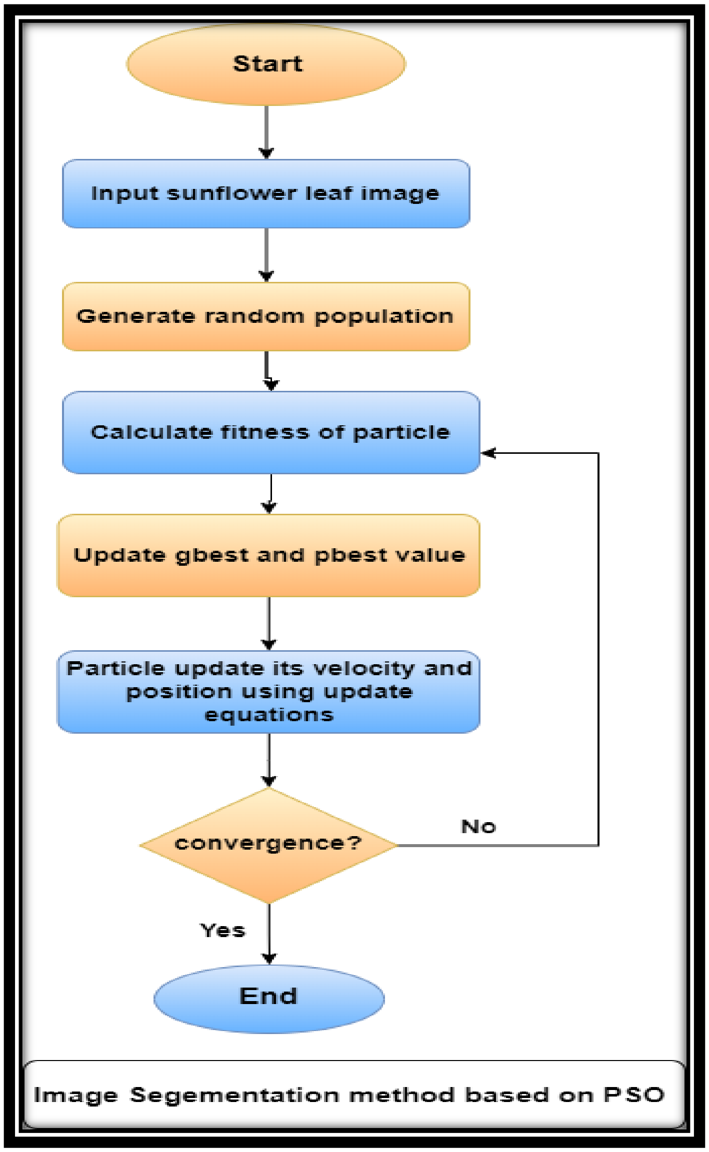

Fig [9] Image segmentation method by PSO

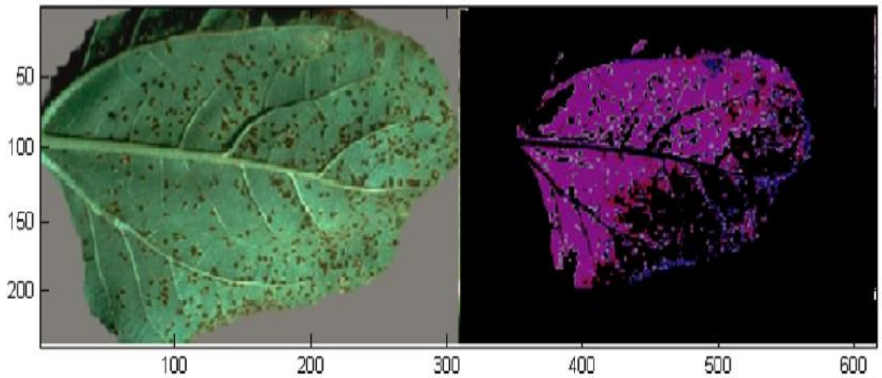

Fig [10] Input and its output segment image of sunflower leaf with sun rust disease

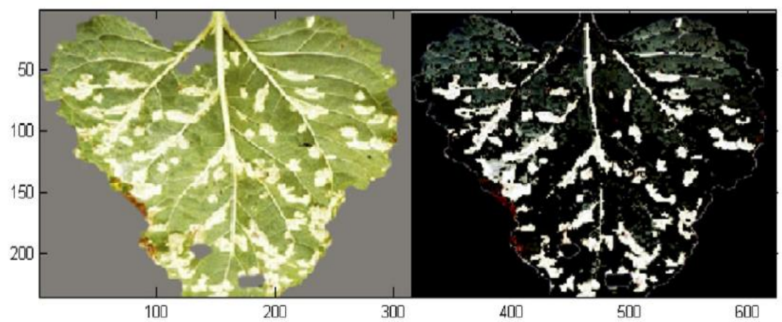

Fig [11] Input and its output segment image of sunflower leaf with White rust disease

4.4 Image segmentation using multilevel thresholding and a harmony search algorithm based on the energy curve

The histogram is a plot between grayscale values of an image on the x-axis and the number of pixels in that image with a specific grayscale value on the y-axis, and the histogram of an image acts as the graphical representation of pixel value distribution in the picture. Traditional histogram-based image segmentation has two key drawbacks: (i) not including information about specific contextual data (importance of pixels in the image) when picking the thresholding level, and (ii) incompetence for multilevel thresholding segmentation. Instead of a histogram, the energy curve can be utilized to address these flaws in image histograms. When determining the threshold level, an energy function is expected to consider contextual information [51]. The image's energy curve resembles (or appears to be) a histogram of the same image; it determines the energy level of each pixel value in the grayscale range, as well as peaks and value points used to locate various objects. Instead of using the histogram of a digital image, we can offer a new segmentation strategy that combines Otsu's method on the energy curve with the Harmony Search Algorithm (HAS) to compute optimum thresholding levels.

As a cure for the shortcomings of histogram-based approaches for picture segmentation, a multilayer threshold (MT) based technique with the energy curve is proposed. When using Otsu's method for MT with Harmony Search Algorithm (HSA) for computing optimized threshold levels by maximizing inter-class variance as an objective function, histogram-based techniques are unable to take spatial contextual information into account when computing optimized levels. The superiority of the energy curve over the histogram is demonstrated in this study. Internal validation methods (Dunn Index, DB, and SD), PRI, mean of the fitness function, PSNR, and time have all been used to assess the success of the suggested method. According to the findings, the energy curve can be used to compute more optimum levels for efficient cluster-based segmentation [51].

4.5 In MRI Brain Image Segmentation, a Novel Approach Based on PSO Optimized K-Means.

Image segmentation is an important task in medical field to propose a method to analyse the MRI brain image which ease the work of clinicians. we proposed to segment MRI brain image into Gray matter (GM), White matter (WM), cerebrospinal fluid (CSF), and skull. Here Particle Swarm Optimization (PSO) is used to optimize the centroid values. These optimized cluster centers are utilized in K-means algorithm to segment the image into various regions. Segmentation plays a major role in medical image processing to segment images into various regions to diagnose the diseases. The images are segmented like bone, muscles and blood vessels, various organs, brain regions etc. Brain image segmentation is very much essential inorder to analyse the tumor in the brain. MRI brain image has many regions like Gray matter, White matter, CSF, skull etc. An efficient segmentation of brain regions must be done which make clinicians, to provide the appropriate treatment [52,53,54].
The MRI brain images are chosen from brain web database. The input image was resized to 256x256. Image enhancement was done to enhance the contrast of the image. Here adaptive histogram equalization was done, and it is shown in Fig 16. A median filter is used to filter the image. Median filter is more robust and preserves sharp edges [55]. Particle Swarm Optimization is used to optimize the cluster value and it is given to the k means clustering [56].

4.6 Different Image Processing Techniques for Underwater Images

Underwater imaging plays a vital role in research of computer graphics and ocean engineering. Removal techniques for underwater haze have become very famous since adoption of different applications in image underwater. The underwater images quality is bad because of light propagation properties in water. When capturing such images reduce due to several factors namely water ripple, lack of light organic matter availability dissolved in water and captured images from little distance must be pre-processed before applying any type of operation on these images various techniques of filtering are feasible for pre-processing underwater images. Usually, the filters are used to enhance the quality of image, suppress the noise preserve the corner in an image, smoothen and enhance the image properly. Underwater image enhancement is the area of image processing, and it is considered as a dynamic sector. Obtaining the objects visibility at short or long distance in underwater scenes is very challenging and a difficult task. The atmospheric light is the main hurdle to process the UW images from bad conditions of visibility under the water, light attenuation, and light scattering due to entire reasons which the UW images faces a lot and influence their contrast and visibility which they comprise originally [57,58,59,60].

5- CONCLUSIONS

This study discussed many bio-inspired algorithms to solve the problem of image segmentation. In general, there were many approaches followed by researchers when using these bio-inspired methods. One approach was to make modifications in these methods for example, by changing their objective functions, their search methods, or their updating strategies, which has also shown to improve the performance of the original methods. Another approach was to combine these methods with other algorithms with a main goal of improving the performance and overcoming the limitations of the individual methods. The combination was twofold. The first one combined the bio-inspired algorithms with other segmentation methods such as thresholding, edge detection, or clustering. The second combination involved combining the bio-inspired algorithms among themselves; for example, PSO was used to initialize the population of ABC. These approaches proved to improve the quality and accuracy of the results as well as to reduce the computation time. Considering these approaches, researchers can propose new techniques for image segmentation by utilizing the advantages of some methods to overcome the limitations of others.

.

REFERENCES

1. Thiruvikraman, P. K. (2019). A Course on Digital Image Processing with MATLAB. IOP Publishing.
2. Yeung, M., Sala, E., Schönlieb, C. B., & Rundo, L. (2022). Unified Focal loss: Generalising Dice and cross entropy-based losses to handle class imbalanced medical image segmentation. Computerized Medical Imaging and Graphics, 95, 102026.
3. Ma, G., & Yue, X. (2022). An improved whale optimization algorithm based on multilevel threshold image segmentation using the Otsu method. Engineering Applications of Artificial Intelligence, 113, 104960.
4. Liu, L., Zhao, D., Yu, F., Heidari, A. A., Ru, J., Chen, H., ... & Pan, Z. (2021). Performance optimization of differential evolution with slime mould algorithm for multilevel breast cancer image segmentation. Computers in Biology and Medicine, 138, 104910.
5. Ebert, L. C., Dobay, A., Franckenberg, S., Thali, M. J., Decker, S., & Ford, J. (2022). Image segmentation of post-mortem computed tomography data in forensic imaging: Methods and applications. Forensic Imaging, 28, 200483.
6. Pal, N. R., & Pal, S. K. (1993). A review on image segmentation techniques. Pattern recognition, 26(9), 1277-1294.
7. Kumar, M. J., Kumar, D. G. R., & Reddy, R. V. K. (2014). Review on image segmentation techniques. International Journal of Scientific Research Engineering & Technology, 3(6), 993-997.
8. Karaboga, Dervis, and Bahriye Basturk. "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm." Journal of global optimization 39.3 (2007): 459-471.
9. Kumar, M. J., Kumar, D. G. R., & Reddy, R. V. K. (2014). Review on image segmentation techniques. International Journal of Scientific Research Engineering & Technology, 3(6), 993-997.
10. Dhiman, Gaurav, and Vijay Kumar. "Seagull optimization algorithm: Theory and its applications for large-scale industrial engineering problems." Knowledge-based systems 165 (2019): 169-196.
11. Wang, Yuyin. "Otsu image threshold segmentation method based on seagull optimization algorithm." Journal of Physics: Conference Series. Vol. 1650. No. 3. IOP Publishing, 2020.

12. Larabi-Marie-Sainte, S., et al. (2021). "Emerging Applications of Bio-Inspired Algorithms in Image Segmentation." Electronics 10(24): 3116.
13. Pare, S., et al. "Image segmentation using multilevel thresholding: a research review." Iranian Journal of Science and Technology, Transactions of Electrical Engineering 44.1 (2020): 1-29.
14. Karaboga, Dervis, and Bahriye Basturk. "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm." Journal of global optimization 39.3 (2007): 459-471
15. Hlaing, Su Hnin, and Aung Soe Khaing. "Weed and crop segmentation and classification using area thresholding." IJRET 3 (2014): 375-382.
16. Kurugollu, Fatih, Bülent Sankur, and A. Emre Harmanci. "Color image segmentation using histogram multithresholding and fusion." Image and vision computing 19.13 (2001): 915-928.
17. Khan, Waseem. "Image segmentation techniques: A survey." Journal of image and graphics 1.4 (2013): 166-170.
18. Saini, Sujata, and Komal Arora. "A study analysis on the different image segmentation techniques." International Journal of Information & Computation Technology 4.14 (2014): 1445-1452.
19. Larabi-Marie-Sainte, S., et al. (2021). "Emerging Applications of Bio-Inspired Algorithms in Image Segmentation." Electronics 10(24): 3116.
20. Fan, Xumei, et al. "Review and classification of bio-inspired algorithms and their applications." Journal of Bionic Engineering 17.3 (2020): 611-631.
21. Shijie, Xu. "The Ant Colony Optimization of Clustering Problems in Data Mining." Journal of Physics: Conference Series. Vol. 1087. No. 3. IOP Publishing, 2018.
22. Liang, Xiaolei, et al. "An improved ant colony optimization algorithm with negative feedback." Journal of Physics: Conference Series. Vol. 2033. No. 1. IOP Publishing, 2021.
23. Srikanth, R., & Bikshalu, K. (2021). Multilevel thresholding image segmentation based on energy curve with harmony Search Algorithm. Ain Shams Engineering Journal, 12(1), 1-20.
24. Wang, Wei, et al. "Design of Digital Filter Based on Artificial Bee Population Algorithm." Journal of Physics: Conference Series. Vol. 2030. No. 1. IOP Publishing, 2021.
25. Chen, Dong, et al. "Optimization of Character Image Matching based on Artificial Bee Colony Algorithm." Journal of Physics: Conference Series. Vol. 2035. No. 1. IOP Publishing, 2021.
26. Srikanth, R., & Bikshalu, K. (2021). Multilevel thresholding image segmentation based on energy curve with harmony Search Algorithm. Ain Shams Engineering Journal, 12(1), 1-20.
27. Chakraborty, Sanjoy, et al. "An enhanced whale optimization algorithm for large scale optimization problems." Knowledge-Based Systems 233 (2021): 107543.

28. Liu, Lisang, and Rongsheng Zhang. "Multistrategy Improved Whale Optimization Algorithm and Its Application." Computational Intelligence and Neuroscience 2022 (2022).
29. Ma, Guoyuan, and Xiaofeng Yue. "An improved whale optimization algorithm based on multilevel threshold image segmentation using the Otsu method." Engineering Applications of Artificial Intelligence 113 (2022): 104960.
30. Kaur, Amanpreet. "A review paper on image segmentation and its various techniques in image processing." Int. J. Sci. Res. ISSN (Online Impact Factor 3.12 (2012): 2319-7064.
31. Chen, Jinlin, et al. "Image segmentation method using Fuzzy C mean clustering based on multi-objective optimization." Journal of Physics: Conference Series. Vol. 1004. No. 1. IOP Publishing, 2018.
32. Wang, Huan. "Material image segmentation based on feature similarity and non-spherical clustering." IOP Conference Series: Materials Science and Engineering. Vol. 652. No. 1. IOP Publishing, 2019.
33. Hou, Xiangru. "A New Clustering Validity Index based on K-means Algorithm." Journal of Physics: Conference Series. Vol. 1187. No. 4. IOP Publishing, 2019.
34. Lu, Xin, et al. "An improved k-means distributed clustering algorithm based on spark parallel computing framework." Journal of Physics: Conference Series. Vol. 1616. No. 1. IOP Publishing, 2020.
35. Tandan, A., et al. (2014). "Image segmentation based on particle swarm optimization technique." Intl J Sci Eng Technol Res 3(2): 257-260.
36. Abdellahoum, Hamza, et al. "CSFCM: An improved fuzzy C-Means image segmentation algorithm using a cooperative approach." Expert Systems with Applications 166 (2021): 114063.
37. Wang, Yuyin. "Otsu image threshold segmentation method based on seagull optimization algorithm." Journal of Physics: Conference Series. Vol. 1650. No. 3. IOP Publishing, 2020.
38. Huang, Chunyan, Xiaorui Li, and Yunliang Wen. "AN OTSU image segmentation based on fruitfly optimization algorithm." Alexandria Engineering Journal 60.1 (2021): 183-188.
39. Patil, Dinesh D., and Sonal G. Deore. "Medical image segmentation: a review." International Journal of Computer Science and Mobile Computing 2.1 (2013): 22-27.
40. Dhiman, Gaurav, and Vijay Kumar. "Seagull optimization algorithm: Theory and its applications for large-scale industrial engineering problems." Knowledge-based systems 165 (2019): 169-196.
41. Chen, Junde, et al. "Segmentation of medical images using an attention embedded lightweight network." Engineering Applications of Artificial Intelligence 116 (2022): 105416.
42. Khani, Masoud. Medical Image Segmentation Using Machine Learning. Diss. The University of Wisconsin-Milwaukee, 2021.

43. Ismi, D. P. "Hyperspectral image segmentation using discriminant independent component analysis and swarm optimization approaches." IOP Conference Series: Materials Science and Engineering. Vol. 674. No. 1. IOP Publishing, 2019.
44. Ismi, D. P. "Hyperspectral image segmentation using discriminant independent component analysis and swarm optimization approaches." IOP Conference Series: Materials Science and Engineering. Vol. 674. No. 1. IOP Publishing, 2019.
45. Gao, Dehua, et al. "In-field chlorophyll estimation based on hyperspectral images segmentation and pixel-wise spectra clustering of wheat canopy." Biosystems Engineering 217 (2022): 41-55.
46. Nirmala, A. "An Investigation of Image Segmentation Method for Remotely Sensed Hyperspectral Images with Region Object Aggregations." International Journal of Computer Applications 975 (2016): 8887.
47. Agrawal, Praveen, et al. "A Method of Segmentation for Hyper spectral & Medical Images Based on Color Image Segmentation." International Journal on Recent and Innovation Trends in Computing and Communication 2.12: 3871-3874.
48. Singh, V. (2019). Sunflower leaf diseases detection using image segmentation based on particle swarm optimization. Artificial Intelligence in Agriculture, 3, 62-68.
49. Ghamisi, Pedram, et al. "Multilevel image segmentation based on fractional-order Darwinian particle swarm optimization." IEEE Transactions on Geoscience and Remote sensing 52.5 (2013): 2382-2394.
50. Gong, Qiyong, et al. "Maximum entropy multi-threshold image segmentation based on improved particle swarm optimization." Journal of physics: conference series. Vol. 1678. No. 1. IOP Publishing, 2020.
51. Li, Na, and Zhiyong Xiong. "Automated brain tumor segmentation from multi-modality MRI data based on Tamura texture feature and SVM model." Journal of Physics: Conference Series. Vol. 1168. No. 3. IOP Publishing, 2019.
52. Prasath, R. and T. Kumanan (2020). Application of Different Techniques for Underwater Image Processing-A Systematic Review. IOP Conference Series: Materials Science and Engineering, IOP Publishing.
53. Ali, H., et al. "MRI brain image segmentation based on cascaded fractional-order darwinian particle swarm optimization and mean shift." International Journal of Intelligent Computing and Information Sciences 15.1 (2015): 71-83.Leo, M. Judith. "MRI brain image segmentation and detection using K-NN classification." Journal of Physics: Conference Series. Vol. 1362. No. 1. IOP Publishing, 2019.
54. Liu, Jie, et al. "A new method based on Dempster–Shafer theory and fuzzy c-means for brain MRI segmentation." Measurement Science and Technology 26.10 (2015): 105402.
55. Liu, L., Zhao, D., Yu, F., Heidari, A. A., Ru, J., Chen, H., ... & Pan, Z. (2021). Performance optimization of differential evolution with slime mould algorithm for multilevel breast cancer image segmentation. Computers in Biology and Medicine, 138, 104910.

56. Li, Na, and Zhiyong Xiong. "Automated brain tumor segmentation from multi-modality MRI data based on Tamura texture feature and SVM model." Journal of Physics: Conference Series. Vol. 1168. No. 3. IOP Publishing, 2019.
57. Hyiamang, Churchill Osei, et al. "Low-cost optical techniques for detecting and imaging different objects underwater." Journal of Physics: Conference Series. Vol. 1865. No. 2. IOP Publishing, 2021.
58. Prasath, R., and T. Kumanan. "Application of Different Techniques for Underwater Image Processing-A Systematic Review." IOP Conference Series: Materials Science and Engineering. Vol. 925. No. 1. IOP Publishing, 2020.
59. Kaur, Maninder, and Sandip Vijay. "Underwater images quality improvement techniques for feature extraction based on comparative analysis for species classification." Multimedia Tools and Applications 81.14 (2022): 19445-19461.
60. Nomura, Kohei, Daisuke Sugimura, and Takayuki Hamamoto. "Underwater image color correction using exposure-bracketing imaging." IEEE Signal Processing Letters 25.6 (2018): 893-897.