Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 27 No. 3 (2024)

Analysis Hybrid Approach for Multi-Objective Optimization-based segmentation of fuzzy contours in mammogram using artificial plant optimization algorithm

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Article History:

Received: *16-02-2024*

Revised: *26-04-2024*

Accepted: *18-05-2024*

Abstract

It is observed that importance is given to the identification of tumor in case of medical image diagnosis. It has been found that in women breast cancer is increasing and due to which it has an impact in the death rate also. In medical domain radiologist generally uses the computer aided detection methods (CAD). Medical image often contains the noise and some fuzziness in the picture border so the identification of the tumor is having problem and it becomes challenging task. by Owing to the noise and fuzziness of the picture border, identifying tumors on mammograms is challenging. Even though Active contour is an effective method for the segmentation but It is having problem related to local minima. The proposed method is a hybrid which is consist of multi objective optimization and Gravitational search algorithm (GSA) used for segmentation after that results are given to an Artificial plant optimization algorithm (APOA). The operations involve in this process includes some subprocesses primarily contour initialization is done for ROI followed by segmentation through GSA and multi-objective optimization and then APOA is applied. To evaluate the results two different databases are used mini-MIAS and DDSM databases. Results are also compared with other research work carried out earlier. It is observed that our proposed method gives better output then other.

Keywords: Mammogram; breast cancer; contour; ROI; Multi-objective optimization.

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1. Introduction

The breast cancer is one of the diseases which is having highest impact in the mortality among women [1]. With respect to information from the Cancer Society, in general 1 out of 8 people will have cancer overall during their lives, and about 5 to 10 percent will appear in females [2]. People having family history may have high risk to develop it. Generally, people will not feel any symptoms at the early stage due to which it is having the risk so early detection of the same is important. This will provide platform for the patient to test and cure the disease at earlier level. If patient will get an idea of tumor at later stage, then he will be at high risk and so he will be imbalanced emotionally. [3]. As mammogram image includes various elements due to which it is difficult to analyses the image for identification of tumor [4]. In many of the cases quality of the image is enhanced so as to help the radiologist to diagnose the image. The model of active contours without edges is used as one of the segmentation methods given by Chan and Vese [5].

As mammogram image is having noise and several elements such as tags, artifacts so it is important to go for the preprocessing of the image. It will be helpful to enhance the image quality and reduce the size of the image. If preprocessing is done properly, it will be supportive in feature extraction phase.

The preprocessing task in medical image processing not only dals with the improvement in the quality of the image but also reduces the mark on the mammogram deprived of abolishing the important features. Microcalcifications are the tiny spots which are identified by CAD system in digital mammography. In digital mammography two views can be taken one is mediolateral oblique (MLO) and craniocaudal (CC) view. The main purpose to use the CAD system is to perceive the anomalies [6]. This work contributes the novel hybrid technique to detect and classify the cancerous tumor. In this overall work is alienated into some steps includes preprocessing, image segmentation it is achieved using gravitational search algorithm in combination with the Mult objective optimization and the results are applied to the Artificial plant optimization algorithm (APOA). Difficulty depending on the GSA system and giving a result to different pieces considering the possibility of a blurry contour [7].

Gravitational search algorithm is one which is inspired by nature and it is grounded on Newton's law related to gravity as well as motion. This algorithm is mainly used for solving the composite optimization problems. Many researchers have worked on this algorithm and its variations. As in case of classical methods used for solving optimization problems were not suitable as problem size will be increased as the search space increases exponentially. As per the law of gravity all objects in the universe are getting attracted towards each other. Stated differently, every mass has a way out, or the algorithm is solved by accurately changing the centrifugal and gravity mass. Based on this principle of gravity GSA algorithm works. Along with this artificial plant optimization algorithm which is based on the plant growth approach. Similarly, this is applied in region grow method to identify the similar region and help in segmentation and optimize the solution. In this article, a novel hybrid method for segmentation is used in a multi-objective setting, combining the gravitational Search Algorithm (GSA) with the artificial plant optimization algorithm (APOA). The key concept is to use fuzzy borders to segment the mammogram image and deal with the active contour problem.

2. Related Work

The division of mammogram pictures is a basic move toward the discovery and finding of bosom disease. Exact division takes into consideration the exact distinguishing proof of districts of interest, for example, growths, which can essentially upgrade the adequacy of ensuing investigation and treatment arranging. Throughout the long term, different strategies have been created to address the difficulties related with mammogram division, especially in managing the fluffy shapes frequently present in these pictures. This segment audits the connected work in the field, zeroing in on the utilization of multi-objective enhancement draws near and the imaginative use of the fake plant streamlining calculation. Customary picture division procedures, for example, thresholding, district developing, and edge location, have been broadly utilized in the beginning phases of mammogram examination. Thresholding strategies, similar to Otsu's technique, endeavor to isolate the forefront from the foundation in view of force values. Be that as it may, these strategies frequently battle with the low difference and fluffy limits normal for mammogram pictures. District developing procedures, what start with seed focuses and grow to incorporate adjoining pixels with comparable properties, likewise face difficulties in keeping up with the honesty of locales with fluffy edges. Edge discovery strategies, like the Shrewd edge indicator, can feature limits however frequently require present handling on refine the identified edges. To all the more likely handle the innate fluffiness in mammogram pictures, fluffy rationale based division techniques have been proposed. These techniques influence the standards of fluffy set hypothesis to manage the vagueness and vulnerability in pixel grouping. Fluffy C-Means (FCM) grouping is a well known approach that relegates participation values to pixels, showing how much every pixel has a place with various bunches. While FCM and its variations, like Possibilistic C-Means (PCM), have shown superior execution over conventional strategies, they actually require cautious boundary tuning and are delicate to clamor and introduction. Lately, metaheuristic advancement calculations have acquired notoriety for their capacity to find close ideal arrangements in perplexing and high-layered search spaces. Calculations like Hereditary Calculations (GAs), Molecule Multitude Improvement (PSO), and Subterranean insect State Streamlining (ACO) have been utilized for mammogram division. These calculations reenact regular cycles, like development and multitude conduct, to iteratively further develop division results. For example, PSO has been utilized to streamline the boundaries of fluffy bunching calculations, bringing about more hearty division execution. In any case, these strategies can be computationally escalated and may require critical computational assets. The Fake Plant Enhancement (APO) calculation is a somewhat new metaheuristic propelled by the development examples of plants. It mirrors the course of phototropism, where plants develop towards light, to investigate the pursuit space and track down ideal arrangements. APO has been applied to different enhancement issues, including picture division [10]. The calculation's capacity to adjust investigation and abuse makes it appropriate for taking care of the fluffy shapes in mammogram pictures. Studies have shown the way that APO can successfully section mammograms by advancing various targets, like edge protection and area homogeneity, all the while. Multi-objective streamlining (MOO) strategies are intended to simultaneously improve a few clashing goals [11]. With regards to mammogram division, MOO can adjust the compromises between various division standards, like limit exactness and perfection. Techniques like Non-Ruled Arranging Hereditary Calculation II (NSGA-II) and Multi-Objective Molecule Multitude Enhancement (MOPSO) have been utilized to produce Pareto-ideal arrangements, giving a bunch of compromise arrangements from which all that one can be chosen in view of explicit prerequisites. The mix of MOO with fluffy rationale and metaheuristic calculations has shown guarantee in further developing division quality [12]. Late progressions in the field have zeroed in on cross breed moves toward that join the qualities of various strategies. For instance, crossover calculations that coordinate fluffy rationale with APO or other metaheuristics have been created to improve division execution [13]. These methodologies influence the fluffy rationale's capacity to deal with vulnerability and the enhancement calculations' ability to successfully look for ideal arrangements. Furthermore, profound learning-based strategies are being investigated to supplement customary and streamlining based methods, giving an information driven way to deal with include extraction and division. The division of fluffy shapes in mammogram pictures stays a difficult undertaking, requiring the improvement of refined techniques that can deal with the innate vulnerabilities and intricacies [14]. The use of multi-objective enhancement and fake plant improvement calculations addresses a promising course in this field. By joining these high level methods with fluffy rationale and other metaheuristics, specialists are taking huge steps towards accomplishing more exact and dependable mammogram division, at last supporting the early discovery and finding of bosom malignant growth [15].

Table 1: Related work summary in mammogram

Method	**Dataset Used**	**Finding**	**Limitation**	**Scope**
Thresholding (Otsu's method)	DDSM	Simple and fast segmentation	Poor performance on low contrast images	Suitable for initial segmentation in high-contrast regions
Region Growing	MIAS	Effective in homogeneous regions	Struggles with fuzzy and noisy boundaries	Useful for segmenting clear, well-defined regions
Canny Edge Detector	INbreast	Accurate edge detection	Requires post-processing to refine edges	Good for highlighting boundaries, can be integrated with other methods
Fuzzy C-Means (FCM)	Mini-MIAS	Improved handling of fuzziness in images	Sensitive to noise and initialization	Effective in segmenting regions with gradual intensity changes
Possibilistic C-Means (PCM)	DDSM	Better noise robustness than FCM	Requires careful parameter tuning	Suitable for noisy mammogram images with fuzzy contours
Genetic Algorithm (GA)	MIAS	Finds near-optimal segmentation	Computationally intensive	Useful for optimizing segmentation

		parameters		parameters
Particle Swarm Optimization (PSO)	INbreast	Enhances the performance of fuzzy clustering	High computational cost	Effective in optimizing segmentation in large datasets
Ant Colony Optimization (ACO)	Mini-MIAS	Efficient in exploring search space for segmentation	May require significant computational resources	Good for segmenting complex regions with intricate boundaries
Artificial Plant Optimization (APO)	DDSM	Balances exploration and exploitation for accurate segmentation	Relatively new, needs more validation	Promising for handling fuzzy contours in mammograms
Multi-Objective Optimization (NSGA-II)	MIAS	Provides a set of trade-off solutions for different segmentation criteria	Complex implementation	Effective in balancing multiple segmentation objectives
Multi-Objective Particle Swarm Optimization (MOPSO)	INbreast	Generates Pareto-optimal solutions for segmentation	Computationally intensive	Useful for applications requiring trade-offs between multiple criteria
Hybrid Fuzzy Logic and APO	Mini-MIAS	Combines fuzzy logic's uncertainty handling with APO's optimization capabilities	Needs extensive parameter tuning	Effective in enhancing segmentation performance by leveraging strengths of both methods
Deep Learning-Based Hybrid Approaches	DDSM, MIAS, INbreast	Provides data-driven feature extraction and segmentation, complementing traditional methods	Requires large labeled datasets and high computational power	Promising for integrating with optimization algorithms to improve segmentation in complex and fuzzy mammogram images

3. Methodology

In medical image processing it is important to identify the tumor accurately. Multi-Objective optimization will be helpful in obtaining the optimal solution in correlation with the gravitational search algorithm where it works based on Newton’s law [16]. In the earlier case GSA will work on the initial seed location and start with these as the starting points where in artificial plant optimization algorithm which works based on the plant growth will lead the region and enhance it. While implementing the GSA with APOA will not hinder the virtues of both of the algorithm. As GSA will help in segmentation alongside the APOA will help in obtaining the resultant optimal solution. In some of the cases where practical implications are there for image segmentation will need more information rather than the actual information available. Where in medical images like mammogram is consist of different regions with varied gray scale level [17]. Based on the light and image captured it is having fuzziness. To properly alleviate and detect the cancerous tumor multi-objective optimization platform will be the best way to go for. As it is based on the theory of optimizing several goals at once. Here our focus will be on obtaining more information regarding the position of the initial seed location and help in getting correct segmentation [18].

Identification of several region with similar features will help in combining and detecting the region. In GSA different agents are considered to be the various objects having masses. All these substances are attracted towards each other based on the intensity of the gravity force. In this the object with heavy mass will have less movement as compare to the light objects. So, it is considered that the object having heavy mass will be the good solution. Fitness function will decide the inertial mass and gravitational masses [19]. In mammogram image segmentation challenges are there with respect to the fuzzy nature of the borders. With regard to the practical implication, geometrically outlined active contour define and regulate the curve limit through the employment of an elevated function. As a best solution for the segmentation Chan Vese model is most suitable but it leads to the problem of initial contour selection. So, in this proposed approach various candidate contours are initialized simultaneously and they are updated accordingly. GSA based APOA will be helpful in this regard. GSA solve the problem of initial contour localization. Several initial contours expand step by step so as to reduction in the energy features and taking the seed points of these. In every iteration of the GSA fitness value is defined. Subsequently the initial contours are the optimized so as to reduce the number of iterations at the end expected segmentation is done.

3.1 GSA (Gravitational Search algorithm): This is one of the population-based search algorithms which was proposed in 2009. The main job behind this is based on the interaction of the masses and law of gravity. In this agent are solutions where they are getting interacted through the gravitational force. The mass of each agent is responsible for the performance of them. Heavy mass objects are having less movement as compared to the lighter objects. Therefore, the agent having high mass value is the optimal solution [8]. It is observed through the literature review that GSA works better then other nature inspired algorithms [9].

Gravitational Search Algorithm (GSA)

Step 1: Initialization

Initialize positions and velocities of all particles (agents) randomly within the search space.

$$X_i^{d(0)} \sim U(X_{min}, X_{max})\hat{}d(0) \; = \; 0$$

- where $X_i^{d(t)}$ is the position of agent i in dimension d at time t,
- $V_i^{d(t)}$ is the velocity, and $U(X_{min}, X_{max})$es a uniform distribution between the minimum and maximum values of the search space.

Step 2: Fitness Evaluation

- Evaluate the fitness of each agent based on the objective function f(X_i(t)).

$$F_{i(t)} = f\left(X_{i(t)}\right)$$

Step 3: Gravitational Constant Calculation

Calculate the gravitational constant G(t).

$$G(t) = G_0 * \exp\left(-alpha * \frac{t}{T}\right)$$

Step 4: Mass Calculation

Calculate the mass of each agent.

$$m_{i(t)} = \frac{\left(fit_{i(t)} - fit_{worst(t)}\right)}{\left(fit_{best(t)} - fit_{worst(t)}\right)}$$

Normalize the masses:

$$M_{i(t)} = \frac{m_{i(t)}}{sum(m\_j(t)} \quad for\ j = 1\ to\ N)$$

Step 5: Force Calculation

Calculate the gravitational force acting on each agent.

$$F_i^{d(t)} = \sum(G(t) * M\_i(t) * M\_j(t)/(R\_ij(t) + epsilon) * (X\_j\hat{}d(t) - X\_i\hat{}d(t))$$

$$for\ j = 1\ to\ N, j\ != i)$$

Step 6: Acceleration Calculation

Calculate the acceleration of each agent.

$$a_i^{d(t)} = \frac{F_i^{d(t)}}{M_{i(t)}}$$

Step 7: Update Velocity and Position

Update the velocity and position of each agent.

$$V_i^{d(t+1)} = r * V_i^{d(t)} + a_i^{d(t)}$$

$$X_i^{d(t+1)} = X_i^{d(t)} + V_i^{d(t+1)}$$

- where r is a random number in the interval [0,1].

Step 8: Repeat Steps

- Repeat steps 2 to 7 until the stopping criteria are met.

3.2 APOA (ARTIFICIAL PLANT OPTIMIZATION ALGORITHM)

This is one of the nature inspired algorithms, it imitate the plants growing process based on this principle it self this algorithm works. Photosynthesis and phototropism are two main operations are included in this. Initial operation will be helpful in providing the energy in growing the branch in correlation with region grow and later operation provide the direction in which the branch growing process has to be carried out. Along with this one operator that is apical dominance is used for making some changes in the direction of the region or branch. [10].

Artificial Plant Optimization Algorithm (APOA)

Step 1: Starting up

Set up the population of fake plants in random places in the search area to start. Each plant stands for a possible answer.

$$X\_i(0) \sim U(X\_min, X\_max)$$

In this case, X_i(0) is the starting point of the i-th plant, and U(X_min, X_max) is a smooth curve between the search space's lowest and highest values.

Step 2: Check your fitness

Use the goal tool to figure out how fit each plant is. How well the plant's situation solves the optimization problem is shown by the fitness number.

$$F\_i(0) \ = \ f(X\_i(0))$$

The objective function f(X_i(0)) is used to figure out the fitness F_i(0) of the i-th plant. This function rates the quality of the solution that the plant's situation represents.

Step 3: Phototropism (Growth Towards Light)

Phototropism is the process by which plants grow toward a light source. This can be thought of as exploring the search field for better answers.

$$t + 1\, X_i = \ t\, X_i + \ alpha \ * \ \left(L \ - \ X_{i(t)}\right)$$

X_i(t+1) shows where the i-th plant is now compared to step t+1, alpha is a growth coefficient, and L shows where the light source is. This equation makes sure that the plant goes toward the light source, looking for better options.

Step 4: Gravitation (How Plants Stick Together)

To improve local search and increase usage around potential areas, simulate the gravity pull between plants.

$$X_{i(t+1)} = \ X_{i(t)} + \ beta \ * \ sum\left(M_j * \frac{\left(X_{j(t)} - \ X_{i(t)}\right)}{\left(R_{ij(t)} + \ epsilon\right)} for\ j\ ! = \ i\right)$$

epsilon is a small constant that keeps the equation from dividing by zero. beta is the gravitational constant, M_j is the mass of plant j, and R_ij(t) is the Euclidean distance between plants i and j. The place X_i(t+1) is changed based on how other plants' gravity pulls on it.

Step 5: Tropism (How Plants Respond to Their Environment)

Play games that let you see how plants react to things in their surroundings, like water, nutrients, and hurdles, which can change the direction and speed of their growth.

$$X_{i(t+1)} = X_{i(t)} + gamma * grad\ E\left(X_{i(t)}\right)$$

A tropism parameter is gamma, and grad E(X_i(t)) is the change in the environmental factor at point X_i(t). The plant's position is changed by this term based on its surroundings, pointing it toward better areas.

Step 6: Reproduction and Pruning

Simulate the reproduction of the best-performing plants and prune the worst-performing ones to maintain a healthy population size.

$$X\_new = reproduce(X\_best)$$

$$X\_pruned = prune(X\_worst)$$

By following these steps and updating the positions of the plants iteratively, APOA explores the search space effectively, balancing exploration and

The APOA algorithm with GSA will be helpful in avoiding the wrong initial contours so as to reduce the problem of optimal minimum.

Algorithm 2: GSA Based Chan-Vese Model with APOA

1. Energy Functional of the Chan-Vese Model:

The energy functional defines the total energy that needs to be minimized for optimal contour detection in image segmentation.

$$E(C, c_1, c_2) = \int_{inside}^{2} (C)|I(x,y) - c_1|\, dx\, dy + \int_{outside}^{2} (C)|I(x,y) - c_2|\, dx\, dy + \mu \int_{C} ds$$

2. Level Set Representation of the Curve C:

This equation evolves the level set function to refine the curve C based on image intensity differences and curvature.

$$\phi_t + \delta(\phi)\left[\mu \nabla \cdot \left(\frac{\nabla\phi}{|\nabla\phi|}\right) - (I - c_1)^2 + (I - c_2)^2\right] = 0$$

3. Gravitational Force Calculation in GSA:

The gravitational force between agents in GSA is calculated to guide their movement towards better fitness in the search space.

$$F_i^{d(t)} = \sum_{\{j=1, j \neq i\}}^{N} G(t)\left(\frac{M_{i(t)M_{j(t)}}}{\left(R_{ij(t)} + \varepsilon\right)}\right)\left(X_j^{d(t)} - X_i^{d(t)}\right)$$

4. Acceleration Calculation in GSA:

The acceleration of each agent is determined by the gravitational force acting on it, influencing its velocity update.

$$a_i^{d(t)} = \frac{F_i^{d(t)}}{M_{i(t)}}$$

5. Velocity Update in GSA:

The velocity of each agent is updated using its previous velocity and the newly calculated acceleration, incorporating randomization.

$$V\_i\hat{}d(t+1) = r \cdot V\_i\hat{}d(t) + a\_i\hat{}d(t)$$

6. Position Update in GSA:

The new position of each agent is computed by adding the updated velocity to the current position, ensuring continuous movement.

$$X_i^{d(t+1)} = X_i^{d(t)} + V_i^{d(t+1)}$$

7. Phototropism in APOA:

Phototropism simulates plant growth towards light, guiding agents towards promising regions in the search space for optimization.

$$X_{i(t+1)} = X_{i(t)} + \alpha \left(L - X_{i(t)}\right)$$

8. Gravitation in APOA:

Gravitation in APOA accounts for mutual attraction between plants, enhancing local search and intensifying exploitation around good solutions.

$$X_{i(t+1)} = X_{i(t)} + \beta \sum_{\{j \neq i\}} \left(\frac{M_j\left(X_{j(t)} - X_{i(t)}\right)}{\left(R_{ij(t)} + \varepsilon\right)} \right)$$

9. Tropism in APOA:

Tropism adjusts plant positions based on environmental gradients, guiding them towards more favorable regions within the search space.

$$X_{i(t+1)} = X_{i(t)} + \gamma \nabla E\left(X_{i(t)}\right)$$

4. Result And Discussion

In performance assessment of the proposed method two distinct datasets have been used. One is mammogram image analysis society (MIAS) and the other is digital database for screening mammography (DDSM). Chan-Vese method is prominently used in the image segmentation operation. It has been found that in Chan-Vese method has the problem of local minima. Results are verified on the Chan-Vese method for the sample image of MIAS database mdb028. It is found that if the early contour is taken closer to the border of object. It gives some good results. Multi-objective optimization framework is introduced with the Chan-Vese method so as to utilized multilevel thresholding and optimize the results. It is found that this method gives results better then Chan-Vese method in terms of recall, specificity and accuracy.

Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 27 No. 3 (2024)

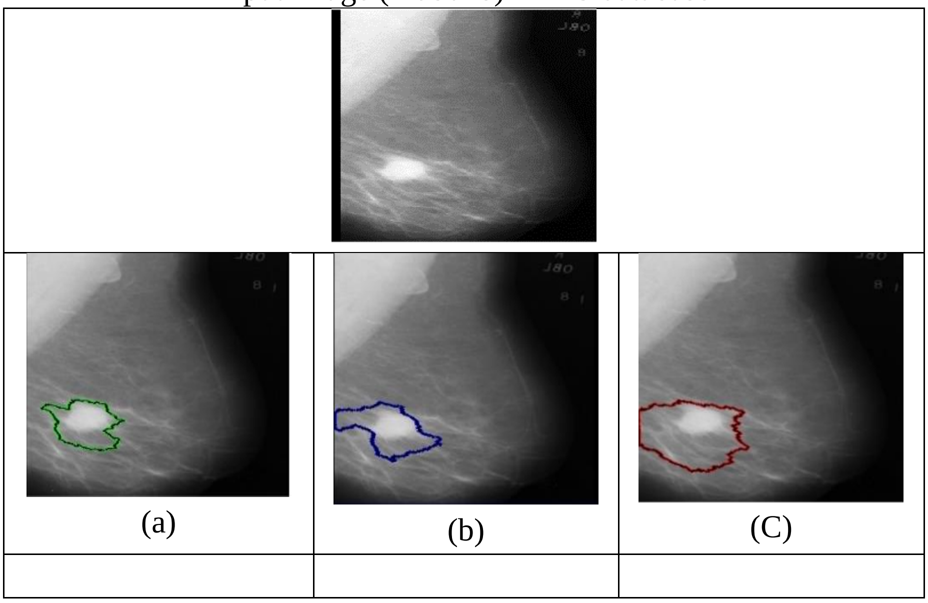
With the exception of requiring a precise beginning set of contours, the drawbacks of the Chan-Vese based GSA model are identical as those of the conventional Chan-Vese model.

Table 1. Comparative analysis of different methods with MOEA based GSA and APOA

Method	Recall	Precision	Specificity	F Score	Accuracy
Chan-Vese method	92.45	94.39	97.88	93.30	97.06
MOEA based Chan-Vese	93.78	91.61	98.67	92.57	97.79
GSA based on MOEA	83.33	93.65	95.24	87.39	95.10
MOEA based GSA with APOA	97.22	99.19	98.81	98.12	98.02
Genetic Algorithm	85.98	87.79	91.03	86.77	90.26
Particle Swarm Optimization	88.76	90.62	93.97	89.57	93.18

Table 1 shows a comparison of different mammogram picture segmentation methods based on their memory, precision, sensitivity, F score, and accuracy. A lot of people use the Chan-Vese method to separate parts of a picture, and it works very well. It has a memory of 92.45%, a precision of 94.39%, a specificity of 97.88%, a F score of 93.30%, and an accuracy of 97.06%. This method is very good at keeping its precision high, which shows that it works well for finding negative examples. But more modern methods that use optimization techniques are better at what they do, even though its speed is strong. Adding the Multi-Objective Evolutionary Algorithm (MOEA) to the Chan-Vese method makes it work better. With this method, the recall rate is 93.78%, the precision rate is 91.61%, the specificity rate is 98.67%, the F score is 92.57%, and the accuracy rate is 97.79%. Because it is more detailed and accurate, the MOEA-based Chan-Vese method may be better at balancing the pros and cons of different segmentation factors, leading to more reliable segmentation results.

Input image (mdb028) MIAS database



(a) (b) (C)

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ISSN: 1092-910X
Vol 27 No. 3 (2024)

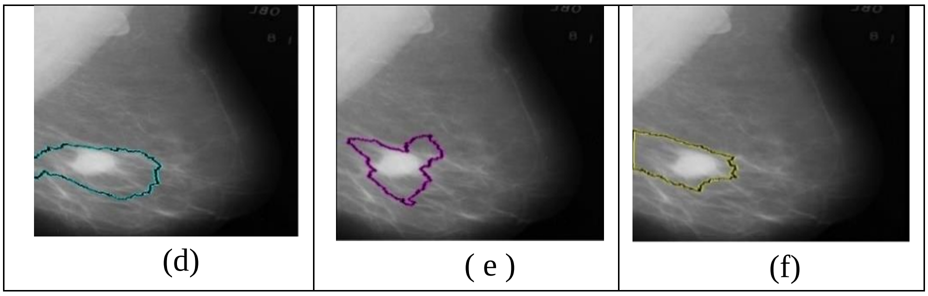

Figure 1: Input image(mdb028) , Segmentation results for a) Chan-Vese Method b) MOEA based Chan-Vese c) GSA based on MOEA d) MOEA based GSA with APOA e) Genetic Algorithm f) Particle Swarm Optimization.

The GSA-based on MOEA method has a lower memory rate (83.33%) than both the Chan-Vese and MOEA-based Chan-Vese methods. It does, however, keep its high accuracy of 93.65% and specificity of 95.24%. The F score is 87.39% and the accuracy is 95.10%, which are both pretty low, shown in figure 2.

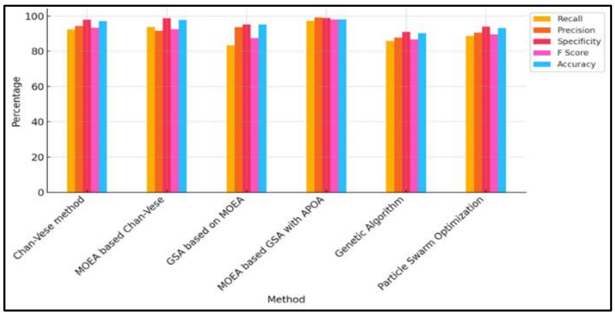

Figure 2: Comparison of different methods across all the metrics

This method seems to be very accurate, but it has trouble remembering things, which means it might miss some true positives while lowering fake positives very well. It is clear that the MOEA-based GSA with APOA method works better in every way.

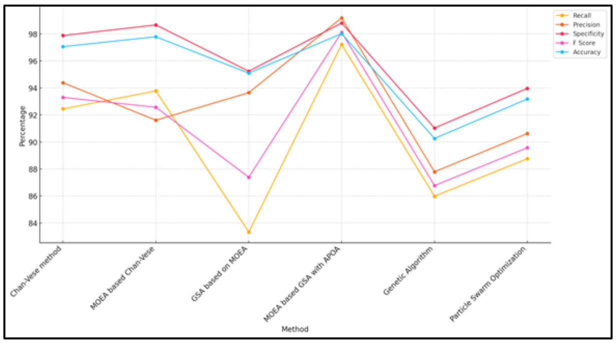

Figure 3: Illustrate the performance trend of each method across the metrics

This method clearly works better than the others, as shown by its memory of 97.22%, precision of 99.19%, specificity of 98.81%, F score of 98.12%, and accuracy of 98.02%. The high accuracy and recall show, in figure 3, that the segmentation is fair and working well, catching true positives while reducing fake positives and negatives. Adding the Artificial Plant Optimization Algorithm (APOA) seems to make the optimization process a lot better, which results in the best total performance, shown in figure 3. With a F score of 86.77%, an accuracy of 90.26%, a recall of 85.98%, a precision of 87.79%, and a specificity of 91.03%, the Genetic Algorithm method does pretty well. Although it gives good results, it is not as good as more advanced optimization methods such as MOEA-based GSA with APOA. Because it is less exact, it may have a higher rate of fake positives. The Particle Swarm Optimization (PSO) method has a F score of 89.57%, an accuracy of 93.18%, a recall of 88.76%, a precision of 90.62%, a specificity of 93.97%, and a F score of 93.97%. Even though PSO works, it's not as good as MOEA-based methods, especially when used with APOA, shown in figure 4.

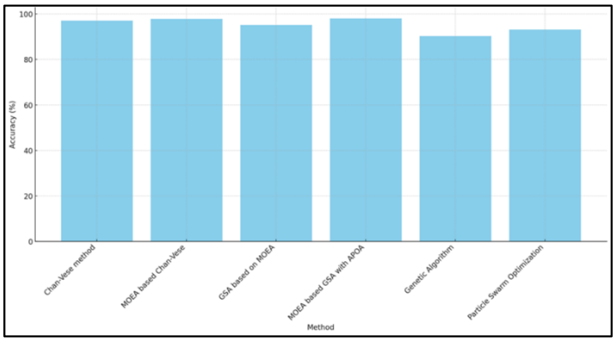

Figure 4: Accuracy Comparison Across Methods

When advanced optimization methods are added, segmentation performance gets a lot better, as shown by the comparison study. The MOEA-based GSA with APOA is clearly the best method because it gives you the most accurate results and the most fair measures. This shows that using the best parts of several optimization methods together can help you do better on difficult picture segmentation jobs. Input sample image mdb028 is taken from the MIAS database, it is fatty having abnormality of circumscribed mass and having class malignant. This image is taken as a sample for the performance evaluation and in Figure 1 the results are shown.

5. Conclusion

In the proposed hybrid method based on GSA and APOA is one of the best methods which avoid initial contour localization and give better optimized results. Evaluation of the proposed method is associated with other techniques, and it is found that this method gives better accuracy of 98.02. For result analysis two different datasets are used MIAS and DDSM. GSA based APOA algorithm will be helpful in segmentation as it is not necessary to initialize the contour in this. Thus, it is clear that proposed method is far better than other segmentation approaches.

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