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Thresholding Segmentation of Skin Lesions with Modified Ant Colony Optimization Algorithm

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Abstract

Image segmentation is the process of breaking up a digital image into many segments, each containing pixels with similar properties. Generally speaking, image segmentation aims to provide an easier-to-analyse and more understandable representation of a picture. Numerous techniques have been presented since this specific topic of picture segmentation was first introduced as a classical issue. The primary content of an image is broken down during the image segmentation process in order to make its representation simpler. Segmenting images involves the separation of pixels into different classes to enable analysis of objects within the image. Multithresholding is a commonly used method for segmentation, but the challenge lies in finding the optimal threshold that accurately segments each image. Metaheuristic methods are high-level procedures that aim to solve optimization problems by searching for acceptable solutions. Recently, researchers have become increasingly interested in using metaheuristics to address image segmentation as an optimization problem. By combining traditional approaches to image segmentation with metaheuristics, researchers have been able to enhance accuracy in various applications.

Keywords: Image, Segmentation, Metaheuristic, Pixels, Multithresholding.

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1 Introduction

The human body comprises several organs, including the skin, which covers the entire body. Skin diseases refer to any abnormalities affecting the skin and are among the most common diseases in humans. Skin and subcutaneous disorders are the leading cause of non-fatal diseases. Specific conditions caused by infections, such as cellulitis, pyoderma, scabies, various fungi, and viruses, are important aspects of these conditions. Skin and soft tissue infections caused by bacteria, viruses, fungi, parasites, and various types of rashes that appear with fever are the most common types of skin lesions in infectious diseases (Yeroushalmi et al., 2020; Kavitha., 2020; Padmanabhan et al., 2011). Skin and delicate tissue contaminations are among the foremost commonly experienced contaminations, counting cellulitis, erysipelas, impetigo, ecthyma, folliculitis, furuncle, carbuncle, canker, disease related with injury, desquamative ulcers, necrotizing fasciitis, Fournier's gangrene, and diseases caused by human or creature nibbles. The introduction, etiology, and seriousness shift (Silverberg, 2021; Indriyani et al., 2023; Solikin et al., 2023). A classic exanthem like measles, dengue fever, rubella, erythema infectiosum, roseola, and chickenpox can be diagnosed with characteristic rashes and other symptoms (Sravana et al., 2022; Asl et al., 2022). In addition, there are unusual exanthems that can accompany fevers or other symptoms and can be caused by infections or toxins via hypersensitivity reactions (Muzumdar et al., 2019; Sut et al., 2020). While some of them provide diagnostic difficulties, the most significant ones are those that arise in medical crises and those that present pressing diagnostic and treatment issues (Patel et al., 2021; Hemasree et al., 2022; Ndife et al., 2022; Prasad Babu et al., 2023). Skin lesions are abnormal alterations in the skin's underlying or outer tissue. Skin lesions typically exhibit uneven growth beyond their typical limitations in relation to the surrounding tissue. The primary cause of this is overexposure to UV radiation. Skin lesions fall into one of two categories: malignant tumors, which are the rarest but most deadly type of skin cancer, or benign skin tumors like nevi. Recent years have seen the early identification of skin cancer using dermoscopy images with the use of computer-aided diagnostics (Camgözlü et al., 2023; Mumtaj, 2022). This is predicated on the feature extraction of data like statistics. The assessment procedure gets more intricate, necessitating longer detection times. To help with early detection, it is therefore vital to take into account the precise and effective detection of these structures (Ramona et al., 2023). In computer vision and image processing, edge detection and image segmentation are well-known tasks. The technique of locating discontinuities in a image is called edge detection (Liu et al., 2019). Edge detection also results in a smaller image size by eliminating superfluous and unnecessary information while maintaining the essential elements of the image. The process of segmenting a image into sections that correspond to distinct objects can also be done via edge detection. In the fields of computer vision and image processing, edge detection and image segmentation are widely recognized tasks. The technique of detecting discontinuities in a image is called edge detection (Liu et al., 2021). The next step in edge detection is to reduce the size of a image by removing superfluous and irrelevant information while keeping the essential information in the image. Additionally, edge detection may be applied to image segmentation, which is the process of splitting an image into sections that correspond to various objects. Enhanced survival is linked to early detection. Every cancer will spread, spread erratically, and behave strangely. Variations in the quantity of pigment produced by melanoma might trigger an immunological response, which will manifest in the tumor's clinical appearance (Albittar et al., 2020). Medical professionals use segmentation extensively in the field of medical image processing to help with the analysis of tissues, organs, and diseases. The increase of multidimensional medical data is the primary cause, since it has made manual segmentation difficult and time-consuming.

Furthermore, since mistakes might occur in the findings, the accuracy is dependent on the doctor's experience. Large medical datasets contain intricate nonlinear relationships that can occasionally be too much for even an experienced professional to handle. Consequently, accurately obtaining findings depends heavily on computer-based segmentation. RGB image segmentation on mammography images, for instance, has been used to identify breast cancer (Azary & Abdoos, 2020; Justaniah et al., 2021). Three distinct elements, red, green, and blue, are combined to form color images, which are represented by the RGB color model's color tone, saturation, and intensity ratio. The Red, Green, and Blue (RGB) color model and space is utilized in color image segmentation with consideration for processing simplicity and speed. For color ratio-based segmentation to work as well as it can in computer vision, the image intensity must be higher than a certain threshold (Pare et al., 2020). The effectiveness of applications utilized heavily influences how well real-world computer vision applications function. Two crucial low-level activities that must be completed are edge detection and medical image segmentation. As a result, several scholars have been working to create different methods for these assignments, and the history of this field is extensive. Certain conventional methods for edge detection and medical image segmentation rely on zero-crossing. Rotem & Zeevi, (1986); Sharifrazi et al., (2021). These methods' primary shortcomings are their incapacity to deal with noise and inaccurate edge identification. There are issues with the LoG operator in grayscale functions, corners, and curves. Numerous methods for segmenting medical images have been used in the literature. Rule-based strategies are among the more well-liked ones. Medical imaging requires that the items observed be connected, and while these methods are computationally straightforward, they do not ensure this. Probabilities are used to create a two-level Markov-Gibbs Random Field (MGRF) image map/model(Chakraborty & Kar, 2017). Large amounts of image noise and/or obscured objects, however, may reduce this model's image segmentation accuracy. Numerous alternative methods derived from thresholding, fuzzy clustering, and other computational methods have been created (Dey et al., 2021; Saadawi et al., 2024).

2 Literature Review

Segmentation is the process of dividing a image into several segments based on homogeneous pixel characteristics. Texture, intensity, and color combine to create segmented images that provide sufficient information for classification and analysis. One characteristic or attribute that may be used to measure the level of uniformity in images of skin lesions is the pixel intensity values. The goal of segmenting skin lesion images is to do this by isolating lesions from healthy skin and classifying images that depict skin illnesses utilizing the characteristics of the skin image that will be used in the classification process. Depending on the method used to estimate the threshold, there are two types of thresholding skin lesion segmentation: point-based and pixel-based. However, because to dermoscopy aberrations, calculating an appropriate threshold is frequently difficult (Hasan et al., 2020). Sivaraj (2020) divided the image into numerous grayscale pixels as part of their research, using a threshold-based segmentation technique. Skin cancer was not thought to have impacted any pixels with intensity levels less than T. Using the Chan-Vese technique, which ignores image borders and minimizes the energy function, along with K-means clustering and active contour, (Gangwar, 2021) approach goes beyond Sivaraj (2020)'s consideration of values smaller than T. This is an iterative process, and K-means uses k clusters to split the target areas. HED Segmentation was used in the segmentation procedure by Hegde (2018). The following outcomes were attained: Color-based feature classification shows that (a) LDA performs better in binary and multi-class scenarios; (b) SVM offers better texture feature accuracy in binary and multi-class classifiers; and (c) for combined features, LDA and SVM classifiers, respectively, perform better in binary and multi-class classification. The Otsu approach was utilized by (Hameed, 2020) for segmentation. With a total of 1800 images and an accuracy of 83% using Support Vector Machine, the input images utilized were typical skin lesions such acne, eczema, psoriasis, and melanoma. The Otsu multi-threshold method was employed by (ALKolifi ALEnezi, 2019) to segment skin images. For image segmentation, (Sinthura, 2020) apply the Otsu thresholding approach, which divides the image into foreground and background using threshold values that are derived by varying the inter-class variance. Senan, (2021), on the other hand, segment using an active contour technique based on surface evolution. This entails splitting the parameters and geometric groups, where the geometric active contours are based on the curve's evolution and the parameters are specified as parametric active contours. Choose a single threshold value and apply it to the whole image during the global thresholding stage. The average value of the pixels is used as the starting threshold value in the iterative procedure. Next, each group's new average is calculated, and the pixels are rearranged in line with that new average. This procedure keeps on until the difference between the old and new threshold values may be disregarded. Heuristic approaches have been extensively studied as segmentation procedures have advanced. In order to identify edges in skin lesion images, which were then utilized for segmentation, (Sengupta, 2022) used the Ant Colony Optimization (ACO) approach in conjunction with Canny edge detection. A segmentation strategy known as SLICACO, which combines Ant Colony Optimization (ACO) and Simple Linear Iterative Clustering (SLIC) is presented by (Singh et al., 2021) research. In order to differentiate benign lesions from malignant melanoma in dermoscopy images, the hybrid SLICACO method—which combines SLIC and ACO—integrates many pipeline approaches for skin lesion segmentation. By adhering to object boundaries with consistent sizes, the SLIC approach modifies the k-means clustering on superpixel intensities. Superior cluster centers are identified with the aid of ACO, which also adaptively chooses the best clusters in the image. SLICACO is thoroughly tested on five sets of skin lesion data, and utilizing the EfficientNet deep learning model, its performance is compared with three other individual methods. The study carried out by (Yang & colleagues, 2022) has demonstrated. The pixel intensity distribution in an image is measured during the segmentation process using the Kapur approach. Considering the extraction of feature signals from the skin image, the maximum entropy value is used to estimate the uniformity of intensity in the image. Good segmentation quality may be achieved with a higher entropy value. Using the ant colony algorithm, the gentle besiege tactic comes after the Kapur method calculation phase. The goal of the gentle besiege approach is to maintain the balance between local and global exploitation. To minimize local risk and influence convergence speed, the soft besiege algorithm procedure begins by taking advantage of the global search space. Up till the greatest outcome in the local search space is discovered, this process is repeated. The image's non-local mean and grayscale value are used in research strategy (Zhao et al., 2021). More information may be expressed about an image using a 2D histogram than a 1D histogram, and it is also less prone to image noise. The following is the suggested multi-level image segmentation (MLIS) model segmentation procedure: (1) The melanoma image is converted to grayscale; (2) the grayscale image is used to create a non-local mean image after image noise is removed; (3) the grayscale and non-local mean images are combined to create a 2D histogram; (4) the chosen threshold population serves as the 2D Kapur entropy, which is the objective function of the Swarm Intelligence Algorithm (SIA). To find the maximum 2D Kapur entropy, SIA takes the pixel data from the 2D histogram.

3 Methodology

Ant Colony Optimization (ACO) Model in Segmentation Process

Using an ant colony search methodology, the ACO approach moves on to a food source. The value of each pixel in the image is determined using this foraging method used in medical segmentation. The ant assigns a weight or pheromone to each transition from pixel i to pixel j, and the total of all the pheromones is used to assess the segmentation outcome of the image.

Definition of Food in ACO

During the image segmentation phase, the food in the ACO algorithm is referred to as a reference item. Said another way, we can initialize the food in the i-th ant's memory at time t = 0 as follows, but we also manually choose the radius r of the $N_r(0)$ neighborhood of pixel 0 in the image in equation 1-2.

$$F_{i,t=0} = N_r(0) \tag{1}$$
$$N_r(0) = \{e \in \mathrm{I} \mid \|e - 0\| < r\} \tag{2}$$

Food Sourcing Procedure

In the ACO system, each ant's job is to locate pixels with comparable characteristics in order to determine what food to eat. Ants are equipped with the capacity to compare pixels with what they discover. The area of radius r of the pixel is Nc if ant c is at radius c in equation 3-4.

$$\mu_k(o,c) = \sqrt{\mu_\varphi}(o,c)\mu_\psi(o,c) \tag{3}$$
$$\mu_k(o,c) = \frac{\min\,(m_o, m_c)}{\max\,(m_o, m_c)} \tag{4}$$

The average gray intensity of Nr(o) and Nr(c) is represented by $\mu_\psi(o,c)$, where the component basis is homogenous. Ants looking for food sources will find pixel c appealing if it above the threshold. The food in the ant's memory at time t = τ is updated using equation 5 when ant i evaluates c as a new food source.

$$F_{i,t=\tau} = aN_r(c) + bF_{i,t=\tau-1} \tag{5}$$

Phase Transition Pixel Value

One ant is chosen at random from the total N of ants that walk sequentially on the image during the S stage of building at the nth step. Figure 1: Using equation 6, an ant travels from a node (*l*,*m*) to one of its surrounding nodes (*i*,*j*) based on a certain transition probability.

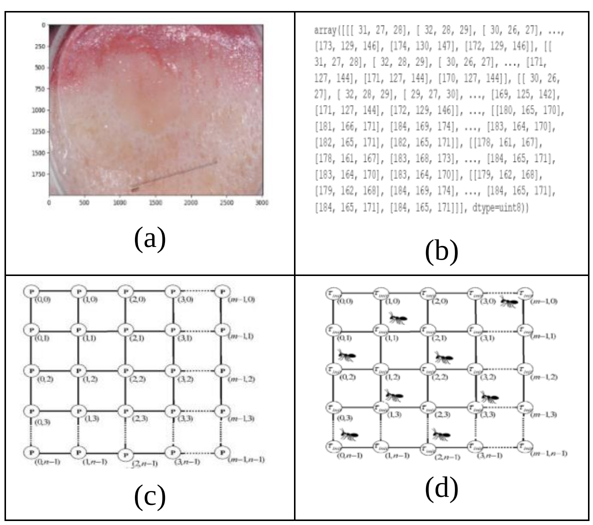


Figure 1: Phase Transition Pixel (a) Original Image, (b). The Result of Converting Image to Array. (c). Transition Nodes. (d). Ant Transition Process

$$P_{(l,m),(i,j)}^{(n)} = \frac{\tau(_{i,j}^{(n-1)})^{\alpha} \ (\eta_{i,j}{}^{\beta})}{\sum_{(i,j)\in\Omega_{l,m}} \tau(_{i,j}^{(n-1)})^{\alpha} \ (\eta_{i,j}{}^{\beta})} \tag{6}$$

A node's pheromone count is shown by $\tau(_{i,j}^{(n-1)})$ its surrounding nodes are indicated by $\Omega(l,m)$ heuristic information about the node (i,j) is indicated by $\eta i, j$. Constants α and β present the pheromone matrix's influence and the heuristic information matrix's effect, respectively. Equation 7 presents the heuristic information, represented by $\eta_{i,j}$which was identified by the application of local statistics at the pixel position (i,j).

$$\eta_{i,j} = \frac{Q_c(I_{(i,j)}}{I_{max}} \tag{7}$$

Here, function $Q_c\big(\ I_{(i,j)}\big)$is a function of the local group of pixels and is dependent on variations in the image intensity values. $\mathrm{I(i,j)}$ indicates the intensity value of the pixel at position $\mathrm{(i,j)}$ of the image, while I_{max} indicates the greatest intensity variation in the entire image.

Pheromone Intensity Rule

An ant (k) stores a set quantity of pheromone t in the element (μf) that it will leave behind before departing for its destination, according to the biological science that controls ant colonies. We refer to them as trace pheromones. to gauge how well the model performs while segmenting, the following guidelines are set in place. The ratio of the number of elements (μf) in the lesion image and the number of elements in the original object, as well as the ratio of the number of segmented elements (μf) that are part of the image and the number of elements (μf) in the image of the lesion, are evaluated by pheromone map analysis after the pheromone map has been examined.

Lesion Area Selection Process

By selecting a certain area from an image or set of data that is thought to be most pertinent to the analysis's findings, the region of the image to be segmented is chosen using the Region of Interest (ROI) tool. Using Ant Colony Optimization, the constant values T1 and T2 are found. Using a rule function shown in Equation 8, the values of T1 and T2 are determined.

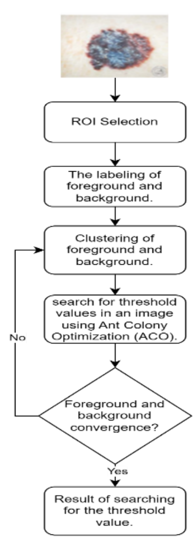


Figure 2: Multithresholding Segmentation Using Ant Colonies

$$g(x) = \begin{cases} 0, & if\ f(x,y) < T_1 \\ 1\ , & if T_1 < f(x,y) < T_2 \\ 0, & if\ f(x,y) \geq T_2 \end{cases} \tag{8}$$

The binary image is denoted by $g(x,y)$, the grayscale image by $f(x,y)$, the lower threshold value is denoted by T1, and the upper threshold value is indicated by T2. It is shown in figure 3 when the ACO metaheuristic is being used to find the threshold values.

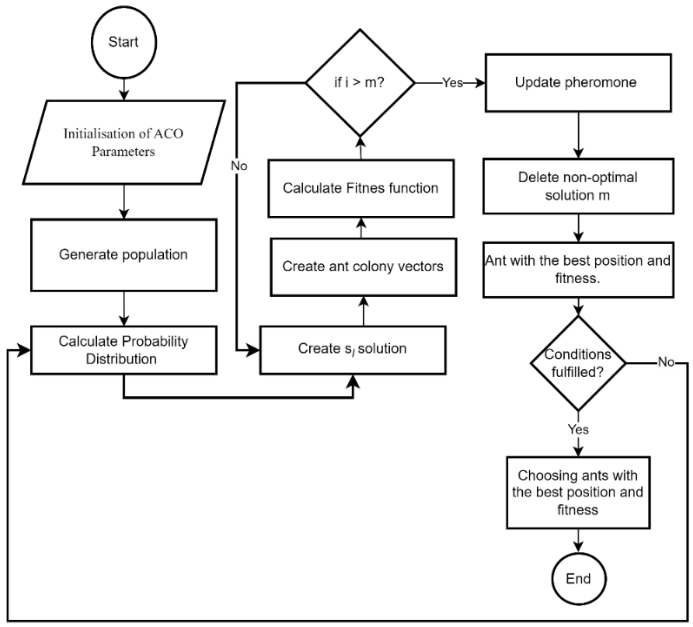


Figure 3: ACOS (Ant Colony Segmentation) Method

Assuming that the ants are evolving in a two-dimensional image, their objective is to create a pheromone matrix in which each entry corresponds to an edge at a pixel point in the image. Ants prefer to migrate toward locations with more fluctuations in intensity values, since their movement is determined by local differences in the image's intensity values. The pheromone matrix is constructed using the suggested method after N repetitions of initialization. The building process and the update process are two iterative procedures that create the matrix. The update phase refreshes the pheromone matrix, which is built with assistance from the construction process. Following the update process, global changes are applied via a mutation mechanism, and a decision-making procedure is carried out by using binary thresholding on the created pheromone matrix. The ACO algorithm determines the highest inter-class variance of the thresholded image in order to solve the threshold selection problem. When building the answer, this algorithm takes ants into account. The test sample's cluster label is represented by each element of the string in the initial empty solution S, which has a length of N.

4 Results

The proposed segmentation algorithm based on ant colony is evaluated on both simulated and real lesion images. The values used to conduct the experiments are chosen to ensure that ants do not overlap with each other. Approximately 10 ants are used, corresponding to the number of pixels in the image. Once the ACO model parameters are determined, the simulated properties to be studied are the pixel intensity levels and the background of the skin lesion image. The lifecycle of the lesion image segmentation process is performed by assigning weights or pheromones to the dermoscopy image map of the skin lesion, as well as the map of the location of the transitions made by each ant. The overall results of pheromone are used to define the segmentation outcome. A total of 500 iterations (Nr) were set, and a pheromone intensity map was taken every 50 iterations. Snapshot maps were taken to compare the performance of each ant and the trends in lesion image search results.

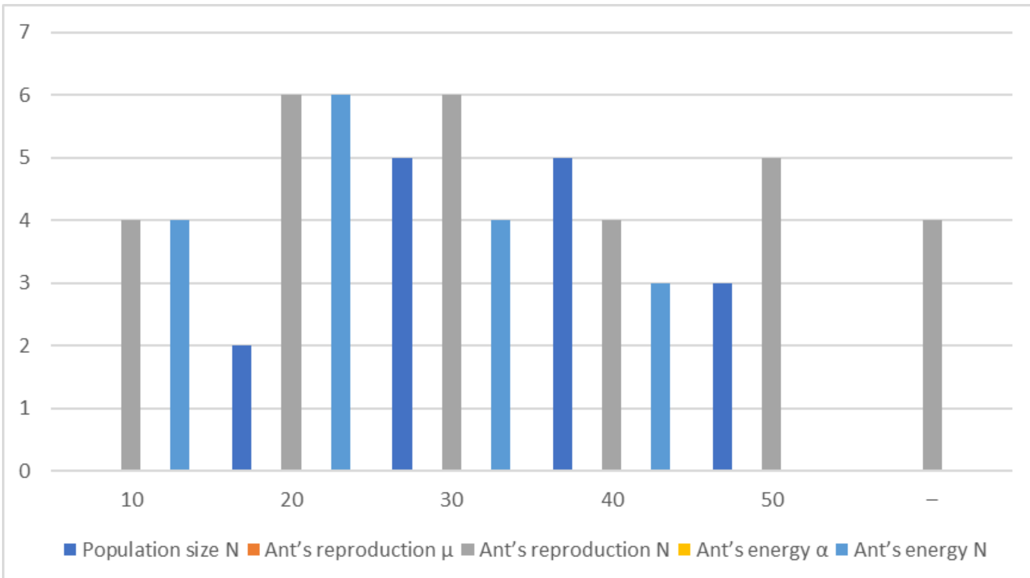


Figure 4: The Estimated Values of the ACO Model Parameters

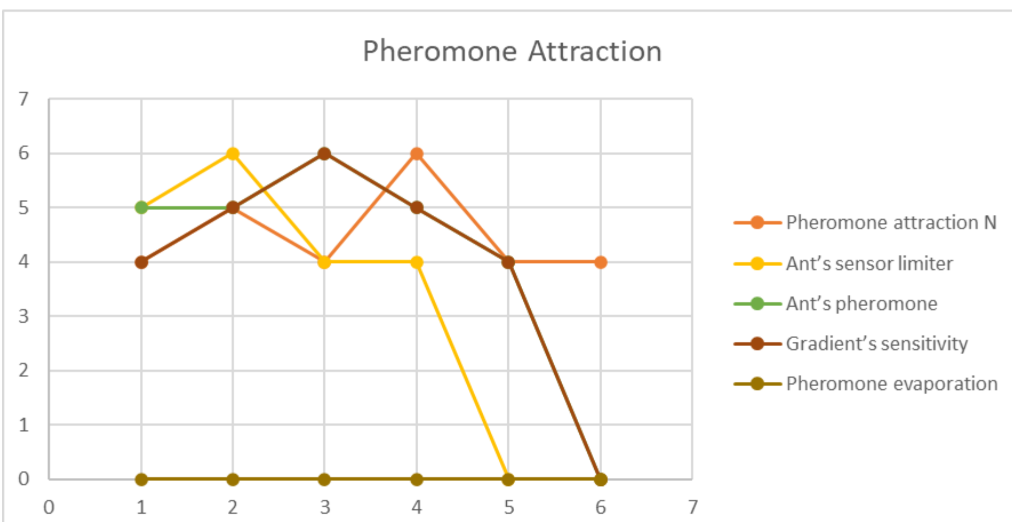


Figure 5: Pheromone Attraction with N Ants

The primary problem in the segmentation of two-dimensional skin lesion images is the overlap of lesions. Overlapping image are therefore used to evaluate the ACO model as well. The procedure of estimating ACO parameters involves optimization. The final findings take longer to compute the greater the ant population. Population size leads to over-segmentation and the concentration of several ant colonies in one area when it is selected to be greater than 40% of the image size. A single ant colony needs a considerable amount of time to reach every area. The computation is quicker when population size is less than 40%, but the image coverage is not dense enough, and the ants could miss certain pheromones. Increasing the reproduction parameter for a considerable amount of time, μ causes ant reproduction in the image, maintaining a very large population size. Often, a single colony has many dominant locations. Because ant colonies inevitably grow older and perish without reproduction, decreasing μ causes ants to die sooner. Furthermore, colonies frequently cover more than one pheromone, and many ant colonies might be found in the same protein location. An ant's ability to traverse great distances before dying and to multiply overall is attributed to its high energy coefficient value α. Ants from the same colony often live in more than one place. Ants die fast and image segmentation is not achieved at low values of α. Ants with increased pheromone sensitivity move about the pheromone protein more widely, increasing the likelihood that they may miss the prime places. Only the gradient governs their movement when the ant values are lower.

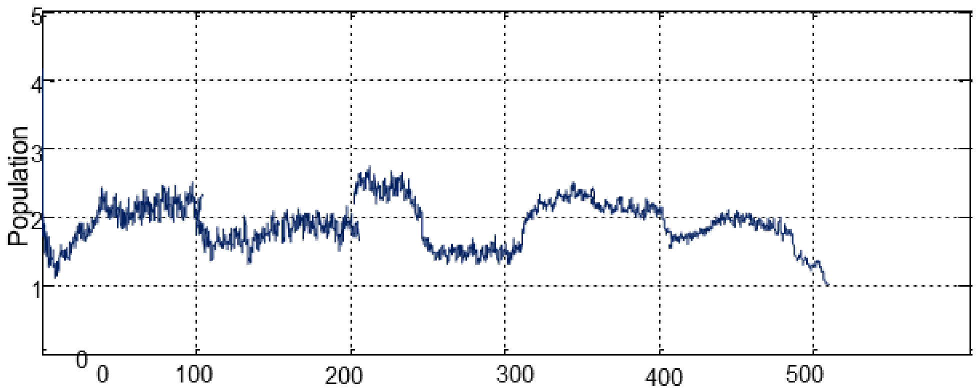


Figure 6: Number of Population

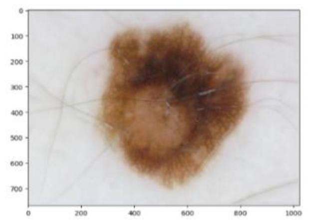
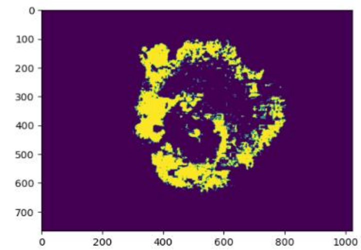
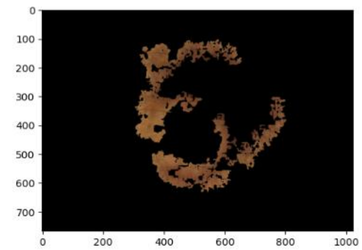
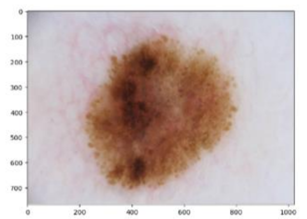
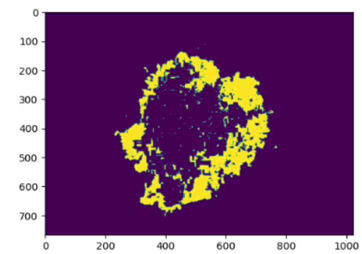
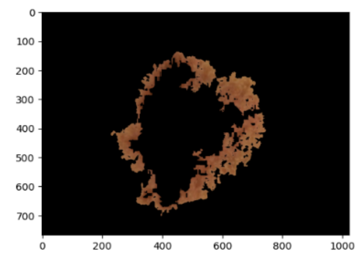
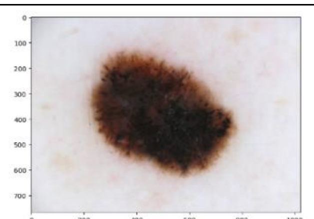
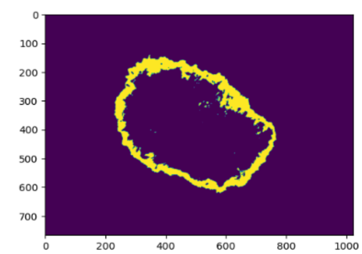
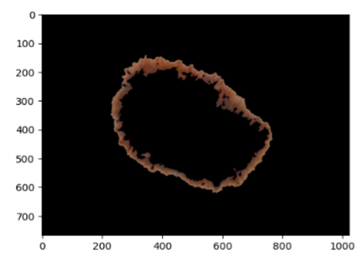
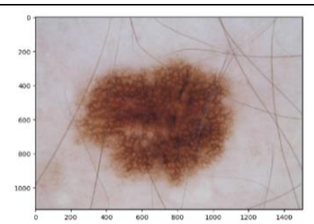
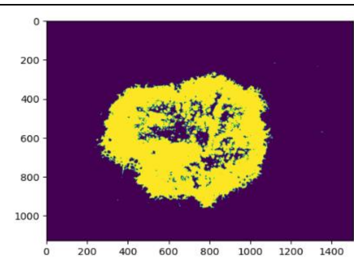
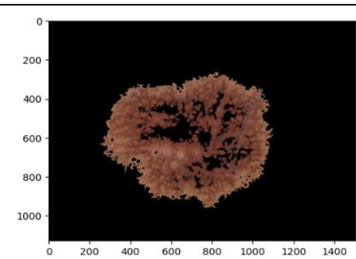
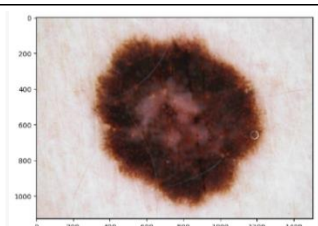
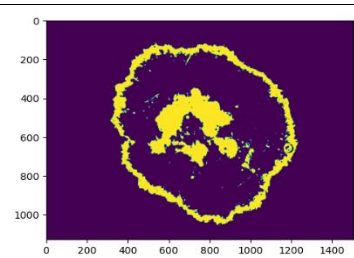
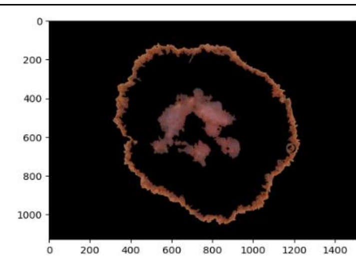
This research paper introduces a modified Ant Colony Optimization (ACO) algorithm for segmenting skin lesions. The accuracy of the thresholding process is crucial for achieving accurate segmentation. Drawing inspiration from the foraging behavior of ants, the ACO algorithm is a metaheuristic optimization technique that searches for the best threshold values to accurately segment skin lesion images. The proposed algorithm is evaluated using both simulated and real skin lesion images, demonstrating its effectiveness in segmenting lesions. A comparison with other segmentation methods shows competitive results. The paper also discusses the selection of evaluation metrics for assessing segmentation performance and provides guidelines for choosing suitable metrics based on specific segmentation requirements. Overall, this research showcases the potential of modified ACO algorithms for skin lesion segmentation and provides valuable insights into evaluating segmentation performance.

Table 1: Number of Iteration

Experiment no.	**Num of iterations**	**Segmented spots, %**
1	100	70
2	250	74.5
3	350	73
4	400	65
5	500	71

An ant colony can segment the findings of the experiment acquired by the image of lesion number 3, but because the points in the lesion image overlap, the ant colony is not able to segment the picture maximum in image number 4.

Table 2: The Results of the ACO Segmentation

Num	Image	Result	
1	 ISIC_0000003.jpg		
2	 ISIC_0000008.jpg		
3	 ISIC_00000013.jpg		
4	 ISIC_0000019		
5	 ISIC_0000029.jpg		

Evaluation Matrix

After obtaining the segmentation results, we compared the segmented images with the ground truth to evaluate the performance of our proposed method. Many methods have been used by other researchers for evaluation, such as Otsu, Coye, and Grabcut. We used several metrics for evaluation, including Accuracy (ACC), Precision (PREC), Sensitivity (SEN), Dice Coefficient (DC), and Jaccard Index (JI).

Table 3: Result the Evaluation Matrix

Num	Image ID	(ACC)	(PREC)	(SEN)	(DC)	(JI)
1	ISIC_0000003.jpg	0.68	0.76	0.62	0.68	0.72
2	ISIC_0000008.jpg	0.77	0.59	0.35	0.64	0.74
3	ISIC_00000013.jpg	0.89	0.61	0.56	0.72	0.76
4	ISIC_0000019.jpg	0.88	0.67	0.64	0.87	0.84
5	ISIC_0000029.jpg	0.80	0.76	0.78	0.87	0.78

The segmentation outcomes are compared to the real number of colors in the supervised color image in order to assess the effectiveness of the suggested approach. 89% of the test image color predictions were correctly predicted. The approach can fairly successfully anticipate the number of colors in color images with this degree of accuracy.

5 Conclusion

This study proposes a modified Ant Colony Optimization (ACO) technique for threshold-based skin lesion image segmentation. Medical image analysis depends on the precise segmentation of skin lesions. The best threshold values for successfully segmenting skin lesion images are found using the ACO algorithm, which draws inspiration from ants' foraging habits. The suggested algorithm's effectiveness is assessed using both synthetic and actual skin lesion images, and the outcomes demonstrate that the lesions may be properly segmented. The algorithm produces competitive results when compared to other segmentation techniques. The study also covers the assessment metrics selection process for segmentation performance measurement and offers recommendations for selecting relevant metrics according to particular segmentation needs. Taken together, these findings show that skin lesion segmentation can benefit from the application of improved ACO algorithms and provide important new information on performance assessment. Based on testing the modified ACO algorithm on both synthetic and actual skin lesion images, this study comes to the conclusion that skin lesion segmentation may be accomplished well using it. The program produced competitive results when compared to other segmentation techniques. The assessment metrics selection for segmentation performance is also covered in the article, along with recommendations for selecting suitable metrics in accordance with particular needs. All things considered, the study shows promise for skin lesion segmentation utilizing modified ACO algorithms and provides guidance on assessing segmentation efficacy. Because metrics range in terms of bias and sensitivity, selecting the right one is a difficult undertaking. In order to assess segmentation with certain criteria and qualities, this study analyzes seven measures, focusing on their attributes and applicability. The analysis ends with recommendations for choosing a subset of applicable metrics while taking the needs and characteristics of the segmentation into account.

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