

# Automated Framework for Segmenting Skin Lesions using Artificial Bee Colony Optimization with Morphological Reconstruction



R.Sumathi,M.Venkatesulu

**Abstract:** Nowadays, Many people are affected by skin cancers. Our proposed work designed a framework to extract the skin cancer using artificial bee colony with morphological reconstruction filters, which helps the demonologist to prevent the severity in early stage, Melanoma is the now become a harmful form of skin cancer which leads the skin cells to grow rapidly and form cancerous tumors. We collected various melanoma images from having used samples from public dataset like ISIC archive and a few from clinical datasets. To remove the noise, median filtering is used for preprocessing in the first step, to segment the tumor boundary Artificial bee colony is used and to remove the unwanted pixels using morphological reconstruction filters. Segmentation metrics like precision, recall, accuracy, Mean Square Error, Peak signal to noise ratio and computational time were calculated. Our proposed method yield 97.7% segmentation accuracy when compared with the level set method and Fuzzy C Means clustering techniques

**Keywords ::** Image Segmentation, Median Filter, Artificial Bee Colony Optimization, Morphological reconstruction filters,

## I INTRODUCTION

Image processing techniques are highly helpful in biomedical image processing, analyzing, classifying the tumor and non tumor and clustering techniques for detecting and extracting the tumor part. Segmentation is used to segment the region of tumor part or detect the edge of tumor part by applying a various segmentation techniques. Melanoma looks and like a mole and it also develops from mole, which may cause skin cancer later times if it not analyzed in early stage, to reduce the death rate of skin cancer many researchers used soft computing techniques and clustering algorithms to segment the tumor part efficiently. Hence automated melanoma identification is necessary. we proposed Artificial Bee

Colony(ABC) techniques used for identify the melanoma. This updating increased the slow convergence and thus helped to find the best solution for the algorithm. To extract the tumor features, it is important to estimate the accurate lesion border which is used for segmentation and classification. Its aim is to segment the tumor part accuracy with less time with efficient results.

To segment the exact shape of skin lesions using semi automatic approach[1] and classify the skin lesions of dermoscopy image dataset.[2] Applying morphological filters and neural network to classify the skin lesions with benign or malignant and ensure its accuracy. [3] Classify the tumor and non tumor by applying the threshold based segmentation and proved that joint statistical texture distinctiveness method leads greater segmentation accuracy. Color lesion segmentation based on Decision Based Neuro Fuzzy Model and segments the skin lesions based on color texture and its limitations are when the color space format changed to other format depends on usability for various kinds of skin cancer images[4]. To detect the skin lesions genetic algorithm is used to segment the tumor part with short duration for different scales and levels of qualities of skin lesion images and reduce the over segmentation[5]. Applying wavelet base networks to segment the dermoscopy images based on four methods like AT, GVF, FBSM, and NN[6]. An automated segmentation model is developed with the combination of SGNN and GA for segmenting the lesions of dermoscopy images with neural network feature set [7]. An automated border detection method is used to extract the pigmented skin lesions using statistical region merging techniques and validate the method with 90 images with ground truth images and proved their accuracy[8]. Combining artificial neural network and gray wolf optimizer[9] produces 90% of classification accuracy and proved that it can able to detect skin malignant melanoma images better than ANN classifier. Skin lesions are segmented and classified using Conventional neural network[10] and it yield 96% of classification and proved its efficiency. An hybrid approach with the Combination of PSO and GWO [11] proved its efficiency with best features obtained from the two methods

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**II METHODS AND MATERIALS**

**2.1 Scope of our work**

Our goal is to segment the tumor part of skin diseases by applying Artificial ant bee colony with morphological reconstruction filters. This automated method is highly used by dermatologist to analyze the tumor growth in advance and reduce the growth of tumor in advance. We proved that our method produce accurate segmentation than level set and FCM method in terms of accuracy and computation time

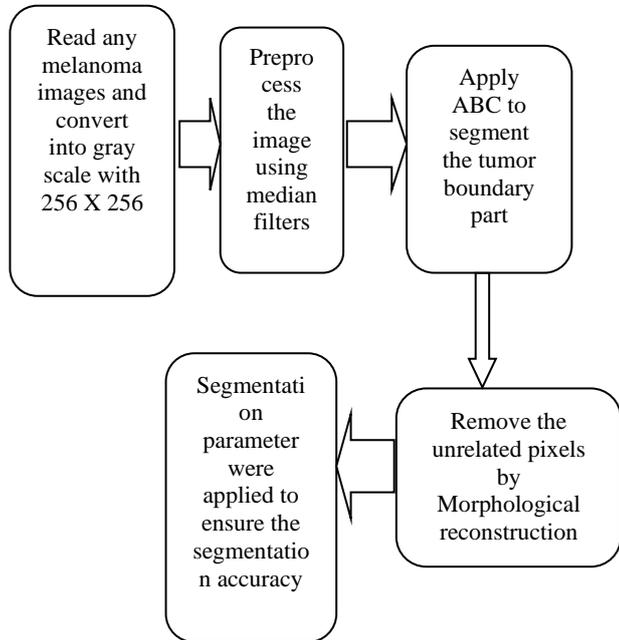
**2.2 Details of Image datasets**

For our study and analyze the melanoma skin cancer images collected from online free datasets like TCIA, dermis dataset and few from clinical datasets for proving the efficiency of our methodology.

**2.3 Image Analysis**

The images were analyzed using the following steps

- Step 1: Read all types of melanoma images and resize the images into 256\*256 grayscale images.
- Step 2: Preprocess the image by applying the median filters to enhance the details of the tumor part for segmentation
- Step 3: To segment the boundary of tumor part by applying the artificial bee colony
- Step 4: To remove the unrelavant pixels near the tumor by appying otsu threshoding method to segment the aaurate tumor part. Figure 1 describes the descriptions of our proposed work.



**Figure 1 : Flow diagram of our proposed work**

**2.4. Median Filtering**

One of the enhancement techniques which removes the impulse noise without reducing the image sharpness [12]

$$A(m, n) = \text{median} \{g(x, y)\} \quad (1)$$

where as  $A(m, n)$  is the median filtered image and  $g(x, y)$  is the input image

**2.5 Artificial Bee Colony**

Artificial bee colony is a famous method which replicates the perspective actions of honey bees. It was divided into two branches like worker bee and onlooker bees, whereas the first half of the group is occupied by worker bee and the remaining part is occupied by the onlooker bees [13]. The preprocessed image is given to ABC for segmenting the boundary of tumor with random initial population based on the number of worker bee food resources generated by the ABC

Let  $Y_i = [Y_{i,1}, Y_{i,2}, \dots, Y_{i,N}]$  denotes the  $i^{\text{th}}$  set of solution in the group, whereas size of the bees represented by  $N$ . Each worker bee-  $Y_i$  creates a new resolution  $Z_i$  in the locality of its nearby position is represented as

$$Z_{i,j} = y_{i,j} + \sigma_{i,j}(y_{i,j} - y_{k,j}) \quad (2)$$

Where  $y_k$  represents the elected resolution,  $J$  represents the length index, the value of  $\sigma_{i,j}$  lies between -1 to +1. Check the value of  $Z_i$ , if it is self-satisfied than old  $Y_i$ , then revision of  $Y_i$  with  $Z_i$ , else the value of  $y_i$  is fixed. When the search task is finished by all  $Y_i$  bees, and shares the value to onlooker bees and then onlooker bee calculates the nectar and selects the best resource among all the possibilities.

Probability selection ( $P_i$ ) is defined as

$$P_i = \frac{F_i}{\sum_{j=1}^{SR} F_i} \quad (3)$$

Where  $F_i$  represents the fitness amount for  $i^{\text{th}}$  persistence within the group. Suppose that the discarded source is  $Y_i$ , the scout bee determines a fresh edible material resource to reinstate with  $Y_i$  by using

$$y_{i,j} = LB_{i,j} + r(UB_{i,j} - LB_{i,j}) \quad (4)$$

Where  $r$  lies between 0 to 1,  $UB$  and  $LB$  defines the minimum and maximum sizes [14]

The following steps explain the algorithm in detail

1. initialize a random set of bees.
2. Using the initial swarm renew the solution.
3. Equation (2) is helped to find the new candidate value of  $Z_i$  and also find the fitness function based on equation (2)
4. Every onlooker bee evaluates  $P_i$  based on Equation (3).
5. Generate a new candidate resolution  $Z_i$  based on Equation (2) and Find the fitness of  $Z_i$  and a hunger selection is utilized to select a best one between  $Y_i$  and  $Z_i$  like the new  $Y_i$ .
6. unwanted bees are updated using the equation (4)
7. Update the superlative resolution institute until it met the stopping condition, and update the value of  $iter = iter + 1$ .
8. check the value of  $iter$ , if it exceeds the specified number of steps then stop and display the output or else goto step 2
- 9: end

**2.6 Morphological Reconstruction Filters**

It is a useful tool for medical image segmentation, image analysis and pattern recognition . To extract the exact shape of the tumor morphological reconstruction filters are preferable. various operations like erosion, dilation, opening and closing are defined as [15]

$$\text{Erosion : } A \ominus B = \{x|B + x \subseteq A\} \quad (5)$$

$$\text{Dialtion : } A \oplus B = \{x|B + x \neq \emptyset\} \quad (6)$$

$$\text{Opening : } A \circ B = \{A \ominus B\} \oplus B \quad (7)$$

$$\text{Closing : } A \cdot B = \{A \oplus B\} \ominus B \quad (8)$$

For segmening the accurate tumor part

$$\beta(A) = A - (A \ominus B) \quad (9)$$

A represents the input image with structural element B.

**III RESULTS AND DISCUSSIONS**

Segmentation metrics like precision, recall, MSE, PSNR, accuracy and computation time are measured to ensure accuracy of our proposed work. It was implemented by using MATLAB 2017a software. The Mean square error is denoted by

$$MSE = \frac{\sum A, B[x_1(a, b) - x_2(a, b)]^2}{A * B} \quad (10)$$

where A and B provides the size of row and column for the input image, whereas PSNR can be calculated by

$$PSNR = 10 \log_{10} \left( \frac{R^2}{MSE} \right) \quad (11)$$

Where R represents the maximum fluctuation value of the given input image . It measures the quality of noise information between the input and segmented image computational time is measured between the given image and extracted output thyroid gland image. Recall measures the area of thyroid gland from the total area of the image

$$Recall = \frac{T_p}{T_p + F_n} \quad (12)$$

Precision calculates the background ratio from the total area of the background

$$Precision = \frac{T_p}{T_p + F_p} \quad (13)$$

Accuracy ensures the segmentation rate between the manual segmentation and expert segmentation

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \quad (14)$$

Our proposed work ensures the segmentation accuracy using various segmentation metrics and also compared with computational time with other existing approach for segmenting the skin cancer tumor in less duration. Table 1 details the MSE and PSNR measures of our proposed

method. Mean square error value is lies between 0-1ensures the less noise ratio and PSNR default value lies between 40 -60 decibels ensures the high quality with less noise signals.

Table 1: performance Measure of our proposed method

Image No	MSE	PSNR
1	0.009	53.46
2	0.007	48.93
3	0.003	55.73
4	0.005	50.08
5	0.004	49.67
6	0.002	51.04
7	0.007	47.05
8	0.006	46.85
<b>Avg</b>	<b>0.005</b>	<b>50.351</b>

Our proposed work yield overall 50.35% of PSNR and 0.005% of MSE whereas FCM produces 32% PSNR and 1.33% MSE and level set produces 37% PSNR and 1.34% MSE values. The quantitative comparison among the existing methods was given in Table 2.

Table 2: Segmentation Metrics of our proposed method

Image No	Accuracy	Time Consumption (s)
1	97.5	8.33
2	98.5	8.43
3	97.77	7.44
4	97.21	8.47
5	99.52	8.4
6	98.22	6.72
7	97.31	6.82
8	97.76	7.89

Recall ensures the quality of the tumor segmentation, whereas accuracy measures ensure the efficiency of skin tumor images with ground truth image segmentation. Time takes for segmenting the tumor is also mentioned in table 2.Computational time among other techniques are compared with our proposed work is mentioned in Table 3.

Table 3 :Comparative Measures of proposed with existing method

Methods	Accuracy	Time Consumption (s)
<b>FCM</b>	<b>94.5</b>	<b>45</b>
<b>Level set</b>	<b>93.6</b>	<b>12</b>
<b>Proposed</b>	<b>97.5</b>	<b>7</b>

## Automated Framework for Segmenting Skin Lesions using Artificial Bee Colony Optimization with Morphological Reconstruction

It was proved that our ABC with morphological reconstruction filters is highly recommended our skin lesions segmentation in near future. A structural element is more useful for removing the extraneous pixels surrounded with tumor part. we used 'disc' as the structural element with 9 X 9 value for all images used in our study .

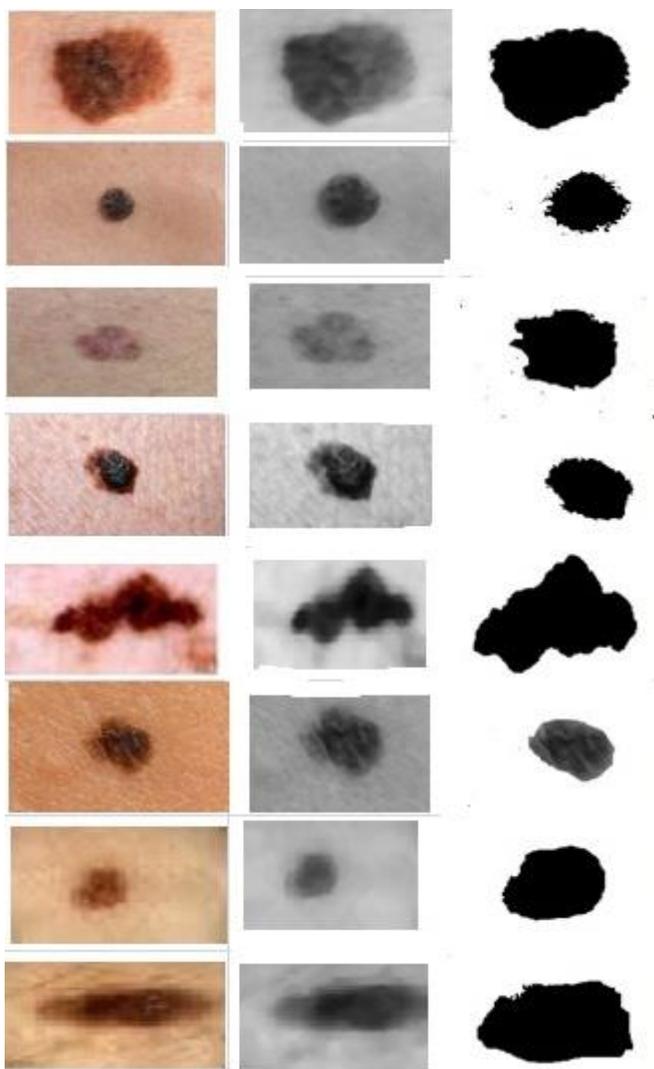


Figure 2 : Melanoma Skin Images collected from Iris and Clinical dataset Figure 2a) input images 2b) contains Median Filtered Image and 2c) contains ABC with morphological reconstruction filtered images

Figure 2a contains original input image and figure 2b contain the median filtered image and Figure 2c contains ABC with morphological reconstruction filter images of our proposed work.

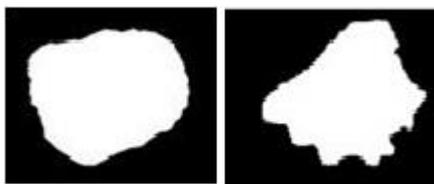


Figure 3 :Ground truth images of skin tumor

Figure 3 contains sample ground truth images of melanoma skin cancer images collected from IRIS dataset .

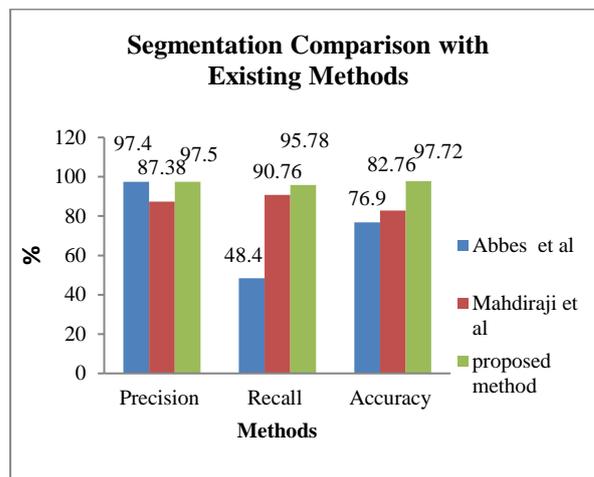


Figure 4: Comparison with other Existing Techniques

Figure 4 compares the performance of segmentation with other existing approaches [16-17]. it was ensured that the proposed work produces best segmentation than the existing approaches also it compares the accuracy measures with state of art

### IV. CONCLUSION

We used an automated design using artificial bee colony with morphological reconstruction filters to segment the skin lesions within short duration. This design is more helpful for the dermatologist for early detection and prevention of tumor growth in advance. The segmentation performance were evaluated and compared the computational time with other state of art methods. It was noticed that some images produces incorrect segmentation and additional pixels are along with the tumor, that limitations are overtaken by the morphological reconstruction filters

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