

# Skin Lesion Segmentation in Dermoscopy Imagery

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**Abstract:** *The main purpose of this study is to find an optimum method for segmentation of skin lesion images. In the present world, Skin cancer has proved to be the most deadly disease. The present research paper has developed a model which encompasses two gradations, the first being pre-processing for the reduction of unwanted artefacts like hair, illumination or many other by enhanced technique using threshold and morphological operations to attain higher accuracy and the second being segmentation by using k-mean with optimized Firefly Algorithm (FFA) technique. The online image database from the International Skin Imaging Collaboration (ISIC) archive dataset and dermatology service of Hospital Pedro Hispano (PH<sup>2</sup>) dataset has been used for input sample images. The parameters on which the proposed method is measured are sensitivity, specificity, dice coefficient, jacquard index, execution time, accuracy, error rate. From the results, authors have observed proposed model gives the average accuracy value of huge number of cancer images using ISIC dataset is 98.9% and using PH<sup>2</sup> dataset is 99.1% with minimize average less error rate. It also estimates the dice coefficient value 0.993 using ISIC and 0.998 using PH<sup>2</sup> datasets. However, the results for the rest of the parameters remain quite the same. Therefore the outcome of this model is highly reassuring.*

**Keywords:** *Automatic detection, FFA, K-mean, pre-processing, segmentation.*

Received October 29, 2019; accepted February 7, 2021

<https://doi.org/10.34028/iajit/19/1/4>

## 1. Introduction

Skin cancer is characterize as a build up in which there is an abnormal reinforcement of certain cells that happens due to alteration in gene expression on the skin layer [34]. These cancerous cells further penetrate neighbourhood cells. In this modern world, huge number of cancer patients has been elevated because human body gets affected by various factors like life span increase, and ultraviolet light exposure or many more [38]. Skin cancer is essentially of two different types which are malignant and benign. The difference between both categories is due to their ability to spread or metastasize to remote tissues and organs. Malignant type of Cancer can effectively invade and can destroy its neighbouring tissues. It can also spread to remote tissues as well as organs through the bloodstream or lymphatic system. Most of the people are infected by this disease [30, 32]. Benign cancer is a more localized type of cancer but it can affect the environment by applying pressure on neighbouring nerves or blood vessels. The growth rate of benign cancer type is less than malignant cancer type. If these cancers are not treated properly, it may lead to harmful effects on the human body. So, skin cancer detection is the main part of proper diagnosis. For the cancer patient, a technique named as biopsy is used which is an invasive operation and gives unpleasant experience. To avoid an unnecessary biopsy, dermoscopy imaging technique is used for detailed inspection of skin layers by using a microscope and other special illumination equipment. The major problem is to determine the presence of skin

lesions in dermoscopy images and to classify the skin lesion type. Few steps are required for the detection of skin lesion such as segmentation [21], feature extraction [5] and classification process [12]. In this paper, an automated segmentation technique is suggested which can be accustomed as an initial measure for skin lesion categorization. This automatic system is used to identify and to locate the skin lesion regions which are very helpful for dermatologists to detect skin cancer [14, 39]. This suggested technique comprises of the following two footsteps:

1. Pre-processing based on enhancement technique using Thresholding and morphological operations for the removal of artefacts like hair, illumination defects and ink markings.
2. Segmentation of pre-processed image using K-mean clustering with optimized Firefly Algorithm (FFA) [17]. International Skin Imaging Collaboration (ISIC) and PH<sup>2</sup> dataset are employed for the performance analysis of this proposed technique and also evaluate some parameters such as specificity, sensitivity, dice coefficient, Jacquard index, accuracy, execution time, error [23, 37]. This paper has been methodically classified in various sections like section 2 describes the literature review. Section 3 mentions the general outline structure and describes the proposed method for segmentation of skin lesion. The section 4 describes the

outcomes of suggested techniques and correlative study. All results and discussion are described in section 5. In the last section conclusion of this suggested work has been mentioned.

## 2. Literature Review

It has been shown by an expert specialist that the accuracy rate calculated is 60% using a visual examination method. So, because of this low accuracy rate, automatic detection system is required for skin cancer detection to achieve high accuracy rate. The basic three methods for automatic detection system are segmentation process, feature extraction process, and classification process. From these, segmentation is the main task; therefore, the accuracy in segmentation directly affects other tasks. However, skin lesion segmentation becomes extremely difficult because of variations in size, boundaries, and color of skin lesion with the distinctive sort of skin. It's very difficult to discriminate the normal skin and skin lesion. And also, Segmentation becomes more challenging because of various artefacts such as hair, remarks and so on in dermoscopy images. There are various types of segmentation and classification methods that can be resorted to resolve these kinds of issues.

Celebi *et al.* [10] introduced region-based, threshold-based and edge-based techniques for the segmentation and detection of skin lesion.

Ahn *et al.* [4] described a saliency-based lesion segmentation method for the segmentation of lesion from the skin images produced by dermoscopy equipment. This proposed technique separates the background part from skin lesion image based on color properties, boundaries, and image regions.

Sadri *et al.* [36] suggested a technique for skin lesion segmentation which is called a Fixed Grid Wavelet Network (FGWN). This method uses the dermoscopy image that gives RGB values which are used as an input and with that it uses orthogonal least square algorithm for the estimation of network weights. This emanates the boundary of skin lesion region.

Kechichian *et al.* [26] mentioned a Graph cut method for segmentation, that takes under the consideration of texture, color, and shape. With the help of the Graph cut method, the classifier is trained by driving the seed pixel from an initial segmentation of skin lesion based on Morphological and logical operators.

Abbas *et al.* [1] described a region-based active contour method to derive the skin lesion region.

Pennisi *et al.* [35] suggested the Delaunay Triangulation (DT) method for the segmentation process. This proposed method was applied to PH<sup>2</sup> dataset.

Ma and Tavares [27] proposed a deformable model in to portion the skin lesion from the

dermoscopy image. It was used to differentiate the skin lesion and regular healthy skin based on segment lesion region.

Abbas *et al.* [3] described the least-square and dynamic programming method to ascertain the ideal boundary of skin lesion.

Silveira *et al.* [40] introduced six different methods for segmentation was suggested on edge-based, threshold-based and region-based algorithms and tested on hundred melanocytic skin lesion images.

Further, Bi *et al.* [6] supported a segmentation technique to grounded on image-wise administered knowledge and multi-scale super pixel supported Cellular Automata (CA).

Garnavi *et al.* [18] suggested a skin lesion border detection arrangement which is grounded on histogram thresholding and colour space analysis. The lesion border was detected by estimation of optimal color channel with hybrid thresholding and morphological operators.

Gomez *et al.* [20] projected an independent histogram method to enhance the structure in skin lesion image. Skin lesion is extracted from this enhanced skin lesion image by histogram Thresholding method.

Yuksel and Borlu [45] proposed a Type-2 fuzzy logic method by which was employed to skin segment lesion image.

Fan *et al.* [16] introduced a technique based on the saliency map method with Ost'u threshold to extract the skin lesion border.

Zhou *et al.* [46] suggested a new mean shift methodology supported fuzzy c-means principle. This method was used to find out the reliable cluster centre point by calculating objective function based on the mean-field and the fuzzy c-means algorithms.

Suer *et al.* [41] employed an segmentation algorithm to get the better precision and used to remove unwanted data for fast computation.

Xie and Bovik [43] proposed a segmentation algorithm to obtain optimized and stabilized clustering based on genetic algorithm.

Celebi and Zornberg [9] mentioned a machine learning method to discriminate significant colours in skin images.

Celebi *et al.* [11] established a fast and exclusive technique is employed for detecting lesion border on the statistical region merging method .

Abbas *et al.* [2] had explained various hair eliminating processes alike in painting by PDE non-linear diffusion, linear interpolation and soon.

## 3. The Proposed Methodology

An automatic learning technique is employed for skin lesion segmentation. This technique consists with two steps such as pre-processing and segmentation. The

first step i.e., pre-processing reduces the artefacts and then this enhanced filtered image is employed for segmentation. This segmentation is done by K-mean clustering with optimized FFA algorithm. The block diagram below throws light on the workflow of the proposed method in Figure 1.

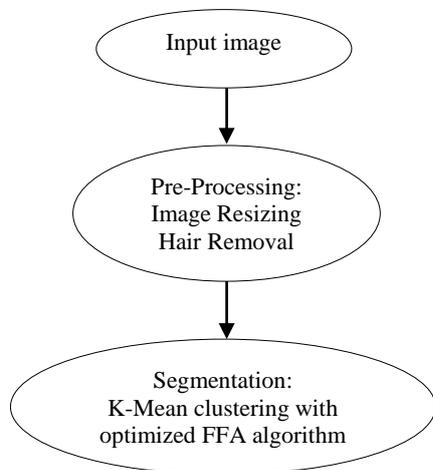


Figure 1. Framework of the proposed segmentation technique.

### 3.1. Pre Processing

It is very difficult to analyze the noisy dermoscopy images. To augment the improvement in quality of skin lesion images, Pre Processing step is used to remove the unwanted noise and eliminate irrelevant information described by [42]. Artefacts such as hairs, markers make the process of segmentation arduous. So, to enhance the preciseness of the segmentation process there is a requirement of some pre-processing steps.

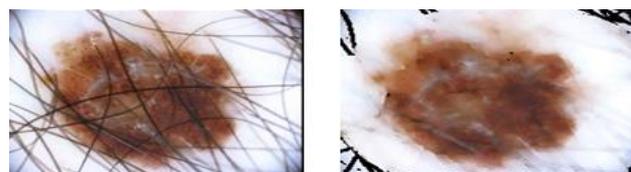
#### 3.1.1. Image Resizing

High resolution dermoscopy images consist with high pixel range. So, their computational complexity becomes very difficult. Therefore to minimize this computation, input high pixel images are scaled down to 50% approximately.

#### 3.1.2. Hair Removal

Segmentation of lesion images becomes very difficult due to the presence of hairs because important features like texture and boundary are affected by hair pixel. Feature extraction process also becomes more difficult due to the hairs. Different types of hair like light and dark colour hairs are segmented by adaptive canny edge detector and rarefaction by morphological operator [42]. The following steps for hair removal are firstly segmentation of hair like artefacts are to be done [19, 28]. After that proper refinement of segmented lines occurs [2]. In this paper, an enhanced technique has been applied to remove this type of artefact by using threshold [13] and morphological operations

Results of pre-processed images from the samples of ISIC are displayed in Figure 2-a) and 2-b).



a) Original image taken from ISIC dataset. b) Pre-processed image.

Figure 2. Original and Pre-processed image.

### 3.2. Segmentations

The second step being, Segmentation is the process to detect the skin lesion border from the dermoscopy image is introduced in [11, 24]. This part of the skin lesion contains important information of the dermoscopy image. It becomes very necessary to examine the precise defined region of lesion for diagnosis. This part differentiates the skin cancer types. Then this part is further used for feature extraction. Many techniques are used for segmentation which are edge-based, region-based and boundary-based methods [7, 8]. This suggested skin lesion segmentation comprises of two phases which are K-mean clustering to localize the exact lesion region and then this clustering gets optimized by FFA algorithm to achieve high accuracy.

#### 3.2.1. K-Mean Clustering

This method is employed to cluster the pixels to obtain foreground and background region in Red Green Blue (RGB) color space [25]. This method automatically choose foremost cluster midpoint from the image pixels. Now, next cluster midpoint is selected from the remaining part of the image input pixels build on the possibility in comparison to its square stretch from the image pixels nearest to the cluster centre. The image pixels consists of interior of the lesion, background of skin lesion, background image and lesion boundary. In this method, the pixel color of cluster which is same to the skin lesion color is maintained form the obtained clusters. This method automatically pursues the information about pixel for identification of cluster as a skin lesion region. The results of K mean algorithm after applying on pre-processed images shown in Figure 3.



a) pre-processed image. b) background region after segmentation. c) foreground region after segmentation.

Figure 3. Outcomes using K-Mean clustering segmentation for input image taken from ISIC dataset.

### 3.2.2. K-Mean with Optimized Fire Fly Algorithm

FFA is the latest swarm intelligence method of this new generation [33]. It is inspired by nature, stochastic and meta-heuristic algorithm which can be used to solve the hardest optimization problem. This algorithm draws its inspiration from the community behaviour of fireflies and based on their attraction and flashing characteristics. In this paper, K-mean clustering gets optimized with an FFA algorithm to achieve the best solution. This proposed method was implemented using a Graphical User Interface (GUI) in Matlab 2014 or higher version. Pre-processing of input sample images is done by the proposed enhanced technique based on threshold and morphological operations. The threshold value of 5 is used and structural element disk is used in morphological operation to reduce artefacts. Then the K-mean clustering technique is applied to the improved image. High accuracy will be achieved with the optimization of FFA technique.

Algorithm (1) contains the functional steps of Firefly algorithm with K-Mean algorithm. The segmented image from the K-Mean algorithm is further processed by using firefly algorithm [17]. It is used to find the best solution in less population. In hybridization of K-mean and FFA, firstly K-mean method is used for segmentation and then FFA gets optimized with the results of K-means as an input of FFA. Here FFA decides a better threshold value which can replace the wrong segment data in the output of K-means by selected threshold value. Figure 4-a-e) represents the steps for the segmentation of the skin lesion region using the proposed method by involving the pre-processing step and the extraction of foreground and background region using K-Mean and K-Mean with FFA technique.

*Algorithm 1: Hybrid Firefly algorithm*

*Step 1. To Define Objective function:*

$$f(x), x = (x_1, x_2, \dots, x_d); \quad (1)$$

*f(x) represents fitness value function;*

*x is no. of fireflies; d defined different number of images*

*Step 2. For the Generation of initial population of fireflies*

$$x_i (i = 1, 2, \dots, n); \quad (2)$$

*here n is the no. of iterations*

*Step 3. Light intensity I is to be formulated so that it is associated with f(x)*

*Step 4. Define absorption coefficient  $\gamma$*

*While (t < Max generation)*

*max generation means: maximum number of items*

*For i = 1: n(all fireflies)*

*I- Brightness (unique attraction)*

*For j = 1: i(n fireflies)*

*if (I<sub>j</sub> > I<sub>i</sub>), to find the most effective solution and*

*update intensity value;*

*End if*

*End for j*

*End for i*

*End while*

*Post-processing the results;*

*End*

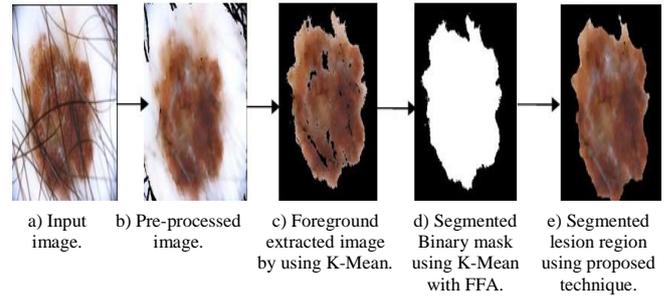


Figure 4. Various images obtained in different steps of segmentation of skin lesion region using the proposed technique.

## 4. Evaluation Metrics

Comparison of segmentation results are shown with some parameters [38] using Specificity ( $S_p$ ), Sensitivity ( $S$ ), Dice Coefficient (DC), Jacquard Index (JI), Execution Time ( $E_T$ ), Accuracy (ACC) [22, 31] and Error ( $E_r$ ). They are defined as:

$$S_p = \frac{T_N}{T_N + F_p} \quad (3)$$

$$S = \frac{T_p}{T_p + F_N} \quad (4)$$

$$DC = \frac{2|G_T \cap A_P|}{|G_T| + |A_P|} \quad (5)$$

$$JI = \frac{|G_T \cap A_P|}{|G_T \cup A_P|} \quad (6)$$

$$ACC = \frac{T_p + T_N}{T_N + F_p + F_N + T_p} \quad (7)$$

$$E_r = \frac{F_p + F_N}{T_N + F_p + F_N + T_p} \quad (8)$$

Where,  $T_p$  is that the true positive pixels represent as lesions,  $G_T$  define ground truth,  $T_N$  is that the true negative pixels represent as background,  $A_P$  is that the algorithm predicted segmentation result,  $F_p$  is that the false positive pixels,  $F_N$  is that the false negative pixels

## 5. Results and Discussion

In this part, the proposed method is assessed using two data sets International Skin Imaging Collaboration (ISIC) dataset consists of more than 1000 images and Hospital Pedro Hispano (PH2) dataset consists of 200 images. The act of the proposed method is measured in terms of sensitivity, specificity, dice coefficient, jacquard index, execution time, accuracy, error etc., Table 1 represents the average value of Specificity and Sensitivity of the proposed method gives better results as compare to K-Mean with Particle Swarm Optimization (PSO) [15, 29] and K-means [25] using ISIC data set images. These parameters are used to showcase an improvised selection of lesion region for segmentation of dataset images and are calculated

based on the area of mask. Therefore total area takes into consideration, it would also vary but the difference between their values would remain more or less the same. It has also been observed that there is a need to focus on segmentation accuracy and error rate for producing better results. So from the analysis, it can be concluded that the fast segmentation process results in less error rate and more segmentation accuracy. Other parameters are calculated to validate the similarity of segmentation based on the dice coefficient and jacquard index technique. From the analysis, it has been found that the achieved value of the dice coefficient and jacquard Index are better in these cases which depend on the quality of skin lesion dermoscopy images [44]. The time taken by the proposed technique for the execution of results is less than K-Mean with PSO and little bit more than the K-Mean technique because of the optimized FFA algorithm. This optimized method gives high accuracy as compare to other methods. As in case of proposed method, the average error rate is very less as compare to other methods. K-Mean algorithm is complex and experimental results obtained with this algorithm are not good as results obtained with FFA. So, to reduce complexity, FFA has been used. It has been found that performance of the proposed method is quite impressive and outperformed than existing techniques. FFA is a Meta- heuristic method and is generally outperformed than simple heuristic (local search) techniques. FFA is also removed the irrelevant extract features. Also, find out the optimal solution in less population. In addition, as on the comparison with other techniques, average accuracy rate is increased by 10.9 % by proposed method and average error rate is reduced by 91%. Therefore, this proposed technique provides high accuracy rate with less error rate. It has

high convergence rate and robust in nature. It is also used to find out the optimal solution in less population in incorporated in the paper. Table 2 represents the outcomes of the proposed technique using PH<sup>2</sup> dataset images based on various parameters. The specificity and sensitivity of the proposed technique is better than K-Mean [25] and K-Mean with PSO technique. A high value of the dice coefficient is used for achieving better segmentation. From the analysis, it has been shown high accuracy and low error rate as compared to other methods. As in case of error rate comparison, this proposed method provides less error rate on the comparison of other methods. Figure 5-(a-f) represents the segmentation steps to locate the exact skin lesion region. Figure 5-a) input sample image Figure 5-b) Input image pre-processed to enhance the quality of the image. Figure 5-c) and Figure 5-d) Enhanced images is being segmented by K-Mean method to find out mask image and segmented image but by this method some part is missing in segmented region So, to overcome this problem. Figure 5-e) represents binary mask image using proposed method Figure 5-f) the proposed technique is used to segment the exact skin lesion region. Hence, this procedure has been applied to

various input sample images using ISIC and PH<sup>2</sup> datasets. Figure 6-a) shows the accuracy and error rate comparison of different ISIC dataset images using K-Mean, K-Mean with PSO and proposed technique. From Figure 6-a) the accuracy of the proposed method is better than other techniques as well as error rate is less than other techniques. Similarly, Figure 6-b) shows the accuracy and error rate comparison of different PH<sup>2</sup> dataset images using K-Mean, K-Mean with PSO and proposed techniques. From Figure 6-b) shows the accuracy rate of the proposed technique is better than other techniques.

Table 1. Results of pre-processed sample input images from ISIC dataset.

Parameters	Results of pre-processed sample input image 1			Results of pre-processed sample input image 2			Results of pre-processed sample input image 3		
	Techniques			Techniques			Techniques		
	Using K-mean	K-mean with PSO	Proposed method (K-Mean with FFA)	Using K-mean	K-mean with PSO	Proposed method (K-Mean with FFA)	Using K-mean	K-mean with PSO	Proposed method (K-Mean with FFA)
<b>Specificity</b>	0.965	0.972	<b>0.973</b>	0.964	0.965	<b>0.966</b>	0.966	0.969	<b>0.970</b>
<b>Sensitivity</b>	0.965	0.980	<b>0.984</b>	0.969	0.972	<b>0.979</b>	0.967	0.970	<b>0.974</b>
<b>Dice coefficient</b>	0.972	0.98	<b>0.995</b>	0.908	0.952	<b>0.998</b>	0.889	0.915	<b>0.993</b>
<b>Jacquard Index</b>	0.901	0.903	<b>0.907</b>	0.903	0.904	<b>0.915</b>	0.903	0.911	<b>0.919</b>
<b>Execution time</b>	1.033	88.51	<b>1.112</b>	0.683	73.64	<b>1.027</b>	0.707	91.98	<b>1.032</b>
<b>Accuracy</b>	0.987	0.847	<b>0.991</b>	0.911	0.905	<b>0.991</b>	0.885	0.884	<b>0.989</b>
<b>Error</b>	8.32	7.25	<b>1.26</b>	9.860	8.422	<b>0.823</b>	11.64	10.57	<b>1.011</b>

Table 2 . Results of pre-processed sample input images from PH<sup>2</sup> dataset.

Parameters	Results of pre-processed sample input image 1			Results of pre-processed sample input image 2			Results of pre-processed sample input image 3		
	Techniques			Techniques			Techniques		
	Using K-mean	K-mean with PSO	Proposed method (K-Mean with FFA)	Using K-mean	K-mean with PSO	Proposed method (K-Mean with FFA)	Using K-mean	K-mean with PSO	Proposed method (K-Mean with FFA)
<b>Specificity</b>	0.970	0.973	<b>0.975</b>	0.968	0.971	<b>0.974</b>	0.967	0.972	<b>0.977</b>
<b>Sensitivity</b>	0.971	0.976	<b>0.978</b>	0.968	0.976	<b>0.978</b>	0.971	0.976	<b>0.978</b>
<b>Dice coefficient</b>	0.930	0.941	<b>0.993</b>	0.892	0.905	<b>0.990</b>	0.875	0.940	<b>0.993</b>
<b>Jacquard Index</b>	0.912	0.927	<b>0.940</b>	0.914	0.933	<b>0.943</b>	0.919	0.923	<b>0.931</b>
<b>Execution time</b>	0.677	75.24	<b>1.00</b>	0.918	91.89	<b>1.05</b>	0.716	74.72	<b>1.149</b>
<b>Accuracy</b>	0.875	0.880	<b>0.989</b>	0.910	0.905	<b>0.991</b>	0.874	0.872	<b>0.989</b>
<b>Error</b>	12.49	11.98	<b>1.075</b>	8.933	8.476	<b>0.808</b>	12.74	10.5	<b>1.09</b>

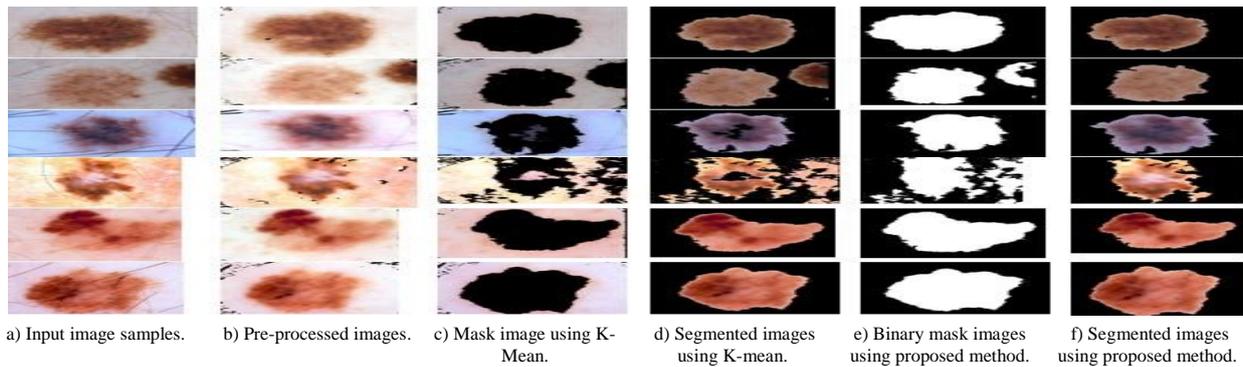
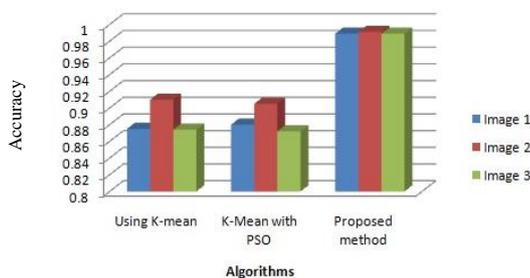
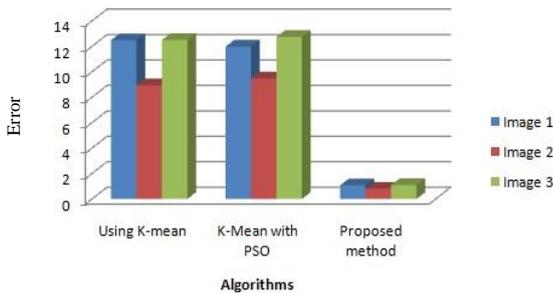


Figure 5. Segmentation results.

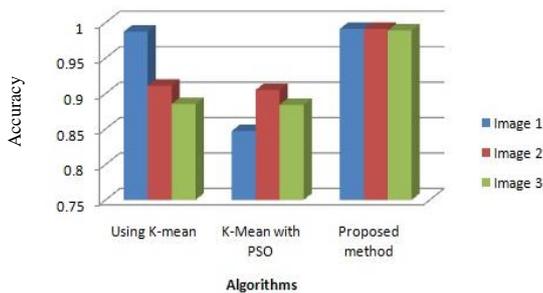
From Figure 6-a) and 6-b) it has been concluded that the proposed method is better for segmentation of skin lesion region as compared to other techniques.



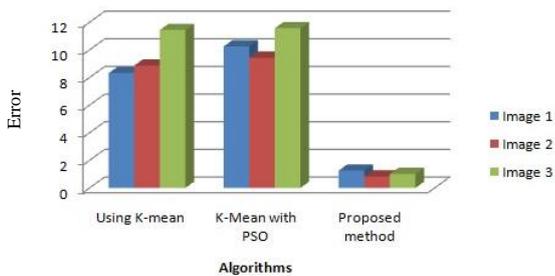
a) Accuracy comparison of different ISIC dataset images.



b) Error comparison of different ISIC datasets.



c) Accuracy comparison of different PH<sup>2</sup> dataset images.



d) Error comparison of different PH<sup>2</sup> datasets.

Figure 6. Accuracy and error comparison using different dataset images.

## 6. Conclusions

In this study, an automatic learning technique is described to segment skin lesion region. This system is useful for dermatologists to automatically find out skin lesion regions in dermoscopy images. The proposed technique consists of two steps pre-processing and segmentation. During the pre-processing, artefacts like hairs, makers are reduced by enhanced technique based on threshold and morphological operations. This pre-processed image is employed for good segmentation of skin lesion region. From the pre-processed image, the lesion region is segmented using proposed algorithm is employed to get the lesion region with improved boundaries. The proposed method is evaluated using ISIC and PH<sup>2</sup> dataset images. From both the datasets, a good accuracy of 0.989 and 0.991 respectively has been obtained. The dice coefficient values of 0.993 and 0.998 are calculated for the ISIC dataset and PH<sup>2</sup> dataset respectively. Therefore, it has been concluded that proposed algorithm provides higher accuracy, induces low error rate as compared to other techniques.

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