

## USING HISTOGRAM SPECIFICATION IN A HYBRID PREPROCESSING TECHNIQUE FOR SEGMENTATION OF MALIGNANT SKIN LESIONS FROM DERMOSCOPIC IMAGES

SONALI PATIL<sup>1</sup> & V R UDUPI<sup>2</sup>

<sup>1</sup>Research Scholar, Shivaji University Kolhapur, Maharashtra, India

<sup>1</sup>Faculty, K J Somaiya College of Engineering, Mumbai, Maharashtra, India

<sup>2</sup>Gogte Institute of Technology, Belgaum, Karnataka, India

### ABSTRACT

Malignant skin lesions in dermoscopic images are characterized by non-uniformity of color. Such skin lesions have different shades of brown or black colors and may also have patches of pink, red, white or blue color. This fact makes segmentation of malignant skin lesions from dermoscopic images difficult than segmentation of uniform benign skin lesions. To overcome this challenge, in this paper, the hybrid pre-processing approach that uses histogram specification process is proposed. The Fuzzy C Means (FCM) segmentation method is used to demonstrate the results. This hybrid preprocessing and FCM segmentation methods are applied to segment the most common types of malignant skin lesions, Melanoma and Basal Cell Carcinoma. The results of Fuzzy C Means segmentation using different preprocessing techniques are illustrated. The results depict that the proposed hybrid approach leads to efficient segmentation of the malignant skin lesions as compared to other commonly used pre-processing approaches.

**KEYWORDS:** Histogram Specification, Fuzzy C Means Clustering (FCM), Melanoma, Basal Cell Carcinoma (BCC)

### INTRODUCTION

A skin lesion is a part of the skin that has an abnormal growth or appearance compared to the skin around it [1]. The most common cause of a skin lesion is an infection on or in the skin. One example is a wart. Warts are caused by a virus that is transmitted by touch.

There are mainly two types of skin lesions primary and secondary. Primary skin lesions are abnormal skin conditions present at birth or acquired over one's lifetime. Birthmarks are primary skin lesions. Other types include blisters, Macule, nodule, Papule, Pustule, Rash, wheals, etc. Secondary skin lesions are the result of irritated or manipulated primary skin lesions. For example, if someone scratches a mole until it bleeds, the resulting lesion, a crust, is now a secondary skin lesion. The most common secondary skin lesions include crust, Ulcer, Scale, Scar and skin atrophy.

Skin Lesions can be broadly categorized as benign and malignant. Benign skin lesions are non-cancerous whereas malignant skin lesions are cancerous. Common Types of Benign Skin Lesions are Melanocytic nevus, Seborrheic keratosis, Acrochordon, Dermatofibroma, Cherry angioma. Common Types of Malignant Skin Lesions are Basal cell carcinoma, Melanoma, Squamous cell carcinoma [1]. Dermoscopy [2] is a non-invasive diagnostic technique for the in vivo observation of pigmented skin lesions, allowing a better visualization of surface and subsurface structures. Dermoscopy acts as an aid in the diagnosis of skin lesions [3].

The dermoscopic images containing lesions can be given to the CAD system for detection and classification of the skin lesion. Accurate segmentation of skin lesions is a vital process in such a CAD system. Precise segmentation enhances the accuracy of the CAD system thereby reducing the false classification due to inaccurate segmentation. Pre-processing of images is the first and important step in image processing applications. It ensures that image is enhanced as compared to that of input image which results in desired segmentation results. With this motivation and the fact that the malignant skin lesions are difficult to segment, different pre-processing techniques which can be applied before segmentation on the dermoscopic images containing malignant skin lesions are looked upon. Common pre-processing techniques like hair removal, median filtering and contrast stretching in combination with Histogram Specification are applied on dermoscopic images containing malignant skin lesions before segmentation.

The rest of the paper is organized as follows. Section 2 gives a description about the related works. Section 3 highlights significance of the work described in this paper. Section 4 describes the skin lesion pre-processing and segmentation system. Section 5 presents the experimental analysis of the systems which describe the implementation part for pre-processing and segmentation as well as present a comparative discussion of the results. Finally, Section 5 presents conclusion from the experimental results.

## RELATED WORKS

Skin lesion detection & segmentation system refers to detecting the skin lesion in the given image dermoscopic image and extracting the lesion from the rest of the skin portion. Dermoscopic image is taken as input and it is suitably pre-processed before segmenting so as to get desired segmented output. Various enhancement and segmentation approaches are used for pre-processing of dermoscopic images containing skin lesions. Over the past decade, extensive research focused on development of the CAD tools for automatic detection of lesions in the skin has been carried out.

Paper [4] describes the non-uniform background of a dermoscopic image which is caused due to water or air bubbles, thick hair, thin blood vessels, skin lines. To minimize the above mentioned factors an adaptive histogram equalization step is employed. Smoothing filters, such as Nagao filter is used which is edge preserving blur filter. They also demonstrated two hair removal algorithms: The first is closing morphological operator and the second, which was shown to be better, was combination of Bicubic interpolation and Top hat transform. The Mean-Shift approach used was to segment the lesions. A database of 60 images consisting of 35 melanomas and 25 benign nevi were used. This paper is preliminary and no indication about the segmentation accuracy is mentioned. Do Hyun Chung et al [5] stated that biomedical images are in general noisy and poorly illuminated, making them difficult to segment and analyze. Histogram equalization using differential equations were considered as preprocessing. In [6], authors have used median filtering which effectively removes noise spikes with preserving spatial resolution which avoids blurring of edges. Contrast stretching is also applied after median filtering. Unsupervised approach to border detection in skin was used. Median filtering was also used in [7] for smoothing image from noise. The Segmentation of lesion was done using thresholding. The authors of [8] applied Median filtering to dermoscopic images further followed by contrast stretching. Impulse noise, brightness and reflection present in the image are reduced using median filtering. It also ensured that unwanted structures are eliminated from the image. In [9] image is converted to greyscale image and 20% salt and pepper noise was added to original image. Further median filter was applied to eliminate noise. The LOG operator was use on the noisy images for successful border detection. Authors [10] proposed use of smoothing filter to reduce the effects of the artifacts. Median filtering with 11\*11 mask was used to smooth the image. Generalized Lloyd algorithm (GLA) was used to vector quantize

the pixel colors. The purpose is to extract a few representative colors that can differentiate neighboring regions in the image. In [11] author compares different filters average, median, bilateral and Gaussian filter. Among these four techniques, the best results were obtained by the bilateral filter. The proposed method by authors for filtering uses the combination of bilateral filtering with spline (Bilt-Sp) which involves selection of the optimal color channel from the RGB image to improve the segmentation accuracy using edge detection. A preprocessing step that enhances color information and image contrast was proposed in [12]. In this work, images with low contrast give low results when it comes to making accurate border detection. Hence Automatic Color Equalization (ACE) is used by these authors, which is based on a model which merges two techniques Grayworld and MaxRGB normalization. Segmentation is done by iterative thresholding approach where optimal thresholding algorithm is used to determine the optimal threshold iteratively. In [13] three pre-processing techniques were used for hair removal, color space transformation and color enhancement. RGB image is converted to different color spaces and colors are extracted. The segmentation was achieved by Thresholding Using Reinforcement Learning Algorithm. Authors have also proposed [14] Contra-Harmonic Filter (CHF) for pre-processing the dermoscopic image which minimizes the various artifacts present in the image like camera flash, dermoscopic gel bubbles. After detection of lesion border and feature extraction, pattern classification was done between two types of skin lesions, melanoma (the malignant one) and Clark nevus (the benign one). In [15], morphological closing filter using a disk as structuring element with radius value as 5 which removes the dark hair was used. Gray-level thresholding was also used to eliminate the dark regions in the four corners of the images. The comparison of four methods used for segmentation was done. The segmentation methods used for comparison were Robust Snake, Level set, Adaptive thresholding and manual segmentation. Total of 50 dermoscopic images were used. The types of lesions were not specified. In [16], authors used image enhancement and edge detection techniques which pre-processed the image for further activity. Unsharpmask, one of the most popular tools for image sharpening was used to sharpen the image. Manual segmentation was used to detect and visualize pigment network structure in the dermoscopic images making use of graphs. Color morphological operators [17] were obtained on the HSI color space for preprocessing of dermoscopic images of Melanoma skin lesions. The morphological filtering highlighted the region of melanoma that was then segmented by binarization method. Heydy et al [18], made use of information in R, G and B channels in wavelet transform space. FCM, K-Means and CPSFCM clustering algorithms were applied on normalized level-1 DWT.

## **SIGNIFICANCE OF OUR WORK**

It can be seen from above related works that most of the researchers have used median filtering for smoothing the dermoscopic images. Some of them have used morphological closing operator for hair removal. Contrast stretching and histogram equalization are also used by some authors for enhancing the dermoscopic images. Also authors have used either general skin lesions or specific malignant melanoma only for their work. Only one author has used other type which is benign Clark Nevus. Most of them have compared different segmentation approaches for segmenting the lesion from the skin dermoscopic image.

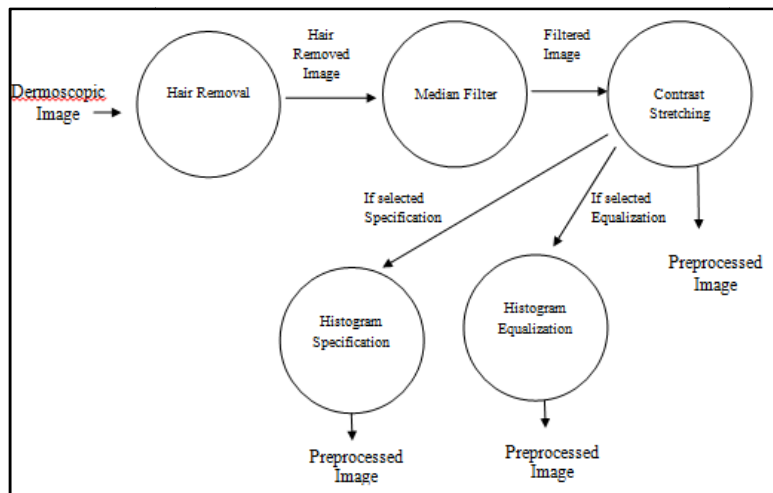
In this work, we have proposed a hybrid pre-processing approach combining histogram specification method in combination with hair removal, median filtering and contrast stretching. To the best of our knowledge no researcher has used histogram specification method for the pre-processing of medical images, especially dermoscopic images. Out of different methods of segmentation we have used Fuzzy C Means clustering algorithm to segment the different pre-processed images. The work compares FCM segmentation results on these pre-processing approaches. As the malignant

lesions are difficult to segment than the benign, in this work two most common types of malignant skin lesions are considered. They are Melanoma and Basal Cell Carcinoma.

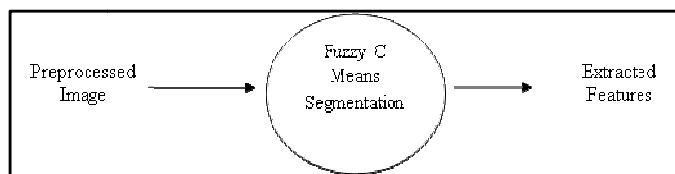
**METHODOLOGY**

The overall methodology proceeds as follows. The dermoscopic images contain hair and impulse noise. These factors can affect the segmentation which in turn can hamper the performance of CAD system. First the process of hair removal is carried out. Then the median filtering is applied to remove the impulse noise. This image after hair removal is given as input to the contrast stretching block. This acts as one pre-process image which can be given to Fuzzy C Means segmentation algorithm. Further on this contrast stretched image the Histogram Equalization [19] is performed. This acts as the second pre-processed image. The last pre-processed image is obtained by performing histogram specification operation on the contrast stretched image using a specified histogram.

Figure 1 and Figure 2 summarizes the entire process of pre-processing and segmentation.



**Figure 1: Process of Pre-Processing**



**Figure 2: Process of Segmentation**

**Pre-Processing**

This section describes about the various pre-processing techniques that are used for skin lesion detection system. Pre-processing is important and crucial step. If pre-processing is done correctly then it results into better segmentation results.

Hair removal from skin lesion images is one of the key problems for the precise segmentation and analysis of the skin lesions. Removal and restoration of hair and hair-like regions within skin lesion images is needed so features within lesions can be more effectively analyzed for benign lesions, cancerous lesions, and for cancer discrimination. For hair removal following algorithm was used:

- Select Input image from the resized (256\*256) dermoscopic images.
- Convert it to Grey scale image.
- Create disk shaped structuring element with radius '5'.
- Apply Bottom Hat filtering
- Fill the region of interest.

The median filter [19] is a nonlinear digital filtering technique, often used to remove impulse noise. Such noise reduction is a typical pre-processing step to improve the results of later processing. Median filtering ensures that unwanted structures are eliminated.

Contrast stretching [19] is a simple image enhancement technique that attempts to improve the contrast in an image by stretching the range of intensity values it contains to span a desired range of values.

Histogram of images provides a global description of the appearance of the image. The information obtained from histogram is enormous. By definition histogram of an image represents the relative frequency of occurrence of the various grey levels in an image. A perfect image is one which has equal number of pixels in all its grey levels.

Histogram Equalization [19] was obtained using following algorithm:

- Select a dermoscopic image which is processed for hair removal and contrast enhancement.
- Calculate Histogram for image
- Calculate Probability Distribution Function(PDF)
- $P_k = \text{Number of pixels in grey level } k / \text{Total number of pixels in the image}$
- Calculate Cumulative Density Function(CDF)
- Multiply CDF by 255, the maximum grey level in the image
- Round off the values obtained from step5
- Map the pixel values to new grey level obtained in step 6.

Histogram Specification [19] is a generalized version of histogram equalization, a standard image processing operation. An equalized image has an equal number of pixels at all brightness levels, resulting in a straight horizontal line on the histogram graph. When you specify a histogram, you actually define the desired shape of the histogram, and a nonlinear stretch operation is applied to force the image histogram to have that shape. In the following algorithm,  $r_1$  and  $r_2$  are grey levels input image and specified image.  $P_r$  the distribution function of the occurrences of the grey levels  $r$ . The  $s_1$  and  $s_2$  are PDFs and  $T_1$  and  $T_2$  are the CDF transformation functions of histogram selected image and that of specified image respectively. The histogram used for specification is shown in figure [3]. This histogram is of good quality image and it is bimodal in nature. Following is the algorithm for Histogram Specification.

- Select a dermoscopic image which is processed for hair removal and contrast enhancement.
- Using histogram equalization algorithm, equalize the input image histogram ( $s_1 = T_1[Pr(r_1)]$ ).

- Select the specified histogram which is bimodal and stretched over the entire range.
- Now equalize the selected specified histogram ( $s_2=T_2[\text{Pr}(r_2)]$ ).
- Inverse map the equalized grey levels of histogram of input image as per the new grey levels of specified image ( $T_2^{-1}(s_1)$ ).

### Segmentation

Out of different methods listed in related works, Fuzzy C Means (FCM) clustering [18][20] method is used for the segmentation of the lesion in pre-processed image. The objective of the skin lesion segmentation step is to distinguish object from the background. It is important that this step is performed accurately because many features used to assess the skin lesion are derived based on segmented output. The FCM works as follows:

- Accept pre-processed image as input
- Convert image matrix to mono dimensional array,  $X$
- Select number of clusters 'c'
- Initialize  $U=[u_{ij}]$  matrix,  $U^{(0)}$
- At step k, calculate centers vector  $C^{(k)}=[C_j]$  with  $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^N u_{ij}^m \cdot x_i}{\sum_{i=1}^N u_{ij}^m}$$

Where,

$x_i$  is the set of data points;  $u_{ij}$  is the degree of membership of  $x_i$  in the cluster  $j$ ;  $N$  is the number of data points;

$c_j$  is the value of center in  $k^{\text{th}}$  iteration. Value of  $m$  should be greater than 1

Update  $U^{(k)}$ ,  $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left( \frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}$$

Where,

$x_i$  is the set of data points;  $u_{ij}$  is the degree of membership of  $x_i$  in the cluster  $j$ ;  $c_j$  is the value of center in  $k^{\text{th}}$  iteration;

$\|x_i - c_j\|$  is similarity measure between data point  $x_i$  and center  $c_j$ . Value of  $m$  should be greater than 1

- If  $\|U^{(k+1)} - U^{(k)}\| < \beta$  then stop, otherwise return to step 5

- Convert the mono dimensional matrix to matrix of size [256,256]
- Segment the image based on membership value.
- Apply mask to segmented image

## EXPERIMENTAL RESULTS AND DISCUSSIONS

All the above mentioned pre-processing and segmentation methods are implemented in MatlabR2012b. To carry out the experiment, 57 dermoscopic images of size 256\*256 were used. The images were taken from the websites [www.pcds.org.uk](http://www.pcds.org.uk) and [www.dermnetnz.org](http://www.dermnetnz.org). Out of 57 images, 33 were with melanoma skin lesions and 24 with the Basal Cell Carcinoma lesions. Figure 4 shows the results of all the pre-processing operations and their segmentation. Here the gray scale image is just the conversion of the original RGB image into gray scale. Approach A for pre-processing involves hair removal, median filtering and contrast stretching. Approach B is combination of Approach A and Histogram Equalization. Approach C, the proposed hybrid approach, is combination of approach A and Histogram Specification. It is clearly seen from the figure that the proposed hybrid approach using histogram specification gives promising results. For most of the images, the proposed approach gave much better results than the other pre-processing approaches, for few images the results were comparable to the other approaches.

To quantify this visually observed advantage of the proposed method over others, all the lesions were manually segmented (Ground truth images) by the non-specialist person. The manually segmented images were shown to the dermatologist for ensuring proper marking and segmentation of the lesions. The segmented images (monochrome) obtained using different approaches mentioned above were compared with manually segmented monochrome images (refer figure 5 for the same). The number of true positive (TP) pixels, true negative pixels (TN), false positive (FP) and false negative (FN) pixels were calculated from segmented image by each approach as compared to the manually segmented image. The metrics were calculated for comparison of different pre-processing techniques as follows:

- Sensitivity =  $TP / (TP + FN)$
- Specificity =  $TN / (TN + FP)$
- Accuracy =  $(TP + TN) / (TP + TN + FP + FN)$
- Precision =  $TP / (TP + FP)$
- Error (XOR) =  $\text{Area}(\text{segmented Image XOR ground truth}) / \text{Area}(\text{ground truth})$
- Similarity =  $2 * TP / (2 * TP + FP + FN)$

Table 1 shows the comparison of FCM segmentation on all the pre-processing approaches. The sensitivity, accuracy and similarity were far better for the proposed approach than the other approaches. The Error is least for the proposed approach. The specificity and the precision are better in approach A but the proposed approach values do not deviate much from approach A.

The total number of true positive and true negative pixels in a segmented image using each method is also compared with the total number of true positive and true negative pixels in a manually segmented image. The method

which gives this value closer to that of the manual segmented image is considered to be the better one. Table 2 shows the statistics of the pre-processing approach used and the number of dermoscopic images that lead to better segmentation using this approach.

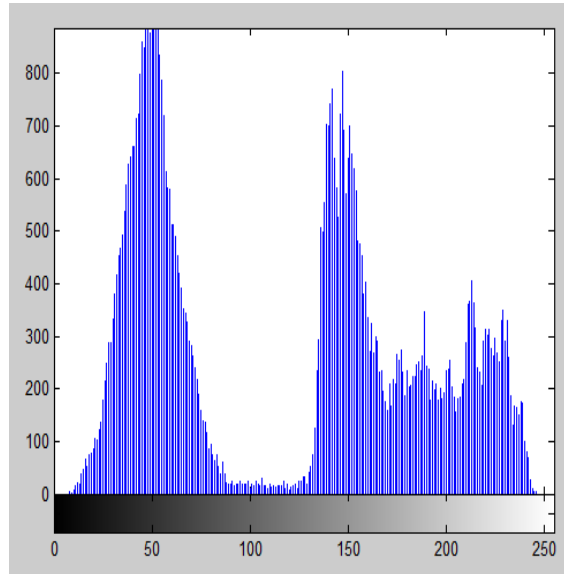


Figure 3: Specified Histogram used Histogram Specification

Type		Original Image	Grayscale Image	Pre-processed Image (Approach A)	Pre-processed Image (Approach B)	Pre-processed Image (Approach C)
Malignant Skin Lesion (Melanoma)	Pre-processing					
	Segmentation					
Malignant Skin Lesion (BCC)	Pre-processing					
	Segmentation					

Figure 4: Results of Pre-Processing and Segmentation on Dermoscopic Image Containing Melanoma Lesion



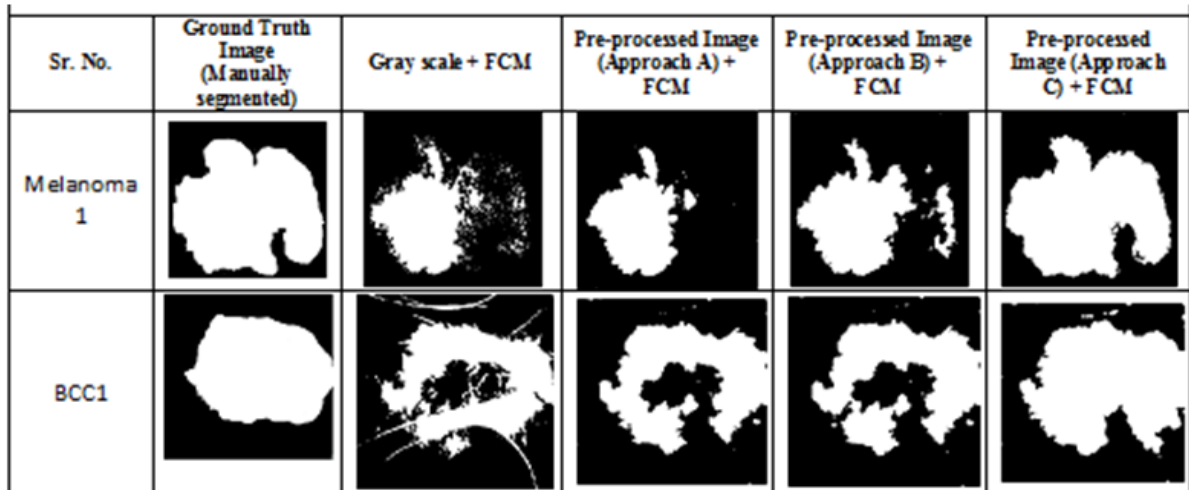


Figure 5: Segmented Images in Monochrome Format for Evaluation of Each Approach

Table 1: Comparison of Segmentation Accuracy using of Different Pre-Processing Techniques

	Sensitivity	Specificity	Accuracy	Precision	Error	Similarity
Gray scale	0.617134	0.986131	0.806502	0.961373	0.404881	0.740224
Approach A	0.636931	0.987618	0.811906	0.977387	0.382111	0.759909
Approach B	0.646692	0.981161	0.802017	0.957234	0.394912	0.762111
Approach C (Proposed one)	0.821029	0.960495	0.885997	0.942383	0.243482	0.87089

Table 2: Number of Dermoscopic Images that Lead to Better Segmentation

Pre-Precession Approach	No of Images Leading to Best Segmentation
Gray scale	3
Approach A	7
Approach B	4
Approach C (Proposed one)	43

## CONCLUSIONS

In this paper we have described various pre-processing techniques as applied on dermoscopic images containing melanoma and BCC skin lesions. These techniques are implemented and are compared with the proposed and implemented hybrid pre-processing technique that uses histogram specification. The evaluation is done on differently pre-processed and segmented skin lesions. Results show that the pre-preprocessed image that uses the proposed hybrid approach for pre-processing gives better segmentation results for majority of the dermoscopic images as compared to that of other pre-processed images. The proposed approach for segmentation of malignant skin lesions can be used without modification to segment benign skin lesions with greater accuracy as the benign lesions are characterized by uniform shade of color as opposed to the malignant lesions making them easy to segment. Thus the proposed hybrid preprocessing approach in combination with FCM segmentation can be used for segmentation of skin lesions in a Computer Aided Diagnostic system to assist the clinical diagnosis of skin lesions.

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