Boundaries Object Detection for Skin Cancer Image using Gray-Level Co-Occurrence Matrix (GLCM) and features minutiae points

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Abstract

In the present paper, Boundaries Object Detection for Skin Cancer Image using Connected Components is proposed. We propose Connected Components algorithm which that capable of Segment with Extraction of connected boundaries for Skin Cancer Image Segmentation . The algorithm is proposed to create a color label image using the local features minutiae points in skin cancer as objects image . The performance of object Detection with Connected Components which are surround influence . The proposed scheme can serve as a low cost preprocessing step for high level tasks such shape based recognition and image retrieval. The experimental results confirm the effectiveness of the proposed algorithm.

Keywords
Skin cancer image, Image Segmentation, Object Detection, Extraction of connected boundaries ,Connected Components .

1- Introduction

Skin has the advantage of being non-sensitive to directions, so we can separate skin regions other parts of the color images and segment face regions accurately through post-processing. The application of color can provide valuable candidate region when detecting stationary targets[1].

Skin color and textures are important cues that people use consciously or unconsciously to infer variety of culture-related aspects about each other. Skin color and texture can be an indication of race, health, age, wealth, beauty, etc. [2]. Skin detection is one of the basic subjects in image processing. In many cases such as human detection and tracking, visual identification and face detection, a skin detection stage is needed. The concept of "skin detection" in an image is the classification of the existence pixels in that image into two skin and Non-skin classes. In this direction, several methods have been presented until now. In most of the proposed methods, researchers have tried to define and extract a feature vector for each pixel of image and in the end, classify the feature vectors[3].

Most of the currently applied anti-cancer agents do not greatly differentiate between cancerous and normal cells. In addition cancer is often diagnosed and treated too late, when the cancer cells have already invaded and metastasized into other parts of the body. At the time of clinical presentation, a great percentage of patients with breast, lung, colon, prostate, and ovarian cancer have hidden and over metastatic colonies[4].

Therefore image processing become our choice for an early detection of the skin cancer, as it is non-expensive technique. The identification of the edges of an object in an image scene is an

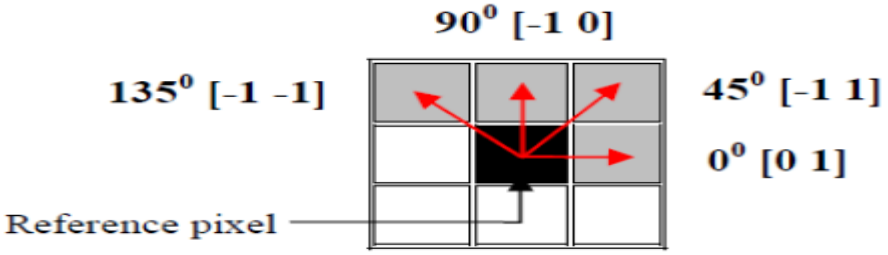
important aspect of the human visual system because it provides information on the basic topology of the object from which an interpretative match can be achieved. In other words, the segmentation of an image into a complex of edges is a useful prerequisite for object identification. However, although many low-level processing methods can be applied for this purpose, the problem is to decide which object boundary each pixel in an image falls within and which high level constraints are necessary[5].

The rest of the paper is organized as follows: Section 2 describes the process of Gray-Level Co-Occurrence Matrix (GLCM), Section 3 describes the process of building the System Design ,summarizes the steps of our algorithms and shows the experimental results obtained using our method. Section 4 gives concluding remarks.

2. Gray-Level Co-Occurrence Matrix (GLCM)

Grey Level Co-occurrence Matrices (GLCM) are one of the earliest techniques used for image texture analysis. The level up to which the subdivision is carried out depends on the problem being solved. A human skin color model is used to decide either a pixel is skin color or non-skin-color[6]. Texture is an important characteristics used in identifying regions of interest in an image. Grey Level Co-occurrence Matrices (GLCM) is one of the earliest methods for texture feature extraction proposed by Haralick et.al. back in 1973. Since then it has been widely used in many texture analysis applications and remained to be an important feature extraction method in the domain of texture analysis[7].

The details of the process to generate four symmetrical co-occurrence matrices considering a 4×4 image represented with four gray-tone values from 0 to 3. For the purpose we considered one neighboring pixel (d=1) along four possible directions as {[0 1] for 0^0; [-1 1] for 45^0; [-1 0] for 900 and [-1 -1] for 135^0]}[8].



Figure(1) Co-occurrence matrix directions for extracting texture features

The quantization level is an equally important consideration for determining the co-occurrence texture features. Also, neighboring co-occurrence matrix elements are highly correlated as they are measures of similar image qualities .Statistics applied to co-occurrence probabilities are [9]:

1- Contrast: It is the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the principal diagonal and features low spatial frequencies.

$$\text{Contrast (con)} = \sum_i \sum_j (i-j)^2 g_{ij} \quad \text{.....(1)}$$

2- Correlation :Measures the joint probability occurrence of the specified pixel pairs. The correlation feature is a measure of gray tone linear dependencies in the image.

$$\text{Correlation (cor)} = \frac{\sum_i \sum_j (ij) g_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y} \quad \text{.....(2)}$$

where μ_x, μ_y, σ_x and σ_y are the means and standard deviations of g_x and g_y

3- Energy: Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment It measures the textural uniformity that is pixel pair repetitions. It detects disorders in textures. Energy reaches a maximum value equal to one.

$$\text{Energy (ene)} = \sum_i \sum_j g_{ij}^2 \quad \text{.....(3)}$$

Where gij = (i,j) th entry in GLCM , $g_x(i)$ = i th entry in marginal probability matrix obtained by summing rows of $g_{ij} = \sum_{j=1}^{N_g} g(i, j)$

4- Homogeneity :It measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. It is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are same. GLCM contrast and homogeneity are strongly, but inversely, correlated in terms of equivalent distribution in the pixel pairs population. It means homogeneity decreases if contrast increases while energy is kept constant.

$$\text{Homogeneity (hom)} = \sum_i \sum_j \frac{1}{1 + (i - j)^2} g_{ij} \quad \text{.....(4)}$$

In the next step we find connected components in binary Skin image .The basic steps in finding the connected components are:

1- Search for the next unlabeled pixel, p.

2- Use a flood-fill algorithm to label all the pixels in the connected component containing p.

3- Repeat steps 1 and 2 until all the pixels are labeled

The four structure field for components are :

1-Connectivity: Connectivity of the connected components (objects)

2-ImageSize: Size of image

3-NumObjects: Number of connected components (objects) in image

4-PixelIdxList: 1-by-NumObjects cell array where the kth element in the cell array is a vector containing the linear indices of the pixels in the kth object.

Where

- Contrast for image Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. `Range = [0 (size(GLCM,1)-1)^2]` Contrast is 0 for a constant image.

- Correlation image Returns a measure of how correlated a pixel is to its neighbor over the whole image. Range = [-1 1], Correlation is 1 or -1 for a perfectly positively or negatively correlated image.
- Energy image eturns the sum of squared elements in the GLCM. Range = [0 1] Energy is 1 for a constant image.
- Homogeneity Range = [0 1] Homogeneity is 1 for a diagonal GLCM

3.System Design and Experimental Results

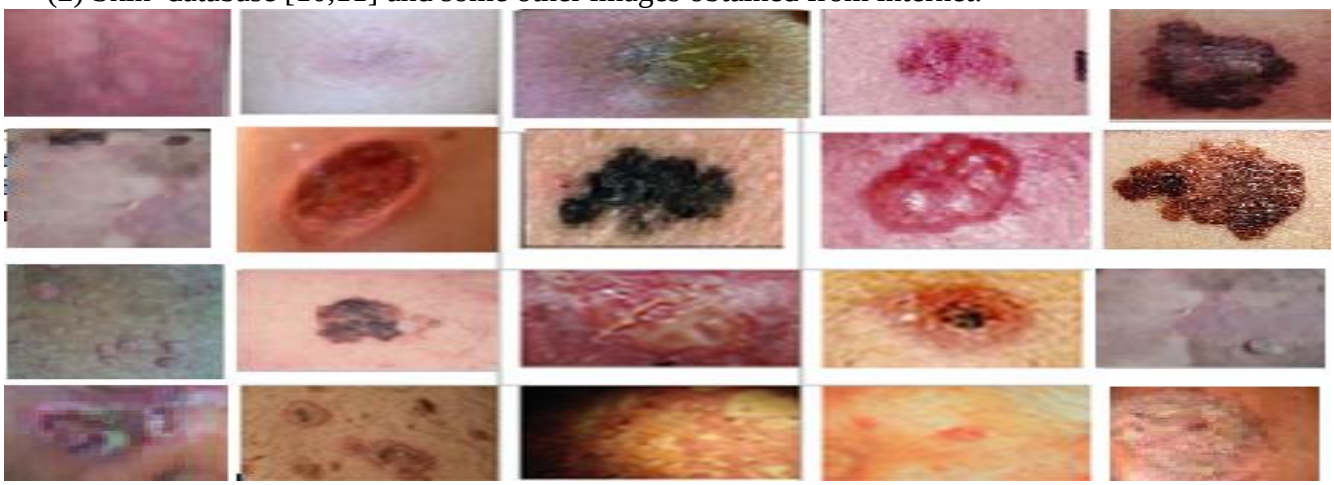
Skin cancer is a disease in which cancer (malignant) cells are found in the outer layers of the skin. The skin protects the body against heat, light, infection, and injury. The skin has two main layers and several kinds of cells. The top layer of skin is called the epidermis. It contains three kinds of cells: flat, scaly cells on the surface called squamous cells; round cells called basal cells; and cells called melanocytes, which give the skin its color[6]. Three processes are done in a sliding window where size is already defined, which is 3x3. For that reason, the original input image matrix must be added with one pixel width of pixel on each side, so that the output of the pixels at the edge of the original image can be calculated.

The steps for Algorithm work are:

1- Start
2- Input skin cancer images
3- Statistics applied to co-occurrence probabilities
4-Find features minutiae points for skin cancer images contains(point number, minutiae coordinates(x,y), Point direction).
5- Comparison between the images by find relationship between extracted points.
6- Draw lines Connected Components
7- Extraction of connected boundaries to segment the Skin Cancer Image.
8- Find Boundaries Object Detection for Skin Cancer Image
9-End

An algorithm is capable of Segment with Extraction of connected boundaries for Skin Cancer Image Segmentation has been presented. We have used two types Skin cancer image databases:

(1) database prepared in our conditions ,images obtained from in Al-Seder Hospital.
(2) Skin database [10,11] and some other images obtained from internet.



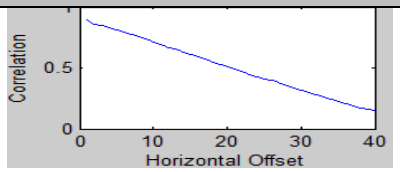
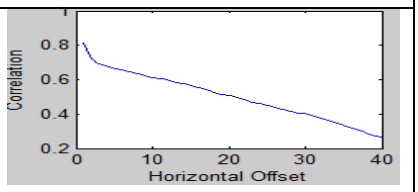
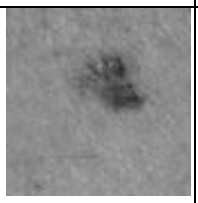
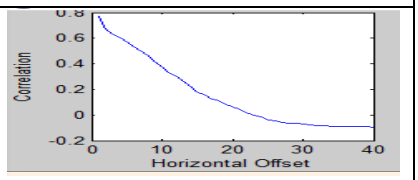
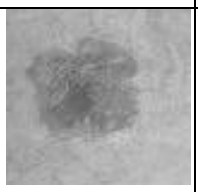
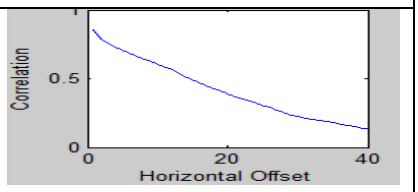
Figure(2): The skin cancer images library for samples of diseases

Table(1) showed Statistics applied to co-occurrence probabilities for sample images and Table(2) Plot correlation as a function of offset for sample images.

Table(1) : Statistics applied to co-occurrence probabilities for sample images

index	Image	Contrast	Correlation	Energy	Homogeneity
1		0.3298	0.9270	0.1646	0.9141
2		0.1558	0.8275	0.3045	0.9223
3		0.0528	0.8105	0.7824	0.9736
4		0.0889	0.8611	0.4754	0.9556

Table(2) Plot correlation as a function of offset

index	Image	Gray image	
1			
2			
3			
4			

The proposed system was applied on 100 images of skin cancer and to find out details of the final results we will take the two images here, one containing the details of the objects and the limits of a few is the image of 1 and the other containing the details of the many is the image of Figure shows us the image of 1 and 2.

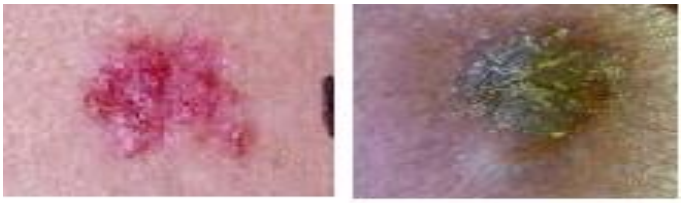


Image 1 Image 2

The minutiae are extacted by scanning the local neighborhoods of each ridge pixel in the image using a 3*3 window. The Crossing Number (CN) value is then computed ,which is defined as half the sum of the differences between pairs of adjacent pixels in the eight neighborhoods. Properties of the Crossing Number(CN) are CN=0 if Isolated point , CN=1 if Ridge End point, CN=2 if Continuing point, CN=3 if Bifurcation point and CN=4 if Crossing point.

Extracted features from thinned image(called minutiae)are used for matching between the original skin image stored in the data base. The algorithm used here depend on Crossing Number(CN) concept. Step3 in algorithm above find number minutiae and minutiae Matrix contain (minutiae no., minutiae coordinates(x,y) begin by 20, minutiae type(end, bifurcation)and minutiae theta) used variables CN:crossing number ,x:raw coordinate ,y:column coordinate, minutiae counter :no. of minutiae found.

Algorithm for Minutiae Extraction

Step1: Start

Step2:Initialize minutiae counter to zero

Step3:For x=20 to (number of row)

For y=20 to (number of column)

Find CN for image(i,j)

If CN=1 or CN =3

Find Theta for image(x,y) with CN found

End if

Minutiae counter = minutiae counter +1

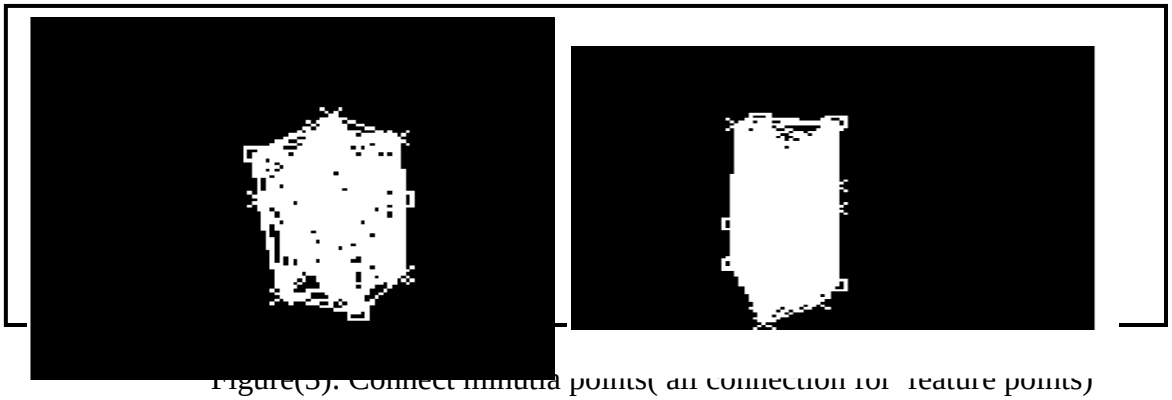
Store minutiae found and its information in minutiae Matrix

End for y

End for x

Step4:End

The result of finding all connections for feature points shown below



Figure(3): Connect minutia points(all connection for feature points)

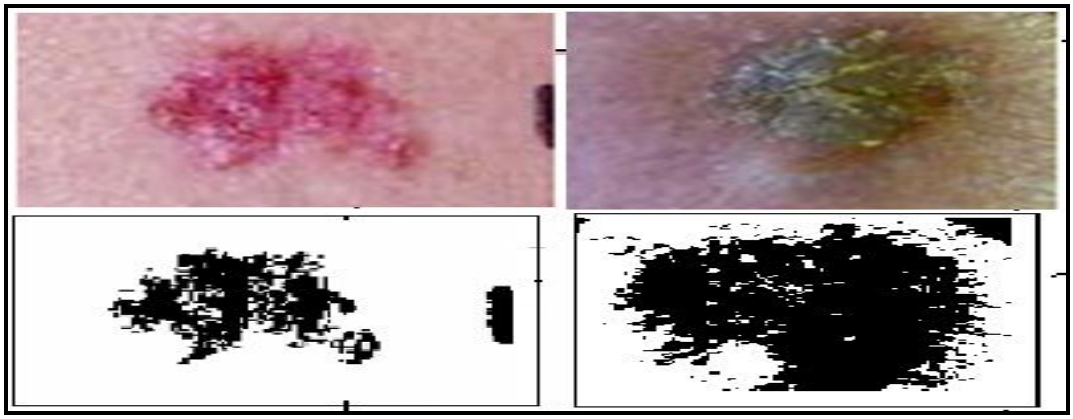
(a)Line Connect for imge1 (b) Line Connect for image2

For Extraction of connected components let **A** represent for all extraction point and **Y** represent a connected component contained in a set **A** and assume that a point p of **Y** is known. Then the following iterative expression yields all the elements of Y

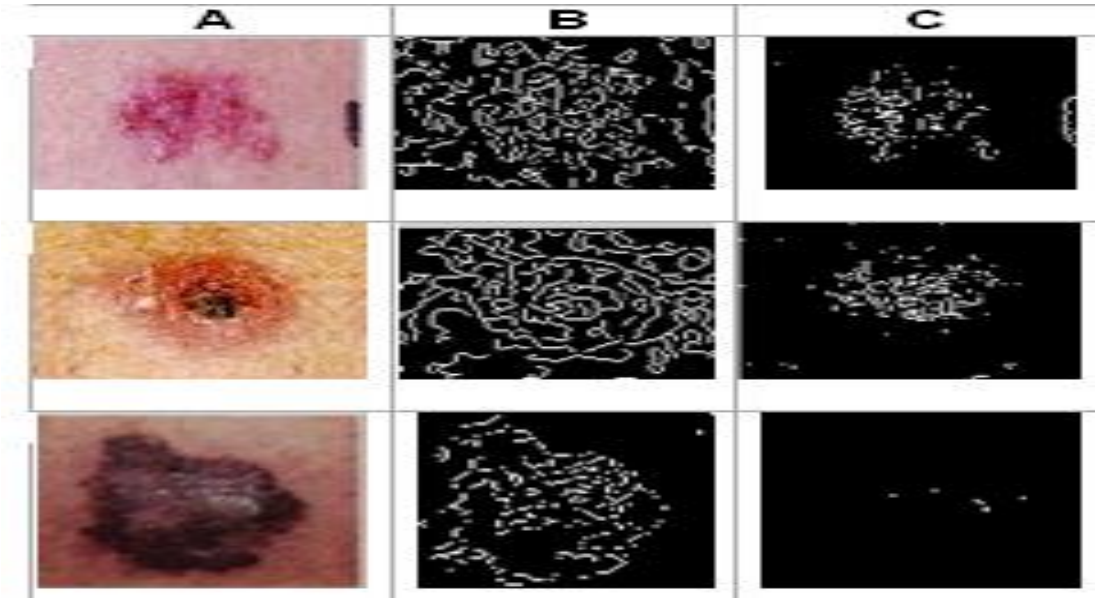
$$X_k = (X_{k-1} \oplus B) \cap A \quad k = 1, 2, 3, \cdots\cdots, n \qquad (5)$$

where X0 = p, and B is a suitable structuring element.

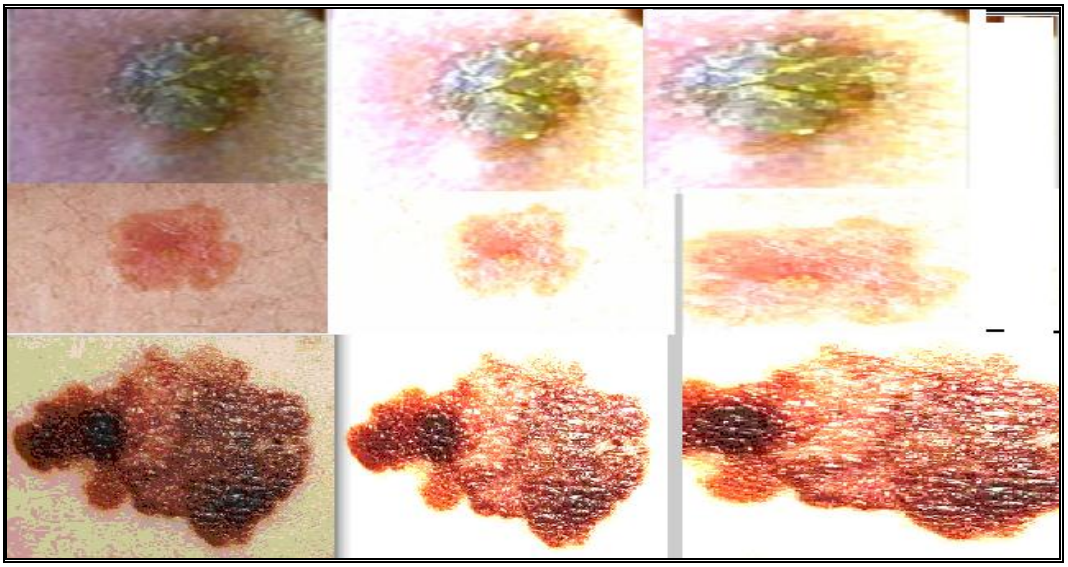
If $X_k = X_{k-1}$, the algorithm has converged and we let $Y = X_k$. This algorithm is applicable to any finite number of sets of connected components contained in A, assuming that a point is known in each connected component.



Figure(4): original Skin images(a),(b) and connected components

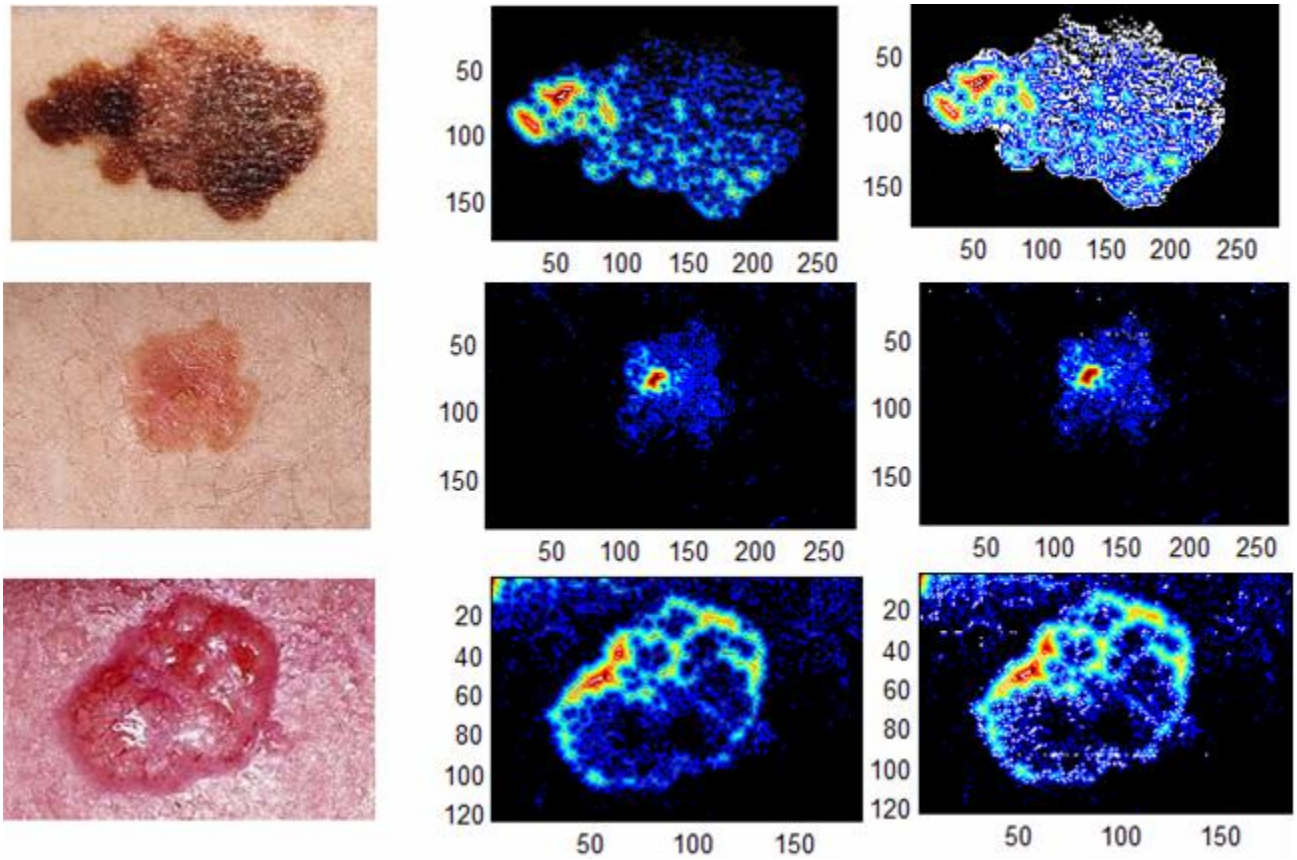


Figure(5):(A):Original Skin Image ,(B)Edge for all region ,(C) Edge for Center Skin Image



Figure(6):(A):Original Skin Image ,(B)objects for all region ,(C) resize objects for all region

Figure (7): Region growing(Green : Boundary pixels of the Region (R), Black and white inside R: Pixels in the growing region R and White outside : Outer neighbor pixels of the region R)
Then find boundaries for Object Detection for Skin Cancer Image in figure (7).



Figure(8): Boundaries Object Detection for Skin Cancer Image

4. Conclusion

We propose new method using the proposed Gray-Level Co-Occurrence Matrix (GLCM) and features minutiae points are capable of Segment with Extraction of connected boundaries for Skin Cancer Image Segmentation . We have proposed an automatic scalable object boundary detection algorithm based on edge detection, and region growing techniques. We have also proposed an efficient merging algorithm to join adjacent regions using adjacency graph to avoid over segmentation of regions. Using smaller number of gray levels (bins) shrinks the size of GLCM which reduces the computational cost of the algorithm and at the same time preserves the high Boundaries Object Detection rates. This can be due to the process of quantization which helps in suppressing the noise of the images at higher grey levels.

Experiment results have demonstrated that the proposed scheme for boundaries works satisfactorily for different levels digital images. Another benefit comes from easy implementation of this method. The experimental results show the satisfying subjective test results and the simulation results are very promising.

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