# Fuzzy Contour based Automatic Segmentation of Skin Lesions in Dermoscopic Images

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**ABSTRACT:**
Malignant Melanoma is considered as the one of the most deadly skin disease if ignored without treatment. The mortality rate caused by melanoma is more than tow times in comparing of other skin malignancies disease. These facts encourage computer scientist to find automated methods to discover the skin cancers. Nowadays, the analysis of skin images is widely used for assistant physicians to discover the first stage of the disease automatically. One of the challenge the computer science researchers faced when try to develop such system is un-clarity of the exist images such appearing of noise like shadows, low contrast, hairs and specular reflections which complicates the process of detect the skin lesions in that images. In this paper, the solution of the above mentioned problem has proposed by using the active contour method, but active contour has a major drawback of seed selection where it should start to process segmentation. In this paper, fuzzy entropy based morphological processing method has been used to find out automatic seed point for active contour. By incorporating this, it can segment the lesion from dermoscopic images automatically. The proposed methodology was tested on standard dataset DermIS and both quantitative as well as qualitative measures was used to check the reliability of the proposed method that shows promising results.

***Keywords:***
*Skin cancer, segmentation, feature, Dermoscopic Images, Melanoma.*

## 1. Introduction

Melanoma is one kind of skin cancer. The recent researches show that melanoma is considered as the most dangerous kind of skin cancer. The important reason is the melanoma caused for around 75% of death related to skin cancer. In 2013, the previous researches show that around 76,690 patients with melanoma and 9,480 of them passed away by the cause of melanoma in United States [1]. Addition to that, 1 in 74 males and 1 in 90 females may infect of melanoma in their life in Canada. Previous researches also show that for non-Hispanic white people, incidence rates have been increased at an annual rate of around 3%. For adults; ages between 15 and 30, melanoma is considered as the most popular diagnose types of cancer [1] [2]. Discovering the melanoma in early stage will increase the probability of remaining alive for 5 years to be 96%. However, in case of discovering it in very advanced stage, that percentage will decrease to 5%. Not only the recovery percentage is affected but also the melanoma treatment cost in advanced stage is 30 times more than the treatment cost of melanoma in early stages [3]. Dermatoscope is a devise that helps the physicians to view the lesion features more clear than naked eye. [4].
The need for computerized skin cancer detecting method is becomes one of the most challenging sciences nowadays. Not only because the detecting process is difficult, but also because the existing skin cancer images may contains noise such as hairs, shadows specular reflections and low contrast that reduce the image quality which cause the accuracy of skin lesion Active contour is a well-known method that can be used for segmentation. In active contour, the main idea is to evolve a segmentation curve. For example, in order to segment an object inside image, the active contour curve is evolving from the initial point till it meets the object's boundary. So starting with the curve around object is main important point in this method. This is the main drawback of the active contour method. This initialization problem also leads to the low performance for concave boundaries and low performance when the contour is started far from the minimum. So one of the main disadvantages of localizing active contour is that sensitive initial boundary to segment the object in the image. Some existing methods has proposed manually assign the initial seed point to start active contour and some methods perform re-initialization if first initialization did not return correct boundary of the object so this computationally expensive as well. For re-initialization method, it will maintain single object segmentation while the initialization method is multiple object segmentation. However, initialization method provides faster computational time than re-initialization. This is the main reason due to which we have proposed a method for initialization of the seed point automatically and it becomes more efficient and faster computational time as compared to re-initialized. Sometimes it also returns more than one object inside each other, which is another drawback.

Manuscript received January 5, 2017
Manuscript revised January 20, 2017

In this research paper, we will review some existing techniques as well as proposed new skin cancer segmentation method.

## 2. Skin Anatomy Overview

The skin and its certain specialized derivatives called appendages constitute the integumentary system. The appendages include the sweat glands, hairs, sebaceous glands and nails. The skin (also called integument or cutis) forms the external covering of the body. It consists of two layers of completely different types of tissues that are attached to each other over their entire extent.

The superficial layer known as epidermis consists of a stratified squamous epithelium, while the deeper layer, called dermis, is composed of dense connective tissue. Together, these two layers form a sheet that varies in thickness from 0.5 to 4 mm in different parts of the body[30].

The skin is generally classified into thick and thin types. The thick type covers palms and soles, while the thin skin is found on remainder of the body. It is important to note that these terms, thick and thin, take into account the thickness of epidermis only, and do not refer to the thickness of the skin as a whole. Fig 1 shows the basics skin layers.

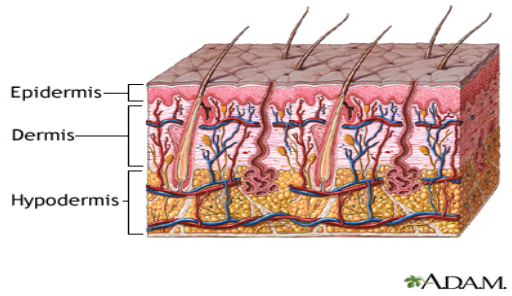


Fig. 1 Skin Layers

### Epidermis

The epidermis is a continuously self-replacing stratified squamous keratinized epithelium. It contains four types of cells: Keratenocytes, Melanocytes, Langerhans cells and Merkel cells. Fig 2 shows the epidermis layers and structures.

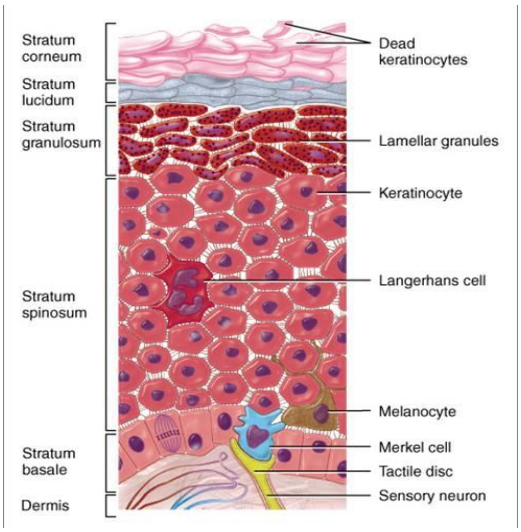


Fig. 2 Skin Layers

### Melanoma Growth Phase

The path of melanoma normally pursues two growth phases [30], namely: Radial growth phase (RGP) and Vertical growth phase (VGP).

Radial growth phase (RGP): This phase generally leads vertical growth phase. During the radial growth phase, cancerous cells spread outward in a radial pattern all the way through the epidermis [31]. At this moment melanin and melanocytes are still constrained to the epidermis (that is to say the skin cancer has not metastasised), so it is considered “in situ”. In order to have a favourable prognosis, this malignant cancer should be detected early when it is its radial growth phase, earlier than the cancer goes into a metastatic vertical growth phase.

Vertical growth phase (VGP): In this phase, melanocytes enter into the dermis deeply, and may also invade the surrounding body tissues through metastatic events. This invasion to distant tissues is very precarious, since the cancer can go wide in the body in several different components of the body [32]. Lesions within the vertical growth phase frequently emerge on the surface as a nodule or bump. This is a really dangerous phase so lesions within this phase need to be immediately addressed.

## 3. Releated Work

Despite of existing research in decision support systems design there exists plenty of room for researchers to explore this research area and propose effective and efficient decision support systems for recognition. In medical domains [6], the methodology for recognition phase mostly utilizes clinical attributes for image matching.

These scientific attributes provide quite useful information to medical experts which assist them in great deal to diagnose the patients. CAD systems are deployed to gain access to experts and practitioners by online access to assist the medical experts to perform their tasks efficiently [7]. These systems are developed by utilizing image visual features but major problem arises in selection of appropriate features during the feature extraction phase. Therefore, this problem will be addressed in our proposed research work to extract and classify the visual features effectively.

In order to segment skin lesion images automatically, a lot of algorithms have proposed. However, like state-of-art algorithms for correction illumination, a lot of proposed segmentation algorithms can be applied only to dermoscopic images, where there is better disparity between particular types of lesions and surrounding skin area [8]. Celebi et al. [9] compiled a newly summary of the popular available algorithms of segmentation for dermoscopic images. In the summary [9],the algorithms are compared include using active contours [10], simple thresholding and region merging [11]. In order to drive the segmentation, a lot of algorithms use only the features derived from pixel color [9]. That implicates the blue channel from the RGB color space, the luminance channel from the CIE 1976 L*u*v* (CIELUV) or CIE 1976 L*a*b* (CIELAB) color spaces, or an orthogonal transform applied to the color channels. However, it is hard to segment lesions accurately with unclear edges when depending only on color features. The designing of these algorithms doesn't work for digital images of skin lesions. In addition, segmentation algorithms based on texture have been used to dermoscopic images. Stocker et al. [12] Have been used the basic statistical methods, such as the gray-level co-occurrence matrix, to analyze the texture in skin images. They found that texture analysis approach could accurately and regions with a smooth texture and that texture analysis can be applied to both segmentation and classification of dermoscopic images. For lesion segmentation, We proposed textural-based algorithms using gray-level co-occurrence matrix [8, 13], first-order region statistics [14], and Markov random field models [15].The new approach proposed by Xu et al. [16] was learning a sample of the natural skin texture in the four edges of the image. The existence of shadows and shining areas caused by lighting variation makes the segmentation process of skin lesion images more complicated. A few different algorithms were explored by Hance et al. [17] including thresholding, active contours and split-and-merge, and change them in order to be specific to lesion images. For Example, in order to account for shining areas, the thresholding algorithm has to be changed. Cavalcanti et al. [18] provided four separate algorithms, including preprocessing step which adjusts the image for lighting variation before thresholding is applied or level-set segmentation algorithm [19]. Thresholding is applied on one color channels [18], multiple color channels and a group of channels derived using main component analysis and other processing steps. Including the pre-processing step helps the algorithms of lesion segmentation proposed by Cavalcanti et al. to perform perfectly. SONALI RAGHUNATH JADHAV, D.K.KAMAT[20] combined Thresholding segmentation technique for founding boundaries in an image with Fuzzy C-Means segmentation to find final segmentation algorithm. S. ManjuBharathi, S. Saraswathi.[21] proposed algorithm based on NC ratio analysis in automatic cell segmentation. The experimental result shows that high efficiency and accuracy of the segmentation process for cancer cells. S. Jeniva, C. Santhi [22] used the concept of texture distribution based on a learned model of natural skin and lesion textures. The texture distribution metric captures the difference between a pair of texture distribution. Then, based on similarity, the images are divided into a large number of smaller regions. This achieves higher segmentation accuracy. Ramya et al. [23] the segmentation approach proposed in this paper focus on identifying skin cancer in the epidermis layer of skin. The nuclei regions; which located in epidermis layer; segment using the K-means clustering algorithm based on space and some color information with k value equal to 3. After that, local region recursive segmentation (LRRS) algorithm which used the intensity and size of nuclei as parameter to filter the candidate nuclei regions is performed to discover the region of nuclei. The final step is applying local double ellipse descriptor (LDED) to distinguish melanocytes from keratinocytes. This approach has good performance even if the original image is complex, where background and foreground both have similar appearance. Nidhalet al. [24] proposed approach uses Wiener filter to remove noise such as hair from the original image. Then, have been using thresholding to segment the skin cancer area of the whole image. Testing this method is provided by comparing the result of segmentation of this approach with the one done by experts in medical filed and measures the distance between these two results by using HM and TDR gives high accuracy with 96.32%. Cheng Luet al.[25] paper proposed segmentation technique of the melanocytes in the skin histopathological image. First, using mean shift and local region recursive segmentation (LRRS) algorithm to extract nuclei areas. Then, the local double ellipse descriptor (LDED) integrates the feature of melanocytes and provides parameters to identify the melanocytes. Using 30 images with different factors as a sample to test this approach, showing that this technique has the ability of segmentation of melanocytes with over 80% sensitivity rate and over 70% positive prediction rate. Binamrata Baralet al.[26] The proposed technique showing in this paper for

segmentation is based on Neuro-Fuzzy model using decision making. Segmentation is performed with some feature works as parameters. This approach gives good accuracy and quality.

## 4. Proposed Method

Our proposed method combines many phases and methods in order to progress the accuracy and robustly of segmentation outcomes. The segmentation processes will be performed to automatic detection and extraction of the lesion from the skin. To segment the image, below steps will be applied:

1. Converting color images into gray image.
2. Applying Fuzzy C Mean (FCM), fuzzy entropy and Morphology based optimal mask selection.
3. The adaptive contour method based upon the optimal mask to segment the skin lesion.
4. Refinement of segmentation using morphology operations.

The segmentation stage will be completely done after applying the above steps. The third step is to extract features from that segmented image.

In this paper, we use adaptive contour (snack) segmentation method. Initialization mask is the most important for active contouring methods to feed the seed point required in that algorithm. One way is to select manually this mask for seed point, but it is very difficult to apply on all types of images. Thus, it is required to propose a method for the selection of mask automatically to apply the active contouring method. We have proposed a technique that based on fuzzy entropy for mask selection. Details of these steps are explained below.

According to many previous studies and researches, there are a lot of methods to perform threshold process. After testing those methods in the real experiments, they may provide accurate result in some cases, but they failed in a lot of them due to the different nature of the images. The main issue the existing algorithms faced is the low quality of the image. Noise sometimes presents in the form of hair or shadow, which affects their results. Those methods must choose either the initial threshold value, which is a big problem, or using calculated average value to be an initial threshold, but using average value may fail in case of low quality/noisy images since the average is not robust to noise. So we used fuzzy entropy technique that gives dynamic and the optimal threshold according to the clusters find out by using well-known method of FCM (Fuzzy C-Mean).

So we used fuzzy entropy technique that gives the number of clusters ,segmented area in our case, after that we will apply fuzzy C-Mean (FCM) to give the optimal threshold.

The mechanism of this technique is described below:

• Fuzzy C Mean (FCM) will apply to the gray image in order to find the optimal threshold; the image will segment into many parts to find out the optimal segments.
• To validate the segments get from the previous step, by using some well-known cluster validity measures.
• Exponential entropy has been used to calculate the optimal threshold value.

Fuzzy C Mean (FCM) will be applied to the gray image to find the optimal threshold.

After that the image will be segment into many parts, we will use fuzzy entropy to cluster the image into many segments.

To select the optimal segment from step2 , we will use Morphology based optimal mask selection.

After applying these 3 steps, the optimal initial point to the adaptive contour will be available. Now we can go to segmentation process.

The objective of this stage is to provide an error function that used to produce dynamic, optimal and adaptive threshold. That threshold will be used in the advanced stage in order to perform the segmentation of the image. The output image from the previous step (Background removal) will be used as input into this stage. First, the input image will be used to find the histogram. Then, based upon the grey level histogram, is fuzzified, and the error function is obtained by determining the contribution of each grey level to the fuzzy entropy of the partition (any fuzziness measure can be employed). We used exponential fuzzy entropy based error functions. The values of the threshold are gained from the error function, as the grey levels with the maximal levels of fuzziness respectively [28].

In order to detect the best seed point and for clear map that represents the lesion in the image, morphological operations has been used. It uses the functions of morphology like opening and closing operation and the structure/synthesized operations of them to produce the image better. There are many factors that affect the accuracy of the output of that algorithm like the feature of structuring element and synthesized modes of the operations. More details, it can consider the synthesized mode of operators reflects the relationship between the processed image & the original one & choosing the synthesized mode will affect the precision and the outcome. Hence, the keys of morphological operations will be generalized for the design of morphological filter structure and the selection of structuring elements. In order to detect the border on the medical images, we have to choose the appropriate structure element by texture features of the image. There are some factors that should be considered like the shape, direction of structuring elements and the size. In most cases, the structuring element is selected to be 3*3 square. Erosion, dilation, opening and closing are the main operations and functions of binary morphology. We

have selected disk-structuring element by using empirical method and size of structuring element used for opening is 9 and for closing it is 25.

Kass was introduced the main concept and the idea of the active contours in his paper 'Snakes: Active Contour Models'[29]. The definition of the snake is a dynamic curve based on parameter, which attempted to move into a minimum energy position. The snack energy can be calculated by using the energy function shown in below formula, which was introduced by Kass.

$$E^*_{snake} = \int_0^1 E_{snake}\left(v(s)\right)ds$$

$$= \int_0^1 E_{int}\left(v(s)\right) + E_{ext}\left(v(s)\right)ds$$

$$= \int_0^1 E_{int}\left(v(s)\right) + E_{img}\left(v(s)\right) + E_{con}\left(v(s)\right)ds$$

\

The energy of the snake segmentation algorithm consists of three major terms. Eint, which denotes the snake's internal energy, Eimg, which represents the forces of the image, and Econ, which rises to external constraint forces. The external snake forces (Eext) can be calculated by summing Eimg and Econ values. The parametric curve "C" is the classical snake that will be used in this research. It is attracted to the area with intense gradients where the normal value of the gradient of any point is high. The principle of snake segmentation is to locate initial contour in the image, which is distorted under various energies. This needs two different kinds of energies internal and external energies.

Internal energy: It depends on the first and second derivatives of the parametric curve that represents the snake. This energy depends on the main properties of the curve and the sum of bending and elastic energy. Below equation shows the internal energy equation.

$$E_{int} = E_{elastic} + E_{bending} = \int_s \frac{1}{2}(\alpha|v_s|^2 + \beta|v_{ss}|^2)d$$

The external energy relates to image characteristics, such as the availability of noise or edges in the image. It guarantees that the snake is on the edge when maximize the amount of the standard gradient over the curve and thus minimize its opposite. External energy (Eext) of the contour is come from the image. It takes on its smaller values of the function of interest for example boundaries. Below equation shows the external energy equation.

$$E_{ext} = \int_s E_{image}\left(v(s)\right)ds$$

First, the initial contour is located in the center of circle in the image. Then, iteration of the algorithm will move, this will cause the total energy to be reduced. A function E will be computed for every neighborhood point (n) of active contour energy point (p). The point p0 attempts to minimizing the energy E0 then choose to exchange contour point P if E > E0. Otherwise, It will keep it the same. This operation will be repeated till convergence. When the contour gained at iteration t is equal to the contour gained at iteration t + 1

After applying the adaptive contour method, sometime it produces more than one segment inside each other. Thus, it is important to fill the big-segmented part. We have used 8 connected neighborhood to fill the larger segment.

## 5. Results and Discussion

In this research, we evaluate the proposed technique performance by using a dataset of 69 dermoscopic images. The images have been collected from Dermatology Information System (DermIS) database [27]. These images belong to the two main classes, melanoma and non-melanoma. The whole number of melanoma images is 43 and it is 26 for non-melanoma. The final result of the proposed segmentation is shown in the table 4. The original image column shows the input image from DermIS dataset. The second column, which is segmented images, shows the output after applying segmentation method. The boundary detection column shows the detection of the boundary of the lesion in that image.

Table 4 shows the original and segmented images after applying the proposed segmentation technique. Some morphology operations have been applied to correct the images and select the mask for the adaptive contour method. We have used adaptive contour method for segmentation. The adaptive contour method required one mask as a seed point to start for segmentation and then it grows with every iteration until stopping condition meet. First, fuzzy entropy has been used to calculate the adaptive and optimal threshold. Based upon this threshold, the image has been segmented and then morphology operations open and closing have been applied to select a specific mask for the adaptive contour method.

Thus, this mask gives a seed point to start adaptive method. Column 1 shows the original images, column 2 shows the segmented binary image after applying the proposed method for segmentation and in the third column, the segmented part is highlighted in the green color in the original image. These images clearly show that proposed method works for all images perfectly. The major reason behind this good segmentation is to find out the optimal mask for active contour. If the extracted mask is good, then segmentation results are very good and effective.

In the previous phase, the segmentation has been performed on dermoscopic images to extract the portion of the lesion. The proposed technique is described in the previous section in detail. In this section only the experimental results are shown.

The performance of the segmentation process is measured and validated by the region base coincidence criteria and Dice Similarity Coefficient that are frequently used in literature. These criterions are given below:

Jaccard Similarity Index for Region Coincidence

The performance of the segmentation method is measured by the Jaccard Similarity Index based on region coincidence criteria [30][31]. The accuracy of the segmentation is measured by the following formula:

$$P(R,A) = \frac{|A \cap R|}{|A \cup R|}, \qquad 0 \leq P(R,A) \leq 1$$

Where $|\ .\ |$, represents the segment area computing operation. A is the ground truth structure and segment R is the detected foreground structure. The factor $|A \cap R|$ indicates how much ground truth structure is detected. The factor $|A \cup R|$ indicates the normalization and this normalizes the accuracy measure. The value 1 indicates the ideal similarity or matching between computed area by system and ground truth.

Dice Similarity Coefficient

Dice Coefficient (Dice, 1945) measures the spatial overlap of two sets. In the proposed system, this method is used to validate the performance of the segmentation method. In our case, the one set is the segmentation by proposed method and the other set is the ground truth segmentation by the expert. The Dice Similarity Coefficient is defined as:

$$DSC_{(A,R)} = \frac{2|A \cap R|}{|A| + |R|}$$

Where A indicates the pixels of segmentation extracted by the proposed system and R is the area by the expert as a ground truth. The value of DSC is ranging from 0 to 1. The ideal value of DSC is 1, i.e. the performance of the segmentation method agrees if DSC values are closer to 1.

## 6. Conclusion and Future Work

In this research, we have proposed new skin lesion segmentation method by combining Fuzzy Entropy based Threshold for Mask Selection, Morphology Operations and Adaptive Contour Method. We use Jaccard Similarity Index for Region Coincidence and Dice Similarity Coefficient to evaluate this method. Our method is shown perfect result when we compare it with the image which segmented by the expert dermatologist. Thus the major contribution is to propose a mask selection for active contour and morphology operations as a pre-processing and post processing of active contour.

In the future, we will extract the features and classify the input skin cancer images into melanoma and non melanoma by using machine learning classifier.

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Table1. Proposed Segmentation steps

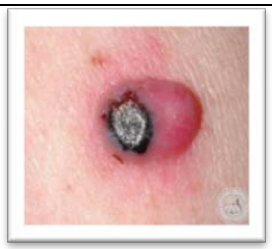
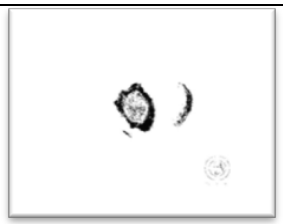
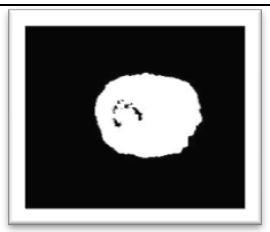
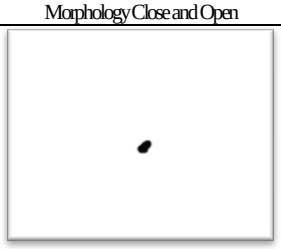
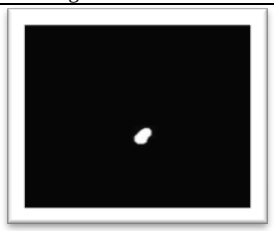
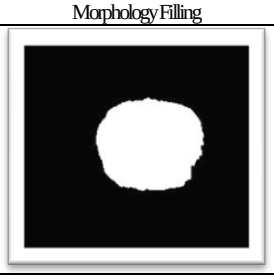
| Original Skin image | Thresholding by using Fuzzy Entropy | Adaptive Contour growing | After Adaptive Contour Segmentation |
|---|---|---|---|
|  |  |  |  |
| **Morphology Close and Open** | **Negative for Seed Selection** | **Morphology Filling** | **Segmented Image** |
|  |  |  |  |

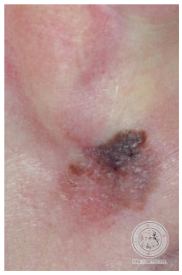
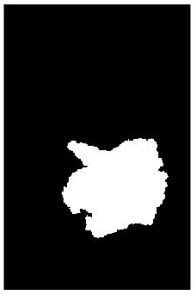
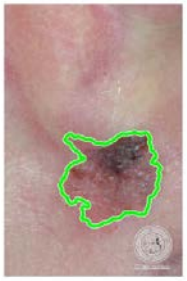
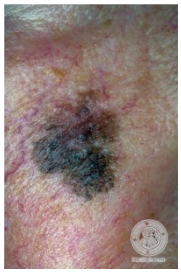
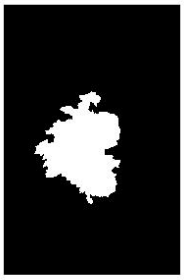
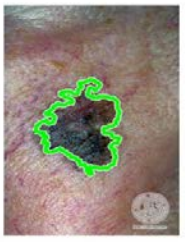
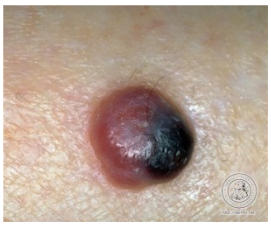
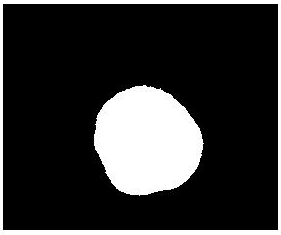
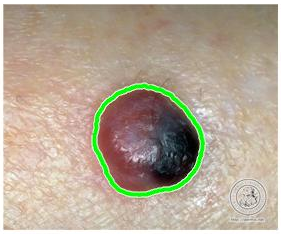
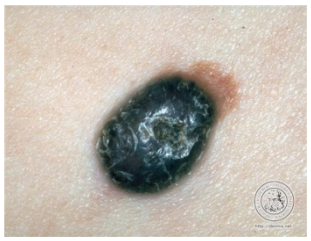
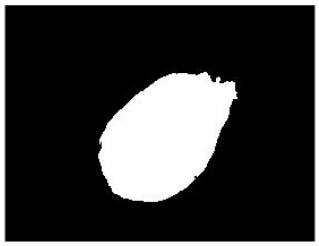
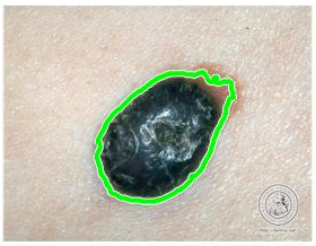
Table 2. Accuracy measure of segmentation with ground truth from melanoma images.

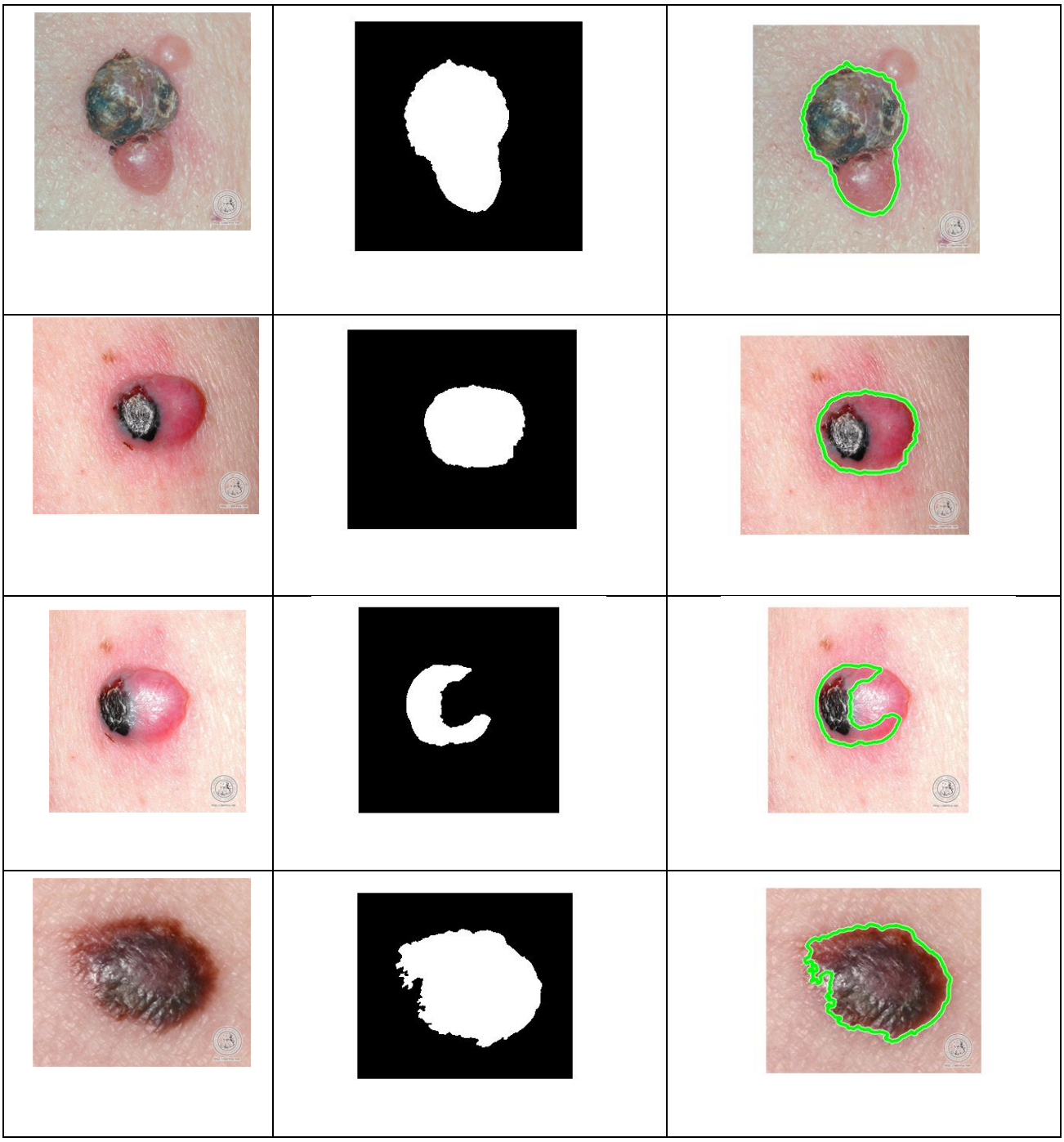
| Dataset | Data Size **(Pixels)** | $\|A \cap R\|$ **(pixels)** | $\|A \cup R\|$ **(pixels)** | P **(Out of 1)** | DSC **(Out of 1)** |
|---|---|---|---|---|---|
| image# 6 | 226x276 | 835 | 845 | **0.967** | **0.963** |
| image# 7 | 226 x 210 | 1794 | 1707 | **0.955** | **0.954** |
| image# 8 | 226 x 276 | 1543 | 1569 | **0.934** | **0.931** |
| image# 9 | 226 x 210 | 1181 | 1189 | **0.924** | **0.952** |
| image# 10 | 224 x 275 | 1303 | 1321 | **0.944** | **0.931** |
| image# 12 | 224 x 275 | 2154 | 2171 | **0.931** | **0.923** |
| image# 14 | 226 x 275 | 1769 | 1784 | **0.947** | **0.951** |
| image# 15 | 226 x 276 | 2711 | 2743 | **0.941** | **0.942** |
| image# 16 | 224 x 276 | 3049 | 3064 | **0.934** | **0.932** |
| image# 27 | 224 x 210 | 1628 | 1643 | **0.942** | **0.943** |

Table 3 The Accuracy Measure of Segmentation with Ground Truth from non-melanoma images

| Dataset | Data Size **(Pixels)** | $\|A \cap R\|$ **(pixels)** | $\|A \cup R\|$ **(pixels)** | P **(Out of 1)** | DSC **(Out of 1)** |
|---|---|---|---|---|---|
| Img44 | 226x276 | 10023 | 10103 | **0.945** | **0.944** |
| Img45 | 226 x 210 | 14324 | 14379 | **0.963** | **0.969** |
| Img46 | 226 x 276 | 3145 | 3304 | **0.952** | **0.958** |
| Img47 | 226 x 210 | 3823 | 4011 | **0.943** | **0.951** |
| Img48 | 224 x 275 | 359 | 367 | **0.927** | **0.923** |
| Img49 | 224 x 275 | 2768 | 2731 | **0.946** | **0.941** |
| Img50 | 226 x 275 | 466 | 456 | **0.933** | **0.939** |
| Img51 | 226 x 276 | 4167 | 4107 | **0.925** | **0.927** |
| Img52 | 224 x 276 | 2572 | 2519 | **0.921** | **0.928** |
| Img53 | 224 x 210 | 933 | 956 | **0.938** | **0.932** |

Table 4 Proposed Segmentation Results

| Original Image | SegmentedImages | BoundaryDetection |
|---|---|---|
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |



## FIGURE LEGENDS

Fig. 1 Shows the human skin layers

Fig. 2 Shows Epidermis Layers and structures of human skin

## TABLE LEGENDS

Table. 1 Shows Proposed Segmentation steps

Table. 2 Accuracy measure of segmentation with ground truth from melanoma images

Table. 3 The Accuracy Measure of Segmentation with Ground Truth from non-melanoma images

Table. 4 Proposed Segmentation Results