ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

A Survey Based On Automated System for Pigmented Skin Lesion.

Melissa S*, and Srilatha K.

Department of Electronics and Communication Engineering, Sathyabama University, Chennai, Tamilnadu, India.

ABSTRACT

This paper reviews different techniques of automated non-invasive diagnostic system used for analyzing skin cancer. Melanoma is the other name for skin cancer. It is one of the diseases which affects the skin layer and leads to fatal, if not diagnosed at an early stage. Skin cancer is divided into two types-benign and malignant melanoma. Malignant melanoma is one of the deadliest skin cancer. Early detection of melanoma can be cured completely. Hence, dermatologists use a device 'Dermascope' to analysis the skin disease. Due to the examination of various patients and diagnosing each of them with careful visual interpretation is time consuming and leads to misdiagnosis. Therefore to minimize such complexities, Computer Aided Diagnostic (CAD) method was introduced which give accurate results than earlier method. This paper focuses on various CAD system techniques which perform a basic function on the dermoscopic images such as preprocessing (filtering), segmentation, feature extraction, and classification.

Keywords: Skin Cancer, Melanoma, segmentation, Dermoscopy, CAD (Computer Analysis of Dermoscopy), feature extraction

**Corresponding author*

INTRODUCTION

Skin is the vital part of human body. Fig (1) shows the image of skin layers. The skin gets affected by various factors such as lifetime sun exposure (UV radiation), sunlamps and tanning booths, medicines (some antibiotics, hormones, or antidepressants that make your skin more sensitive to the sun) which increase the risk of skin cancer [1]. Another name for skin cancer is ‘melanoma'. Melanoma occurs due to the disorder in the synthesis of melanin in melanocytic cells present in the basal cell of epidermis layer of the skin [2]. Basal cell and melanocytic cell are shown in figure (2). Skin cancer is classified into two types-benign and malignant (non-melanoma and melanoma). Malignant melanoma is the most common and fatal disease type of skin cancer. Though the curing of melanoma takes place at a higher rate, yet survivors of melanoma cancer is low than that of non-melanoma [3]. As cases of the skin cancer patient are increasing, there is a great demand for a system to detect and diagnose skin cancer [4]. Melanoma is curable at an early stage.

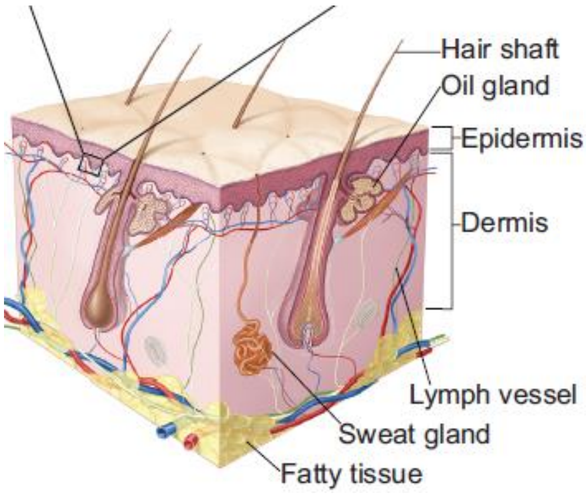


Figure 1: Skin Image

Hence at an earlier period, Dermatologists use a device ‘Dermatoscope' to diagnose any skin diseases [5]. Earlier signs of melanoma are analyzed by "ABCDE" rule: **A**symmetry**, B**orders, Color, Diameter (greater than 6 mm), and **E**volving over time as shown in figure (3). Due to the examination of various patients and diagnosing each of them with careful visual interpretation becomes difficult and lead to complexity in diagnosis. Automated analysis system for skin cancer was introduced. Since, earlier developed automated skin analysis system evaluates the melanoma acquired by digital dermoscopic images [6]-[9].

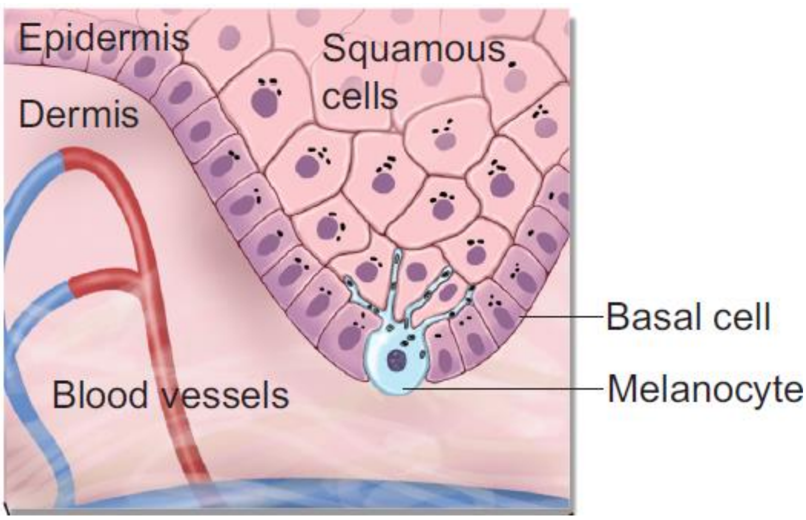


Figure 2: Basal and melanocyte cell Image

Computerized aided diagnostic system of dermoscopic images was introduced which provide an accurate result of the patient at an early stage of skin cancer [10]. A basic CAD system has four steps: Preprocessing (Image noise reduction and hair removal), image segmentation, feature extraction and classification.

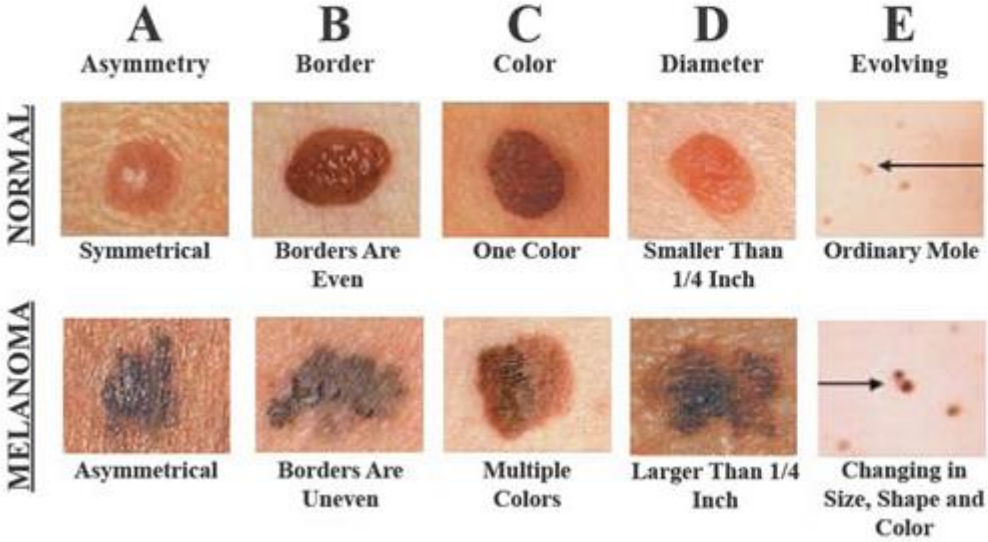


Figure 3: ABCDEs of Detecting Melanoma

METHODOLOGY

Automated Skin lesion techniques follow five basic stages as depicted in the flow chart as shown in figure (4). The following sections elaborate each step in details.

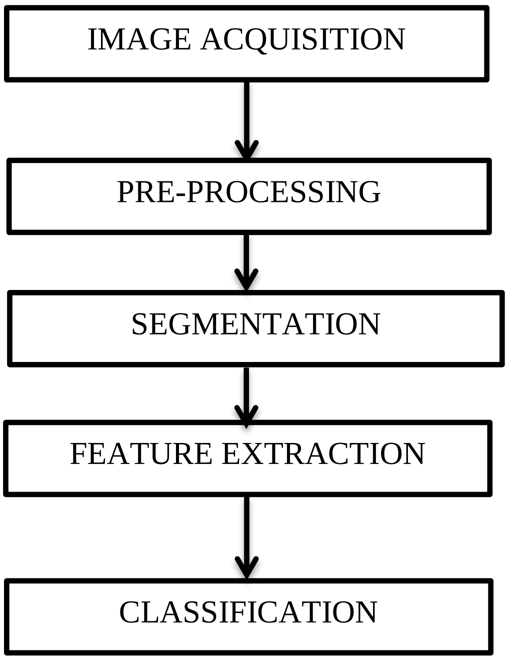


Figure 4: Five stages CAD system for skin lesions

Image Acquisition System

This is the initial process. In this Image Acquisition system, the affected area of the skin is taken in image form [11]. There are two types of image-clinical image and dermoscopic image. The clinical image is taken by a standard camera (photographic image).A dermoscopic image is acquired from a device 'dermatoscope' (handheld microscope), known as dermoscopic technique. In this technique, a liquid (oil or alcohol) is placed in the skin lesion and by using lighting (low angle of incidence or cross-polarization) and magnifier the surface of the skin are seen more clearly. These images (clinical or dermoscopic) are fed to the system for further process explained below.

Pre-Processing

The dermoscopic or clinical image has hair and other noise covering the affected area (lesion) on the skin. Thus, causing inappropriate in output results and becoming a hindrance to the further processing step (segmentation, feature extraction, classification).The removal of noises and hair from the image is done by filtering technique.

Segmentation

Segmentation is a process in which Region of Interest (ROI) is separated from the image. It means the affected areas (lesion) in the skin are isolated from the input image. Segmentation method plays a vital role in image processing technique [12]. There are four basic methods upon which different types of segmentation method are classified:

- Threshold
- Region based
- Edge based
- Clustering based

Feature Extraction

It is the process in which characteristics of the segmented image are calculated by evaluating the image parameters like texture, color, and shape.

Classification

The last step is classification. There are many existing classification methods as mentioned in (paper to be listed).The input image parameters (features) extracted during feature extraction is fed into the classifier, which classifies whether the affected area (lesion) in the skin are benign or malignant i.e., cancerous or non-cancerous.

LITERATURE REVIEW

	UV index	Skin Type	Environment	SPF Level	ITSB (minutes)	National weather service (minutes)
Case I	3	Light Skin	Snow	10	3	35-45
Case 2	9	Medium Light Skin	Cloud	None	2	18-28
Case 3	5	Fair light Skin	Water (sailing)	30	5	50-60
Case 4	2	Medium Dark Skin	Sand	None	1	100-110
Case 5	8	Dark skin	Grass (park)	15	1	125-135
Case 6	7	Light Skin	Building (city)	20	4	40-50
Case 7	6	Deep Dark skin	Sand	5	7	70-80
Case 8	I	Fair light Skin	Snow	40	3	300-310
Case 9	4	Dark skin	Cloud	None	9	90-100

Table 1: Evaluate data and TTSB values provided by the national weather service.

ISSN: 0975-8585

Omar abuzaghleh et al [13] proposed a novel real-time automated image analysis technique for early detection of melanoma in the skin.It contains two models. The first model is a real-time alert system which aide the user to detect the skin burn caused by the sun rays.It uses 'time to skin burn' (TTSB) novel equation to derive the burn frequency level and UV radiation index level as shown in Table (1).

The second model is an automated dermoscopy image analysis system. In this system, firstly the RGB skin image (color image) is converted to a gray scale image. In order to exclude the hair from the image, it is passed through 2-D Gaussian filter .After the image is filtered, the skin lesion is segmented using Otsu thresholding method. The output image after segmentation has irregular edges in the image. The edges are smoothened by radial decomposition using periodic lines. Then the feature extraction of the image is done by five different feature set (2D-Fast Fourier Transform, 2D-Discrete Cosine Transform, Complexity Feature set, Color Feature Set, Pigment N/W Feature set). Finally, the extracted features are passed to the three types of classifier-one-level classifier(A), two level classifier(B, C) to predict the type of skin cancer (Atypical, benign, melanoma).All the classifiers use Support Vector Machine(SVM) classification.

<table>
<tr><td rowspan="2"></td><td colspan="2">Classifier I (%)</td><td colspan="3" rowspan="3">Classifier II (%)</td></tr>
<tr><td>B</td><td>Ab</td></tr>
<tr><td>Benign (B)</td><td>96.3</td><td>3.7</td></tr>
<tr><td rowspan="3">Abnormal (Ab)</td><td rowspan="3">2. 5</td><td rowspan="3">97.5</td><td></td><td>At</td><td>NI</td></tr>
<tr><td>Atypical (At)</td><td>95.7</td><td>4.3</td></tr>
<tr><td>Melanoma (M)</td><td>2.5</td><td>97.5</td></tr>
</table>

Table 2: Results of Classifier (I and II)

Thus, the classification results classify the benign, atypical & melanoma images with an accuracy of 96.3%, 95.7%, 97.5% respectively as tabulated in Table no.2. The proposed system achieves high classification accuracy and detects melanoma at an early stage and prevents further problems.

Chen Lu et al [14] presents a new method for epidermal area segmentation in skin whole Side image (WSI).To achieve effective segmentation, the monochromatic color should be determined first. Hence, the red channel of the original RGB image is determined .First, this method performs initial segmentation by Otsu thresholding and eliminate unwanted region using shape analysis on the binary image. Then, the Template matching (TM) method is carried out depending upon the outcome result of initial segmentation. An automatic circle shape template is created for TM method. This template is applied to the red channel to increase the signal on the melanocytic epidermal region .This method gives a response value image where the melanocytic region is represented by higher response value and other regions by lower value response. Finally, Probability Density Function (PDF) analysis is done by calculating the threshold value for effective epidermal segmentation. The final threshold value is obtained by finding the average between initial segmentation threshold value and the present higher response value obtained from TM method.

Technique	ASEN%	ASPE%	APRE %
EMBS	91.68	99.76	56.05
CLAHE	93.93	96.94	53.80
the proposed	95.68	99.41	93.13

Table 3: Proposed system performance evaluation of the epidermis segmentation

Thus, this system has evaluated 105 skins WSI and has achieved better segmentation result of sensitivity at 95.68% and the precision rate at 93.13 % as shown in Table no.3

Aswin et al [15] this paper presents a new system for detecting the skin cancer at an early stage. In this algorithm, the first step is to remove the noise and refine the border of the dermoscopic image. The removal of hair is done by Dull Razor software and the noise is filtered using a mean filtering technique as shown in figure (5).

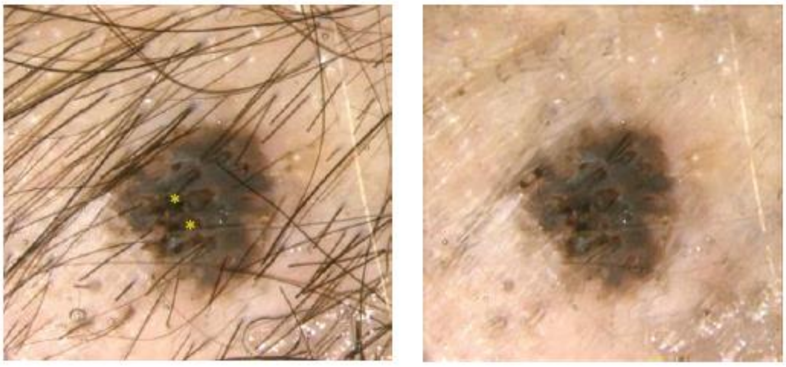


Figure 5: (a) Image containing hairs (b) Image after hair removal

After filtering, Otsu threshold segmentation is done on the image in order to isolate the pigmented lesion area of the skin for next process as illustrated in figure (6). Now to identify the type of lesion, the feature extraction is done via Gray Local Co-occurrence Matrix (GLCM) and Normalized Red, Blue, Green methods. Malignant melanoma is identified by high contrast value and variation of mix red, blue, green colors as benign melanoma has low contrast and uniform color .finally the extracted feature is classified to cancer lesion or non-cancer lesion. The classification is done by Artificial Neural Network (ANN) through Hybrid Genetic Algorithm (HGA).HGA gives an accurate and optimized value.

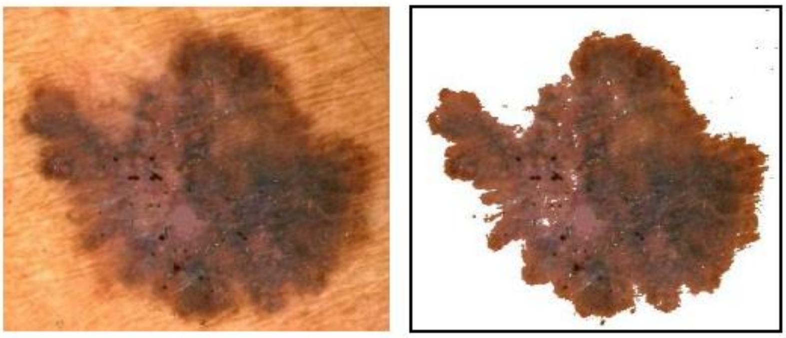


Figure 6: Image before and after segmentation

Thus, the system was trained with 30 sets of melanoma datasets and produces an overall accuracy of 88%.

Mariam Ahmed et al [16] have designed a new automated system for diagnosing pigmented skin lesions. Both clinical image (standard camera) and dermoscopic image (Dermascope) can be used in this system. The image is resized to 470 × 640 pixels and enhances the border of the lesion. The Image Enhancement is done by two steps-noise filtration (median filter) and then conversion of RGB image to Gray Scale Image. Next step, contrast adjustment and segmentation, where the image is contrasted and the lesion is isolated from the skin background by Otsu threshold method as shown in figure (7).

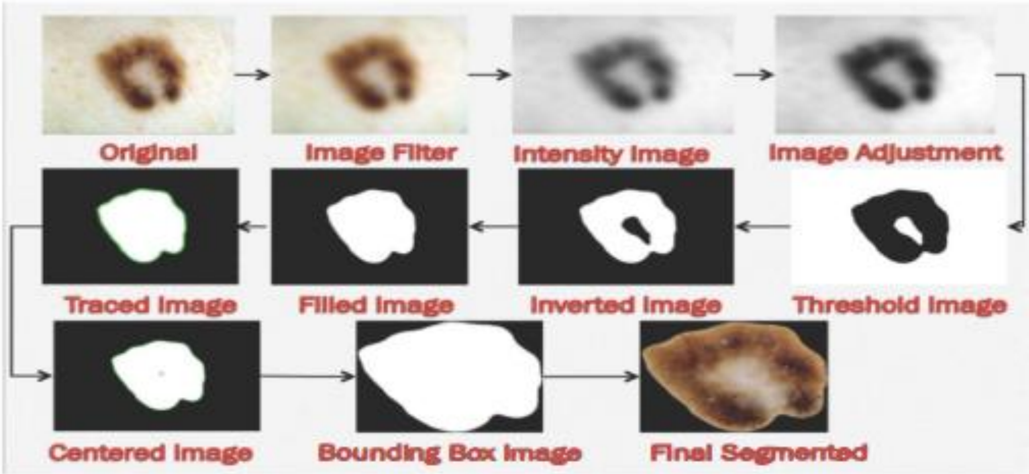


Figure 7: Schematic representation for image Segmentation steps

For extracting the features from the pigmented skin lesion two feature sets-geometric features (Shape) and chromatic feature (color) are used to extract the feature. Extracted features were calculated by two different types of Feature selection t-test and Fisher Score to find the significant one .The selected feature is classified by two classifiers-Artificial Neural Network and Support Vector Machine (SVM).Thus, the designed system was trained with 320 pigmented skin lesion images for clinical and dermoscopic images. The proposed ANN system which has been designed with combined geometric and chromatic feature has Fisher score ranking enable to have accuracy over 95% for dermoscopic images (SVM) and 93.75% for clinical images (ANN).

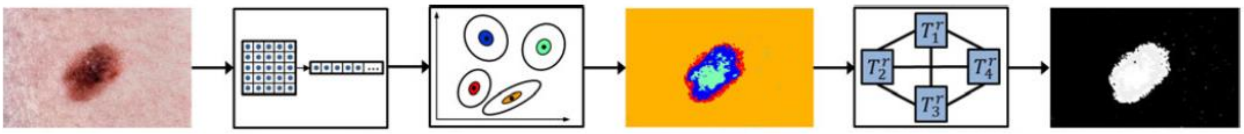
Mohammad Khalad et al [17] This paper presents a novel Computer-Aided Diagnostic (CAD) system for the melanocytic skin segmentation in the histopathalogical image.at the pre-processing stage, the image is resized, cropped and filtered by three filters-wiener, Gabor and adaptive median filter. Before segmentation, histogram equalization is done to enhance the image contrast. Then, this image is segmented by Edge Detection method. The system uses SFS (Sequential forward selection) to reduce the feature parameter and enhance the performance for SVM (Support Vector Machine) classification. The proposed system was analyzed with 42 images of microscopic slides and had gained accuracy of 81%, Sensitivity at 76% and Specificity of 100% as tabulated in Table no.4.

No of images	Sensitivity	Specificity	Accuracy
42	76	100	81

Table 4: Output Result after Training the (SVM) Network with (SFS) Technique

Emre Celebi et al [18] proposed an automated system for dermoscopic images based on clinically significant colors. In this technique, the dermoscopic images which have N colors are reduced to few colors by K-means clustering algorithm. The value of K obtained from clustering algorithm lies between 2 to 16.These values are separately calculated by five cluster validity criteria. After evaluation done by cluster validity, the value acquired from it are analyzed on a set of 617 images by Symbolic Regression Algorithm.Finally, the Regression Algorithm gives a mathematical equation which classifying the skin cancer(benign or malignant).If the output value is lesser than 0.5 it is benign otherwise malignant. This method has acquired an overall accuracy of 72%, Sensitivity of 62% and Specificity of 76%.

Jeffery et al [19].In this paper, a novel segmentation method based on the texture of the skin of the photographic pigmented skin lesion image as shown in figure (8).



(a) (b) (c) (d) (e) (f)

Figure 8: Illustrate the steps to calculate TD metric and learn representative texture distributions (a)Input Image, (b) Texture Representation, (c) Learn Texture Distribution, (d) Sparse Texture Distribution, (e) Texture Distinctiveness modeling, (f) Texture Distinctiveness map.

At pre-processing step , the bright spots and other noise caused by variation of illumination in the photographic image is removed by Multistage illumination modeling (MSIM).This output image is segmented by Texture Distinctiveness Lesion Segmentation (TDLS) method. This method has two major steps. First step, a set of normal skin and lesion skin texture are analyzed on the basis of sparse texture. Sparse texture method is learned by incorporating probabilistic information method and TD metric is calculated. If TD metric value is small, it's a normal skin or else it's a skin lesion. In the second step, classifying the normal and lesion skin based on results produced by sparse texture distributions and TD metric value occurs. Evaluate textural distinctiveness metric based on the distribution of texture then find the initial region by SRM algorithm. Now region distinctiveness metric is calculated using the value of the initial region. Finally the threshold value which defines the two types-normal and lesion skin is evaluated and threshold value 1 represents lesion skin and 0 represents normal skin. After classification, the lesion image is smoothened at edges of the border. This method has achieved total accuracy of 98.3%, Sensitivity of 91.2% and Specificity of 99.0%.

Francesco Peruch et al [20] proposed a new approach for automated segmentation system based in MEDS (Mimicking Expert Dermatologists Segmentation) model .At Pre-processing step; the Virtual Shave (an automated hair removal technique) is used to remove the hairs in dermoscopic images. Then the PCA (Principal Component analysis) tool reduce the color space dimension to 1 i.e., conversion of the color image to gray scale image .The resultant image of PCA has noise which is filtered by the mean filter. Next step, pixels are separated to two clusters (lesion/non-lesion) by MEDS algorithm as shown in figure (9). At last .the patches in the image are removed and classify the image is lesional or not. This method acquires good accuracy for segmentation method than other existing methods.

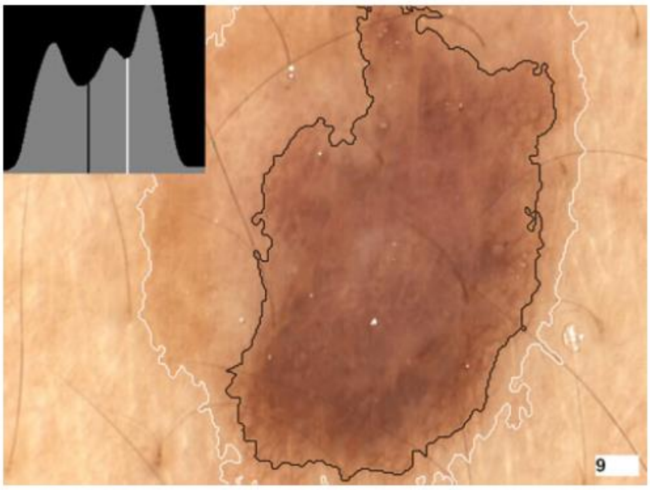


Figure 9: Illustration of separation point between lesional and non-lesional colors as black and white

CONCLUSION

Increasing rate of skin cancer is high in the present scenario. This Survey paper presented a various automated system for analyzing the skin cancer, by highlighting the Computer Aided Diagnosis (CAD) of the present day. Early detection of melanoma is very important, as it can be prevented and cured by detecting at an early stage. CAD (Computerized Aided Diagnosis) System aide in early detection of skin cancer .We have reviewed earlier algorithm used for diagnosing melanoma which have some disadvantages. But these drawbacks are overcome by algorithms based on CAD (Computer Aided Diagnosis) system. Therefore, automated system for detecting and accurate screening of various skin lesions at the early stages of skin cancer is very much needed, so that preventive measures can be taken to cure the lesions.

REFERENCES

[1] Rademaker.M and Oakley.A, Journal of Primary Health Care 2010; 4: 268-272.
[2] Suer.S, Kockara.S and Mete.M,BMC Bioinformatics 2011; 10: 1-10.
[3] Abuzaghleh.O, Barkana.B.D and Faezipour.M, IEEE Southwest Symposium Image Anal. Interpretation (SSIAI) 2014; 85-88.
[4] Abuzaghleh.O, Barkana.B.D and Faezipour.M, IEEE Long Island Syst., Appl. Technology Conference (LISAT) 2014; 1-6.
[5] Iyatomi.H, Celebi.M, Schaefer.G and Tanaka.M, Computerized Medical Imaging and Graphics 2011; 2: 89–98.
[6] Celebi.M.E, Kingravi.H.A, Uddin.B, Iyatomi.H, Aslandogan.Y.A, Stoecker.W.V, and Moss.R.H, Computerized Medical Imaging and Graphics 2007; 6:362–373.
[7] Menzies.S.W, Bischof.L, Talbot.H et al.,Archives Dermatology 2005; 11: pp.1388–1396.
[8] Iyatomi.H, Oka.H, Celebi.M. E, Hashimoto.M, Hagiwara. M, Tanaka.M, and Ogawa.K, Computerized Medical Imaging and Graphics 2008; 7:566-579.
[9] Ganster.H, Pinz.A, Rohrer.R, Wildling.E, Binder.M, and Kittler.H,IEEE Trans. Medical Imaging 2001; 3: 233–239.
[10] Cavalcanti P. G. and Scharcanski J, Computerized Medical Imaging and Graphics 2011; 6:481–491.
[11] Snehal Salunke, International Journal of Image Processing and Data Visualization 2014; 1:1-5.
[12] Saranya.D, Malini.M, International Journal of Advanced Research in Computer Science and Software Engineering 2015; 4: 1043-1047.
[13] Omar Abuzaghleh, Buket Barkana D., Miad Faezipour, IEEE Journal of Translational Engineering in Health and Medicine 2015;1-12.
[14] Cheng Lu, Zhen Ma, Mrinal Mandal, IET Image Processing Journal 2015; 735-742.
[15] Aswin.R.B, Abdul Jaleel.J, Sibi Salim, International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT) 2014; 1304-1309.
[16] Mariam Ahmed Shehal, Amr Sharwy, Mai Mabrouk.S, Cairo International Biomedical Engineering Conference 2014;115-120.
[17] Mohamed Khalad Abu Mahmoud, Mohamed Khalad Abu Mahmoud, IEEE Conference Publications 2014;1-6.
[18] Emre Celebi.M, Azaria Zornberg, IEEE Systems Journal 2014; 3:980-984.
[19] Jeffrey Glaister, Alexander Wong, David Clausi.A,IEEE Transactions on Biomedical Engineering 2014; 4: 1220-1229.
[20] Francesco Peruch, Federica Bogo, Michele Bonazza, Vincenzo-Maria Cappelleri, Enoch Peserico,IEEE Transactions On Biomedical Engineering 2014;2:557-565.