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A Survey on Image Processing Techniques to Detect Melanoma

Neha Katariya¹, Dr. D. G. Thakore², Dr. U. K. Jaliya³
^{1, 2, 3} Computer Engineering Department, BVM Engineering College

Abstract: Cancer a word itself is very impactful to scare a patient. So, it is very important for the physicians to detect cancer in its early stage and try to prevent it before it become reason of life loss. From last some years a melanocytic cancer become a most death causing cancer in the human kind. Dermatologist are expecting a computer aided system that can detect it in early stage. In this paper we present a survey on available image processing techniques to detect melanoma. Image pre-processing techniques like thin artifacts removal methods and wiener filter. Image segmentation methods like automatic border detection, Otsu's thresholding followed by binary tracing and adaptive thresholding; some feature extraction techniques like geometry-based method, feature extraction using Gray Level Co-Occurrence Matrix (GLCM) and color correlogram & texture analysis; and some classification techniques like support vector machine, Bayesian classifier and extreme learning machine are presented. **Keywords:** Melanoma, Pre-Processing, Segmentation, Feature Extraction, Classification.

I. INTRODUCTION

The skin is the layer all over the body that protects against sunlight, injury etc. Skin plays an important role in control of body temperature, storage of water and fat of the body. Nowadays, skin cancer has become one of common reasons behind death. Basically, skin cancer is the abnormal growth of cells, most often bloom on body skin uncover to the sunlight [1].

There are three types of skin cancers in medical science. The most common one is Basal cell carcinoma, second one is Squamous cell carcinoma and the rarest one is melanoma. Non-melanocytic skin cancer always responds to treatments and rarely spread to other skin tissues. Melanoma is the most hazardous than other types of skin cancer [1]. Out of 100 skin cancer related deaths 75 are because of melanoma [2]. It has affected large sector of population in United State and Australia. It is responsible for the death of more than 10000 people in 2016. Normally malignant melanoma begins on upper layer of skin where it is easy to see and treat. Then it spread deep into the skin and reaches at the blood vessels. Finally, it will spread to other part of the body and start affecting organs [4].

Therefore, in last few years, many computer aided diagnosis (CAD) systems of digital dermoscopic images have been developed for automatic detection of melanoma [2]. These approaches use single features like color, shape or size or combined features to characterize the lesions, reporting suitable terms in accuracy [7]. Initially dermatologist are uses a ABCD (A- Asymmetry, B- Boundary, C- Color, D- Diameter) rule to detect melanoma. But, very known fact is that computer aided systems are faster and accurate.

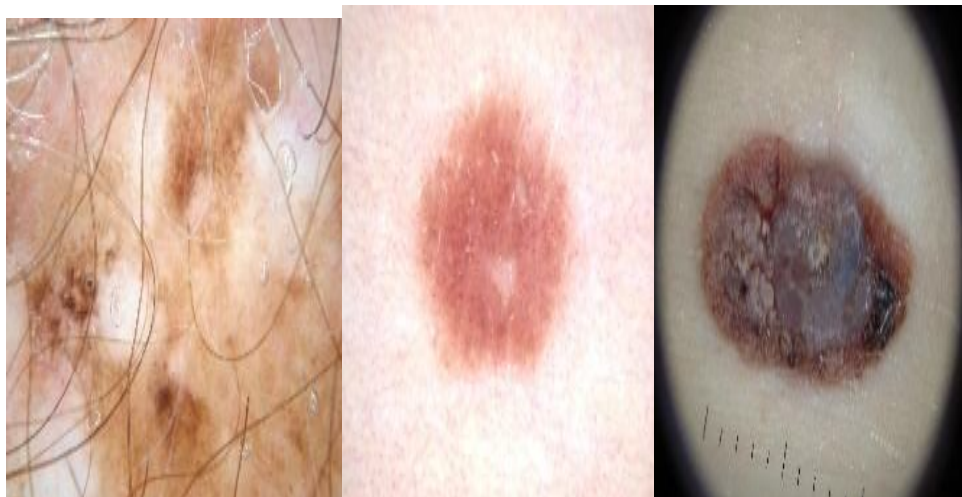


Fig. 1 Skin lesion images of melanoma cancer [14]

II. IMAGE PRE-PROCESSING AND SEGMENTATION TECHNIQUES

A. Image Pre-Processing Techniques

The reason behind pre-processing an image is to remove some unwanted distortions and noise from the image, enhance image quality, remove artifacts and resizing of image. Here we will discuss some pre-processing techniques in detail.

- 1) *Weiner Filter*: Normally the input image contain noise like hair, to remove such noise from input image a wiener filter is used [10]. In this technique input is skin lesion image then we have to apply gaussian noise to the image and in the end wiener filter is applied on image.
- 2) *Thin Artifacts Removal Methods*: The first method to find artifacts pixels is kernel-base edge detection. In this method the convolution of original image with kernels G_x and G_y is used. Kernels are defined as equation (1)

$$G_y = \begin{bmatrix} -1 & -1 & -1 & 6 & -1 & -1 & -1 \\ -1 & -1 & -1 & 6 & -1 & -1 & -1 \end{bmatrix}, G_x = G_y^T \quad (1)$$

After an original image is filtered with these kernels, results are summed together and thresholded. Thus, only the edges with strong response are considered. In the end morphological opening is used to remove small elements and morphological dilation is used to segment thick hairs [11].

Second method is based on second order derivative of Gaussian. This approach is similar to previous one, only the second order derivative with respect to x and y are calculated here instead of using kernels G_x and G_y . The morphological dilation is not required here, since this method is robust and identifies also the thicker artifacts [12].

Third method is based on mathematical morphology, where in the disk structuring element is defined and morphological bottom-hat filtering is performed. The resulting image is thresholded by the Otsu method and the morphological opening is used to subtract small elements [13].

B. Image Segmentation Techniques

Segmentation is process of removing area of interest from input image [1]. The segmentation step has to be done more accurately, since it affects the accuracy of the subsequent steps of feature extraction from the boundary of the lesion and classification [2].

- 1) *Automatic Border Detection*: This approach is based on the JSEG algorithm. Following the pre-processing step to smooth the image and a color quantization stage, the image is thresholded to approximate outline of the lesion. Then this is refined using region growing on a local homogeneity channel and color base region merging. In the end background regions and isolated areas are removed from the original image, so last regions are merged to give the final segmentation [13].
- 2) *Otsu's Thresholding and Boundary Tracing*: In this approach once the input is converted to grey image, Otsu's method is applied on it. Otsu's method uses trial and error approach to decide threshold, which minimizes inter class variance. Within class variance is defined as a weighted sum which is the variances of the two classes. The class $\alpha_1(t)$ probability is computed from histogram as t . Likewise, you can calculate $\alpha_2(t)$ and μ_2 for the bins greater than t . then binary tracing is applied on segmented to image for further segmentation.
- 3) *Adaptive Thresholding*: We can reduce average error by adaptive thresholding and when two or more techniques are combined, accuracy can be improved further.

The images were at first filtered with the morphological closing filter using disk as structuring element (radius = 5 pixels) in order to remove dark hair median filter (3 x 3 neighbourhood) is applied. After that, an adaptive thresholding method is used by automatically selecting the color component. Then morphological erosion, opening and closing operations have been employed respectively. The erosion encloses edge pixels that connect to neighbouring edge pixels to form a figure. And the closing operation can fill the gap between figures to form enclosed area. Finally, region growing is applied to remove the corners [2].

III. FEATURE EXTRACTION AND LESION CLASSIFICATION TECHNIQUES

A. Feature Extraction Techniques

There are generally 4 main features used to detect melanoma, which is also known as ABCD rule. Where A is for Asymmetry, B is for Border irregularity, C is for Color of the lesion and D is for Diameter of the lesion (includes maximum as well as minimum diameter). Automated border detection is generally first step in the automated analysis of dermoscopy images and is crucial for two main reasons. First is the border structure which provides the important information about accurate diagnosis. Second is the extraction of clinical features like atypical pigment network, globules and blue white areas, which critically depends on the accuracy of detected border [10].

- 1) *Geometry-based Method*: Here goal is to extract some geometric features like Area, Perimeter, MajorAxisLength and MinorAxisLength. Where area is number of pixels of lesion and perimeter is number of pixels of lesion boundary.
- 2) *Major Axis Length*: The length of the line passing through lesion centroid and connecting the two farthest boundary points. The (X_c, Y_c) is given by equation (2)

$$(X_c, Y_c) = \left(\frac{\sum_{i=1}^n X_i}{n}, \frac{\sum_{i=1}^n Y_i}{n} \right) \tag{2}$$

Where n is the number of pixels inside the lesion, and (X_i, Y_i) is the coordinates of the *i*th lesion pixel. discussed about the relation for finding the output of (X_c, Y_c) [11].

- 3) *Minor Axis Length*: The length of the line passing through lesion blob centroid and connecting the two nearest boundary points [10].
- 4) *Asymmetry*: Equation (3) is used to determine asymmetry value. Where, ΔP is Pixel difference, P =Total Pixel count of lesion [10]. $Asymmetry = (\Delta p/p) * 10$ (3)
- 5) *Border*: Equation (4) is used to determine border irregularity. Where, A is Area of lesion, $\pi = 22/7$

$$B = \frac{perimeter^2}{4\pi A} \tag{4}$$

(5)

- 6) *Color Correlogram and Texture Analysis*: In spatial data analysis, correlogram is an image of correlation statistics. The results of spatial data analysis depend on the location of the object being analysed [4]. Color correlogram vector indicates color correlation of neighbourhood pixels in the indexed image. Here a user defined distance vector is present, which indicates the different distances from which the color distribution is calculated. In color correlogram, feature vectors of each image database are computed and values are stored as their color image [5]. Then the vector value of tested images is calculated and compared with the feature vectors of trained images. Correlogram with small distance value is selected to reduce computational cost. The correlogram stores the index value of pairs of colors (i, j) in a table, where i and j are two pixels at a distance d and the d^{th} entry shows the probability of finding j from i. Let [D] denote a set of D fixed distances $\{d_1, \dots, d_D\}$ Then the correlogram, $\gamma^{d_{ci,cj}}(I)$ of the image I is defined for colour pair (c_i, c_j) at a distance d is,

$$\gamma^{d_{ci,cj}}(I) = \frac{1}{P_{ci} P_{cj}} \sum_{\{p_1, p_2 \in I \mid |p_1 - p_2| = d\}} [p_1 \in c_i, p_2 \in c_j] \tag{9}$$

The auto correlation is the spatial correlation between two similar colors. Auto correlogram of image, I is represented by equation (10).

$$\alpha^{d_{ci,cj}}(I) = \gamma^{d_{ci,cj}}(I) \tag{10}$$

Texture: In segmentation Fractal Texture Analysis (SFTA) the fractal dimensions of the segmented region are calculated and then describe the texture patterns of that region [6]. The fractal dimension gives an idea about the boundary complexity and structure. Suppose the binary image is $I_b(x, y)$ then the border image is given by the given equation (11),

$$\Delta(x, y) = \begin{cases} 1, & \text{if } (x', y') \in N_8[(x, y)] \\ & I_b(x', y') = 0 \\ & I_b(x, y) = 1 \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

B. Image Classification Techniques

Most image-based skin cancer classification method follows pipelining of pre-processing, segmentation, feature extraction and classification. Classification usually separates the images into cancerous class or non-cancerous class.

- 1) *Support Vector Machine (SVM)*: SVM takes set of images and classify them into two classes cancerous and non-cancerous. As here we are classifying our images into two classes SVM creates a hyper plan which separate those classes with maximum gape. In given algorithm features extracted using GLCM are given as input to SVM classifier, which classifies the input images into cancerous and non-cancerous class. [1]
- 2) *Bayesian Classifier*: Bayesian classifier is applied to achieve approximate classification result for large data sets. The basic idea of a Bayesian classifier is that it assumes any one feature of image for classification, means output is not related to any of another feature. Here the system classifies images into cancerous, non-cancer on the basis of extracted features. Working of Bayesian classifier is based on Bayes' theorem. According to Bayes' theorem posterior probability can found which is given by the equation (12),

$$\text{Posterior probability, } P(c/x) = \frac{P(x/c)P(c)}{P(x)} \quad (12)$$

where $p(x)$ is prior probability of predictor, $p(c)$ is predictor probability of class and $p(x/c)$ is the likelihood [4].

- 3) *Extreme Learning Machine*: The next step of the process is two-class lesion classification of lesions as cancerous and non-cancerous by utilizing the Extreme Learning Machine (ELM) techniques. ELM is a single hidden layer feed-forward neural network (SLFNs) learning algorithm that at first randomly assigns weights and biases for hidden nodes, and then analytically defines the output weights by using the least square method [15]. ELM achieves superior generalization performance because training phase complete effectively with very less time-consuming learning iteration. For a given a training set consists of N samples (x_i, y_i) with $x_i \in R^d$ and $y_i \in R^d$ the output function y_i with N hidden nodes can be described as follows.

$$y_i = \sum_{j=1}^m \beta_j g(\omega_j x_i + b_j), 1 \leq j \leq N \quad (13)$$

where β_j is the output weights, ω_j the input weights, b_j the biases of the j 'th hidden node. And $g(\cdot)$ is the activation function. It first randomly assigns weights and biases for hidden nodes, and then analytically defines the output weights by using the least square method. Due to the random selection of weights and biases for hidden nodes, the ELM can decrease the learning time considerably and also can achieve superior generalization performance [2].

IV. CONCLUSION

In this survey, we have discussed different methods for melanoma diagnosis, in comparison with clinical diagnosis image processing techniques produce more efficient results to detect melanoma from skin lesion image. The process of melanoma diagnosis is carried out in four stages like pre-processing, segmentation, feature extraction and classification which employs new techniques for getting accurate results. When these techniques are used together and performed on skin lesion images, detection of melanoma in initial stage will be achieved.

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