Skin Lesion Classification of MELONAMA Using ABCD Parameters by Contour Edge Detection

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Abstract- Malignant Melanoma is one of the rare and the deadliest form of skin cancer if left untreated. Death rate due to this cancer is three times more than all other skin-related malignancies combined. Incidence rates of melanoma have been increasing, especially among young adults, but survival rates are high if detected early. Unfortunately, the time and costs required for dermatologists to screen all patients for melanoma are prohibitively expensive. There is a need for an automated system to assess a patient's risk of melanoma using digital dermoscopy, that is, a skin imaging technique widely used for pigmented skin lesion inspection. In this research, we aim to propose an intelligent automated method for identification of the type of skin lesions using machine learning techniques. Two types of texture feature have been used to perform classification of melanoma and non-melanoma. First local information through Local Binary Pattern (LBP) on different scales and Gray Level Co-Occurrence Matrix (GLCM) at different angles has been extracted as a texture features. These features are robust due to scale invariant property of LBP and rotation invariant property of GLCM features. Global information of different colors channels has been incorporated through four different moments extracted in six different color spaces like RGB, HSV, YCbCr, NTSc, CIE L*u*v and CIE L*a*b. Thus a fused hybrid texture local and color as global features has been proposed to classify the melanoma and non melanoma. Support vector machine has been used as a classifier to classify melanoma and non-melanoma. Experiments have been tested on well-known dataset dermis that is freely available on the Internet. The proposed method has been compared with state of the art methods and shows better performance in comparison to the existing methods.

Keywords- LBP, Feature Extraction, Neural Network, Accuracy and Precision

I. INTRODUCTION

Skin cancer is a type of dangerous diseases diagnosed around the world. It can be divided into melanoma and non-melanoma [1]. Melanoma cancer is less common than non-melanoma, however, the probability to spread on the skin tissue and cause fatal is high [2]. Although the skin cancer is death disease and may affect the human life, but it can be treated if detected in early stage. According to the previous researches, if the cancer detected in early stage, the treatment rate will be more than 90% while it will be less than 50% if detected lately [3]. In recent statistical, the most fatal type of skin cancer caused by melanoma. As statistical studies in the United States, It shows that 76,690 patients with melanoma and 9,480 of them passed away with the cause of melanoma in 2013 [5]. In Canada, Melanoma occurred about 1.4% of all cancer deaths. There are around 6500 diagnosed with melanoma and 1,050 of them passed away in 2014 [4]. The expectation of growing the melanoma in Canadians during their lifetime is 1 in 73 women and 1 in 59 men; 1 in 395 women and 1 in 240 men will die of it [4]. During the past 25 years, the incident rate of melanoma has been increased [4]. The 5- year relative survival rate for melanoma is 92% in women and 85% in men [4].One of the most important factors to reduce the mortality rate of melanoma is detecting it early. But distinguishing the skin cancer from other benign pigmented skin lesions is a big challenge and not an easy task even for dermatologists. Several clinical methods have been used to improve diagnostic accuracy, but effective ways to extend the diagnoses to dermatologist are still lacking. Hence, the motivation of developing a computer aided diagnose system was most evident these days. In this research, we will proposed a method to classify the pigmented dermoscopic images into melanoma and non-melanoma.

II. RELATED WORK

Stoecker et al. [6] have been used basic statistical approaches, such as the gray-level co-occurrence matrix, to analyze 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 dermoscopy images. Sonali et al. [7] combined Thresholding segmentation technique to establishing boundaries in image with Fuzzy C-Means segmentation to fi\,m , lml, nd final segmentation algorithm S. ManjuBharathi , S. Saraswathi .[8] proposed algorithm based on NC ratio analysis in automatic cell segmentation. The experimental result shows that high efficiency and accuracy of segmentation process for cancer cell. S. Jeniva , C. Santhi [9] 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 136 IJCSNS International Journal of Computer Science and Network Security, VOL.16 No.4, April 2016 pair of texture distribution. Then, based on similarity, the images are divided into large number of smaller regions. This achieves higher segmentation accuracy. Ramya et al. [10] the segmentation approach proposed in this paper focus on identifies skin cancer in epidermis layer of skin. The nuclei regions; which located on 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 intensity and size of nuclei as parameter to filter the candidate nuclei regions is performed to discover the region of nuclei. 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. [11] The proposed approach uses Wiener filter to remove noise such as hair from original image then, used thresholding to segment the skin cancer area from 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.[12]This 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 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. BinamrataBaralet al.[13]. The proposed technique showing in this paper for segmentation is based on Neuro-Fuzzy model using decision-making. Segmentation is performed with some features works as parameters. This approach gives good accuracy and quality.

III. PROPOSED METHODOLOGY:

Our proposed method combines many steps and techniques in order to get accurate and robust classification results. First, we collect the dermoscopic melanoma & non-melanoma images from DermIs. The second step is to extract features from that segmented image. Since these images have some texture characteristics, we will use two common texture feature extraction algorithms; Local Binary Pattern (LBP) and Gray Level Co-Occurrence Matrix (GLCM). In addition, the color is an important feature, which distinguish skin lesion to others. Hence, extracting color feature is important to important, combining these features together may give us good classification results. The fourth and final step is using NN classifier in order to classify the input image into one of the two classes melanoma and non-melanoma. In next sections, a detailed description of our contribution is mentioned. For more illustration, below diagram shows our proposed method.

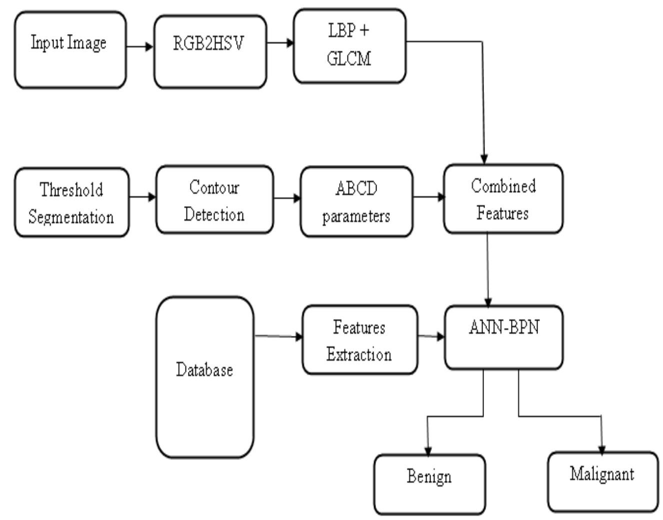
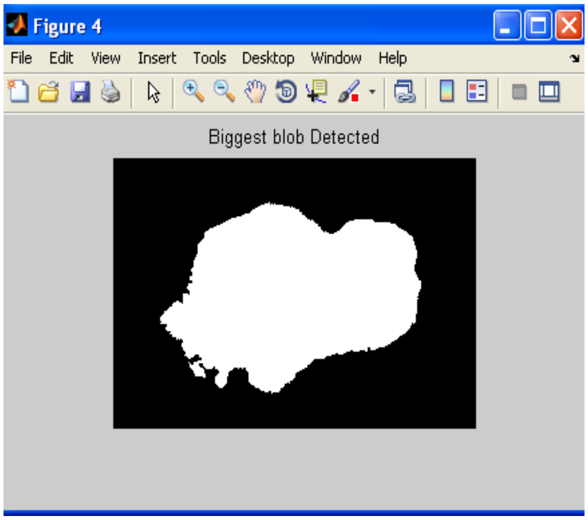


Fig.1 Block diagram of skin lesion

AREA OF SEGMENTATION:

Region of interest (ROI) is extract by segmentation. Segmentation is done using thresholding [7]. The aim of segmentation process is to divide the image into homogenous, self-consistent regions. Segmentation is the process of partition the image into the group of pixels which are homogenous with respect to some criterion [6]. Thresholding technique produces segments having pixels with similar intensities. Usually the cancer remains in image after segmentation. Thresholding is a technique for established a boundaries in image that contain solid objects resting on contrasting background [6]. Segmentation converts any image into a series of Black text written on a White background. Thresholding is a simplest method of image segmentation. From gray scale image, threholding can be used to create binary image. Thresholding can be used to separate light and dark region [8]. Image thresholding classifies pixel into two categories:- Those to which some property measured from the image fall below the threshold, and those at which the property equal and exceeds a threshold



CONTOUR EDGE detection:

The edge is define by pixels where sudden changes occur in the intensity of binarized images. In this paper the lesions are represented by black color and the skin are represented by white color. Scanning the image pixel by pixel, when there is a change in color, the pixel at the same position in the original image receives white color to define the edge of lesion. In order to obtain a result that best represents the edges of the lesion, tests were conducted to evaluate two techniques for skin lesions segmentation: the thresholding and the Chan-Vese model. Both techniques were applied to the smoothed images by anisotropic diffusion. Then it was defined the edges of the lesions from the post processed images by morphological filters

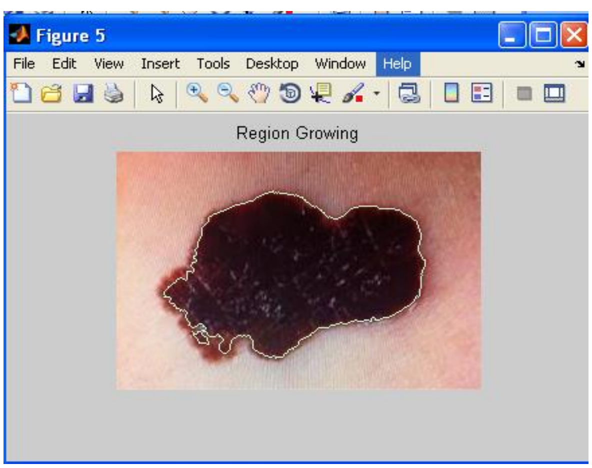


Fig.2 region growing in contour detection

ABCD PARAMETERS:

ABCD parameter (asymmetry, border, color, and diameter) is used to detect the melanoma. The main features of the Melanoma skin Lesion are its Geometric Feature. Hence, we propose to extract the Geometric Features of segmented skin lesion. Here, we used some standard geometry features (Area, Perimeter, Greatest Diameter, Circularity Index, Irregularity Index) adopted from.11 From the Segmented image containing only skin lesion, the image blob of the skin lesion is analyzed to extract the its geometrical features.

The Different Features extracted are as follows:

- Area (A): Number of pixels of the lesion.
- Perimeter (P):
- Number of edge pixels. Major Axis Length or Greatest Diameter (GD): The length of the line passing through lesion centroid and connecting the two farthest boundary points

Major Axis Length or Greatest Diameter (GD): The length of the line passing through lesion centroid and connecting the two farthest boundary points. Minor Axis Length or Shortest Diameter (SD): The length of the line passing through lesion blob centroid and connecting the two nearest boundary points. Circularity Index (CRC):It gives the shape uniformity. CRC = 4A*pi/P^2

- Irregularity Index A (IrA): IrA = P/A
- Irregularity Index B (IrB): IrB = P/GD
- Irregularity Index C (IrC): IrC = P*(1/SD-1/GD)
- Irregularity Index D (IrD): IrD = GD-SD

IV. FEATURES EXTRACTION PROCESS

Feature Extraction starts from an initial set of measured data and builds derived values (features) intended to be informative, non redundant, facilitating the subsequent learning and generalization steps, in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named features vector). This process is called *feature extraction*. The extracted features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classificationalgorithm which overfits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. For example; with an 8 grey-level image representation and a vector *t* that considers only one neighbor, we would find;Entropy, Energy, Contrast, Correlation Coefficient and Homogeneity.

Color is the appearance of an object when exposed to light, this definition will help us understand the chromatic features such as color space. The aspect of color space can be understood through studying the three primary colors such as red, green and blue. The aspect of color mixing can also be demonstrated by employing CMYK as well as HSL among others. The objective of using color feature technique is identifying the presented color in the segmented lesion regions. This can be achieved by extracting four statistics usually called color moments or color feature which is mean, standard deviation, variation and skewness through individual channels of six various color spaces: RGB, HSV, YCbCr,NTSc, CIE L*u*v and CIE L*a*b 3, 7, 8 from that segmented lesion areas. Let P is the color channel, i is the image, N is number of pixels of image on a color space.Pj is the jth pixel of that color channel P of an image i with N pixels in a color space. The definition of the four color features/ moments are shown below: • Moment 1- Mean is the average value of color values in the channel which is calculated by below expression, (1) • Moment 2- Standard deviation is the square root of the variance of the distribution, which is computed by, (2) • Moment 3- characterizes the degree of asymmetry of a distribution around its mean which is given by, IJCSNS International Journal of Computer Science and Network Security, VOL.16 No.4, April 2016 137 (3) • Moment 4- Variance is the variation of the color distribution, which is calculated by below expression. (4) The above described four features are calculated over every single channel which results in 72 color features obtained by the following combination: (4 features) × (6 color spaces) × (3 channels in each color space).

Texture Feature In this research, we combined two features, color and texture. For texture feature, local binary pattern and gray level co-occurrence metrics are combined.

Local Binary Pattern

Local images on the different representations of original skin pigment image .The local Binary Pattern (LBP) is such type of a feature that transforms the image into an array. Hence, we have applied LBP operator on every pixel of the image in order to obtain the coded LBP image. The idea of LBP is to compare each pixel on the image with its neighbors. The procedure is as follows. Each pixel is compared with its 3 x 3 neighborhood that is comprised of eight other pixels. In that process the center pixel value is subtracted by all the neighbors. The resulting negative values are labeled as 0, and all the others with 1. Afterwards, for each pixel, the binary values, starting from the one of its top-left neighbor, are concatenated in a clockwise direction, creating a new binary number. The obtained decimal value is then used for labeling the given pixel and is referred to as LBP codes [20, 21]. Given a pixel (xc, yc), LBP can be formally expressed in decimal form: (5) Where and are gray-level values of the central pixel and surrounding pixels in the circle neighborhood with a radius . The function is defined to be 1 for all $x \geq 0$ and to be 0 for all $x < 0$.

Gray Level Co-Occurrence Matrix (GLCM)

We use five of the classical statistical texture measures of Haralick et al. [14]: entropy, energy, contrast, correlation and homogeneity, which are derived from a grey level cooccurrence matrix (GLCM). The GLCM is a tabulation of how often different combinations of pixel luminance values (grey levels) occur in a specific pixel pairing of an image. Using a two-dimensional gray-level co-occurrence matrix is commonly and widely used in the field of texture analysis In order to find the locative dependence of brightness (gray-level) values, which helps to find valuable information about the neighboring pixels in an image. The definition of co-occurrence matrix p of an image I of size N*N is given below

Discussion and Limitation

One over-arching conclusion can be drawn from the experimental results: Color is important to distinguish melanoma and non-melanoma. Sousing different color channels moments will extract important features. Texture captures relevant information for melanoma detection. We showed that a small set of GLCM can increase classification performance when combined with a large set of LBP features, The performance of the GLCM themselves are not as powerful as we would have hoped, however they do present one significant advantage over large LBP feature sets: a small GLCM set requires much less data to adequately populate the multi-dimensional feature space. A larger data set may allow the LBP set to perform better, as the classifier could be trained on more representative class distributions.

Training Process:

Neural Network:

The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

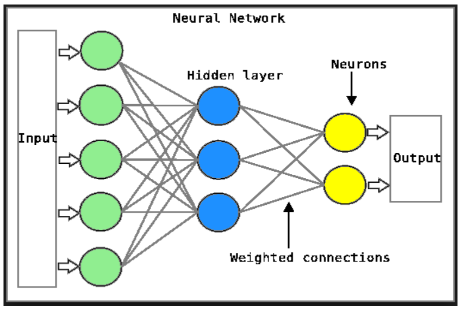


Fig.3: Architecture of Neural Network

V. EXPERIMENTAL RESULTS

Results of a selected part of the real image representing the microscopic image of crystals are presented in Figure. Image segmentation using wavelet transform is able to detect most of image segments even though the problem of fault class boundaries can arise in some cases.

Performance Evaluation:

In the proposed method the performance evaluation is done through statistical analysis, for this first calculate True Positive, False Positive, False Negative and True Negative. From this, Sensitivity, Specificity, Accuracy, Precision and F-measureare calculated.

$$\text{Sensitivity}=TP/ (TP+FN)$$
$$\text{Specificity}=TN/ (TN+FP)$$
$$\text{Accuracy}= (TP+TN)/ (TP+FP+TN+FN)$$
$$\text{Precision}=TP/ (TP+FP)$$
$$\text{F-measure}= (2* \text{Precision}* \text{Sensitivity}) / (\text{Precision} + \text{Sensitivity})$$

VI. CONCLUSION

In this research, we have proposed a new feature extraction technique for classification of dermoscopic images into melanoma and non-melanoma. Two types of features have been used, color and texture. For texture features, GLCM and LBP have been used. Combining these features improves the accuracy of the classification results. In this way, our proposed technique has been able to better classify dermoscopic images intoMelanoma and Non-Melanoma groups. In order to evaluate the usefulness and performance of proposed model, experimentation is performed on standard dataset of dermIS. The experiments showed good results for the proposed methodology. Both qualitative and quantitative error Methods discussed in the paper have been applied to analysis of shapes of microscopic images of crystals. Similar methods can be used in other applications in a wide range of interdisciplinary problems of texture analysis including biomedical imaging, processing of satellite images, communications and remote earth observations.

Future Work

The future work can be implement with other algorithms related to this process when perceive used methodologies have some constraints. Further research will focus on collection of more samples to yield better performance and building an overall system for cancer classification

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