Classification of Dermoscopic Skin Cancer Images Using Color and Hybrid Texture Features

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Summary
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.

Key words:
Feature extraction, glcm, lbp , svm , color feature

1. 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 caused 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.

2. 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

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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.

3. Proposed Method

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 Support Vector Machine (SVM) 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.

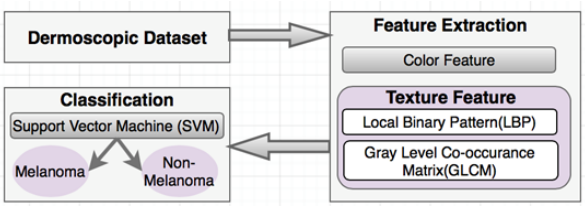

Fig 1 Proposed Method

3.1 Feature Extraction

3.1.1 Color Feature

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,

$$\mu = \frac{1}{N}\sum_{j=1}^{N} p \qquad (1)$$

- Moment 2- Standard deviation is the square root of the variance of the distribution, which is computed by,

$$\sigma = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(p_j - \mu)^2} \qquad (2)$$

- Moment 3- characterizes the degree of asymmetry of a distribution around its mean which is given by,

$$S = \sqrt[3]{\frac{1}{N}\left(\sum_{j=1}^{N}(p_j - \mu)^3\right)} \quad (3)$$

- Moment 4- Variance is the variation of the color distribution, which is calculated by below expression.

$$V = \frac{1}{N}\sum_{j=1}^{N}(p_j - \mu)^2 \quad (4)$$

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).

3.1.2 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.

3.1.2.1Local 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:

$$LBP_{P,R(x_c,y_c)} = \sum_{p=0}^{p-1} s(i_p - i_c)\,2^p \quad (5)$$

Where i_p and i_c are gray-level values of the central pixel and P surrounding pixels in the circle neighborhood with a radius R. The function $s(x)$ is defined to be 1 for all $x \geq 0$ and to be 0 for all $x < 0$.

3.1.2.2 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 co-occurrence 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

$$P(i,j) = \sum_{x=1}^{N}\sum_{y=1}^{N}\begin{cases}1, & if I(x,y) = i and I(x+\Delta_{x,y}+\Delta_y) = j \\ 0, & otherwise\end{cases} \quad (6)$$

Here, the distance between the interested pixel and its neighbor is defined as the offset (Δx ,Δy).
Then, we can extract four different features from GLCM. The feature of Entropy, Energy, Contrast and Homogeneity are given below:

$$Entropy = -\sum_i\sum_j P[i,j]\log P[i,j] \quad (7)$$

$$Energy = \sum_i\sum_j P^2[i,j] \quad (8)$$

$$Contrast = \sum_i\sum_j (i-j)^2 P[i,j] \quad (9)$$

$$Homogeneity = \sum_i\sum_j \frac{P[i,j]}{1+|i-j|} \quad (10)$$

3.2 Classification

We will use support vector machine (SVM) classifier to classify the input image into one of two groups: melanoma and non-melanoma. We chose support vector machine (SVM) to be a classifier in this study since it interprets image much quickly as well as effectively. The support vector machine (SVM) classifier also has the ability for the detection and classification of the complex pattern of data given. All the features of dataset images are being used for the purpose of training. All the data belongs to the same group or classed sharing some features.

4. Results and Discussions

4.1 Dataset

In this research, we evaluate the proposed method performance by using a dataset of 69dermoscopic images. The images have been collected from Dermatology Information System (DermIS) database [15].Those images belong to two main classes, melanoma and non-melanoma. The total number of melanoma images is 43 and non-melanoma is 26.

4.2 Feature Extraction and Classifications

For simplicity of discussion and analysis, the following notation is used throughout this section:

- SL{set of Local Binary Pattern features describing texture}.
- SG {set of GLCM features}.
- ST {set of texture features by appending SL and SG (ST=SL U SG) .
- SC {set of Color chromatic features obtained from four different color spaces}
- S_{TC} {set of texture color features by appending S_T and S_C (S_{TC}=S_T U S_C)

All these different feature sets have been used for training to the SVM and for testing. Three different measures like accuracy, sensitivity and specificity has been measured to check the performance of all these different feature sets.
The performance of classifiers is calculated and analyzed by the following performance measures.

- Accuracy: Number of classified mass / Number of total mass= (TP + TN)/(TP + TN + FP + FN)
- Sensitivity: Number of correct classified malignant mass / Number of total malign masses =(TP) /(TP + FN)
- Specificity: Number of correct classified benign masses / Number of total benign masses

  = (TN) /(TN + FP)

Where TP is True positive, FP is false positive FN is false negative and TN is true negative. The performance of a classifier could be estimated in terms of the number of true positives and false positives. The performance validation measures are accuracy, sensitivity, and specificity.
The results using the classification scheme with the feature sets SG, SL, ST are summarized in table 1. The sensitivity and specificity scores were therefore obtained over 10 independent classification runs. The mean and standard deviation of the accuracy metrics across the 10 trials were used to show the consistency of the results. The best mean results in table 10 are bolded for each metric (i.e., sensitivity, specificity, accuracy). The following observations can be made from the results. ST consistently attains slightly higher accuracy, sensitivity and specificity metrics than the individual feature sets. Scatter plots in below figure shows different features behaviors. Like 1st and 2nd rows show that features are overlapped with each other's and difficult to classify as comparative to the features shown in 3th row where features are separated clearly and less overlapped.

Table 1 Performance Results for Different Feature Sets

	Accuracy (%)		Specificity (%)		Sensitivity (%)	
	μ	σ	μ	σ	μ	σ
GLCM	85.24	2.32	72.56	2.05	88.23	2.34
LBP	87.35	1.04	75.17	2.02	90.24	1.49
Color	83.50	1.24	91.18	1.25	78.14	2.13
Texture	87.98	1.34	77.53	2.42	93.14	1.82
Proposed Method	90.32	2.36	85.84	1.23	93.97	2.05

Analyzing the Results of GLCM Features S_G
Interesting metrics were observed for the SGfeature set. The results show that it attains very high sensitivity (consistently around 90%) but conversely low specificity (consistently below 80%). This behavior is due to the effects exhibited by using a linear classifier in a low dimensional feature space on a small data set. This can be explained by considering the following case.

Analyzing the Results of Local Binary Patterns S_L
Interesting metrics were also observed for the SL feature set. The results show that it attains very high specificity (consistently around 90%) but conversely low sensitivity (consistently below 75%). This behavior is due to the effects exhibited by using a linear classifier in a low dimensional feature space on a small data set. This can be explained by considering the following case.

Analyzing the Results of Texture Features S_T
The results show that ST feature set achieves very high accuracy around 90 % sensitivity (consistently around 90%) and specificity (consistently more than 95%).

Analyzing the Results of Color Features S_C
The most remarkable finding for ST feature set is its very high accuracy around 90 % sensitivity (consistently around 90%) and specificity (consistently more than 95%).

Analyzing the Results of Texture Color Features S_{TC}
ST feature set demonstrates very high accuracy around 90 % sensitivity (consistently around 90%) and specificity (consistently more than 95%).

Table 2. Comparing the proposed results with existing results

Authors	Accuracy (%)	Sensitivity (%)	Specificity (%)
Cavalcanti et. al [16]	79.61	83.19	74.71
Amelard et. al [18]	87.38	90.76	82.76
Amelard et. al [17]	81.17	**96.64**	65.06
Proposed Method	**90.32**	85.84	**93.97**

4.3 Discussion and Limitation

One over-arching conclusion can be drawn from the experimental results: Color is important to distinguish melanoma and non-melanoma. So,using 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.

5. 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 into Melanoma 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 measures are used to assess the system performance.

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