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Perceptual Image Segmentation Using Local Binary Pattern Algorithm for Analysis of Psoriasis Skin Image

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Abstract: Psoriasis is an immune-mediated skin disease that cannot be cured completely but statuesque can be maintained under medication. The proposed work deals with automation for system analysis of psoriasis skin disease using image processing techniques. There are four types of psoriasis viz. Guttate, Nail, Plaque and Pustular. The objective of the paper is to diagnose the type of psoriasis treatment based on color features. The proposed work deals with the perceptual image segmentation using Local Binary Pattern (LBP) feature extraction algorithm. The perceptual segmentation is used to obtain segmentation that produces a small number of segmented regions and each region should represent a meaningful part of an object without paying much attention to region interiors.

Key words: Segmentation, Edge Detection, Psoriasis, Local Binary Pattern (LBP).

I. INTRODUCTION

Now a day's people of different age groups are suffering from skin diseases and lesions such as eczema, scalp ringworm, skin fungal, skin cancer of different intensity, diabetic ulcers, psoriasis symptoms etc. The above said diseases strike suddenly without warning and have been one among the major disease that has life risk for the past ten years. Psoriasis is a genetically determined, systemic immune-mediated chronic inflammatory disease that affects primarily the skin and joints. It has been estimated to affect 1-3% of the general population worldwide. The goal of treatment is to improve and maintain patient's health-related quality of life through control of symptoms and signs of psoriasis. Implementing and regular monitoring of treatment goals based on disease severity and patients' preferences are necessary to ensure long-term effective treatment and to prevent complications from uncontrolled disease activity. If skin diseases are not treated at earlier stage, then it may lead to complications in the body including spreading of the infection from one individual to the other. The skin diseases can be prevented by investigating the infected region at an early stage. The characteristic of the skin images are diversified, so that it is challenging job to devise an efficient and robust algorithm for automatic detection of the skin disease and its severity. Skin tone and skin color plays an important role in skin disease detection. Color and coarseness of skin are visually different. Automatic processing of such images for skin analysis requires quantitative discriminator to differentiate the diseases. So, the choice of color becomes an important component in skin disease detection. Hence, an attempt is made to propose a new system for the analysis of psoriasis skin disease based on the color features. Image Segmentation is the process of partitioning a digital image into multiple regions or sets of pixels. The partitions are different objects in image which have the same texture or color. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. All of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. Segmentation aims at dividing pixels into similar region that is crisp sets. Detection is one of the most frequently used techniques in digital image processing. The boundaries of object surfaces in a scene often lead to oriented localized changes in intensity of an image, called edges. This observation combined with a commonly held belief that edge detection is the first step in image segmentation, has fueled a long search for a good edge detection algorithm to use in image processing. Skin diseases are one of the diseases that are wide spread. Recently there are many machine vision systems developed for skin disease like skin cancer, eczema, scalp ringworm, psoriasis etc. Psoriasis is a common, chronic, relapsing, inflammatory skin disorder with a strong genetic basis. A diagnosis of psoriasis is usually based on the appearance of the skin. So the image processing techniques help in diagnosing the disease by extracting the features from the infected skin images.

The paper is organized as follows. The related work is introduced in section II. Section III, contains methodology. Section IV, contains results and discussions concluding remarks are given in section V.

II. RELATED WORK

Mirmehdi and Petrou [1] proposed the method based on the multiscale perceptual tower and the probabilistic relaxation method. Shi and Malik [2] proposed the perceptual grouping method based on graph theory, and Ma and Manjunath [3] proposed the technique based on the Gabor Filters and the Edge Flow. Carson *et al.* [4] proposed the Blobworld representation based on expectation-maximization

Algorithm, and Chen *et al.* [5] proposed the approach based on the adaptive clustering algorithm and the steerable filter decomposition. Brabazon et. al. [6] have developed online credit card fraud and Artificial Immune Systems, to calculate the effectiveness of Artificial Immune Systems (AIS) for credit card fraud detection using a large dataset obtained from an on-line retailer. Three AIS algorithms were implemented and their performance was benchmarked against a logistic regression model. Shailesh S. Dhok [7] presented credit card fraud transaction for online shopping, paying bills, it is shown that credit card fraud can be detected using Hidden Markov Model during transactions. Mohd Avesh Zubair Khan et. al. [8] system to detect the Credit Card developed a Fraud, modeled the sequence of transactions in credit card processing using an HMM and k-means clustering A. K. Jain, A. Ross, and S. Prabhakar , U. Park, Y. Tong, and A. K. Jain, R. Gross, S. Baker, I. Matthews, T. Kanade, G. Hua and A. Akbarzadeh [9, 10, 11, 12] focused on face .Anal Kumar Mittra et al.[13] proposed an automated system for recognizing disease conditions of human skin using texture feature. Disease conditions are studied by using Gray Level Co-occurrence Matrix. Multilayer

Perception (MLP) classifier is used to detect the diseases and they have obtained 96.6% accuracy for disease detection. S.Arivazhagan et al.[14] presented an automated system for recognizing human skin diseases using texture

Features. The texture features are extracted from the gray level run-length matrices and Minimum Distance Classifier is used to classify the type of human skin diseases and have obtained an accuracy of 92.72%.

Alaa Yaseen Taqa et al. [15], developed a robust skin detection method that integrates both color and texture features. The Back-propagation neural network is used for classification. They found that their proposed skin detection method achieves a true positive rate of approximately 94.5% and a false positive rate of approximately 0.89%. Color, texture and shape features are integrated by Zhiwei Jiang et al. [16] for the detection of skin disease. A marker driven watershed transform is used to demonstrate the accuracy of 94.8% C.Prema et al.

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III. PROPOSED METHODOLOGY

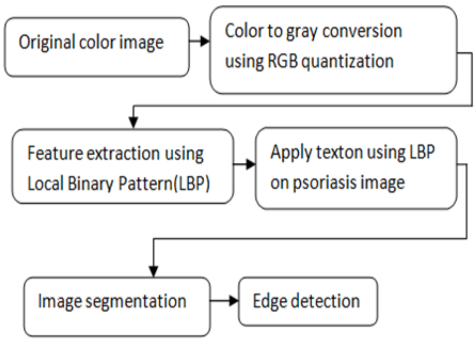

Fig1.proposed methodology

The proposed segmentation methodology is shown in figure1.

Step1:

The input images of psoriasis are used to convert color image to grey level image based on RGB color quantization method as shown in figure1. In order to extract grey level features from color information the proposed Local Binary Pattern method utilized the RGB color space which quantizes the color space into 8-bins to obtain 256 grey levels. Color is one of the most important features that make possible the recognition of images by human. Color is a property that depends on the reflection of light to the eye and the processing of that information in the brain.

Step2:

Texture, on its own does not have the capability of finding similar images, but it can be used to classify textured images from non-textured ones and then combined with another visual attribute like color to make the retrieval more effective. Analysis of texture requires the identification of those texture attributes which can be used for segmentation, discrimination, recognition, or shape computation. To evaluate micro texture features of an image and to make texture features of an image relatively invariant with respect to changes in illumination, image rotation, the present paper integrated the features of textons and LBP for edge detection. The textons are having a close relationship with image features, an emergent pattern sharing a common property and local distribution properties. LBP represents precisely local textural information with respect to changes in illumination, image rotation. Textons refer to fundamental micro-structures in images (and videos) and are considered as the atoms of pre-attentive human visual perception. Firstly, decomposing an image into its constituent components reduces information redundancy and thus leads to better image coding algorithms. Secondly, the decomposed image representation often has much reduced dimensions and less dependence between variables (coefficients), therefore it facilitates image modeling which is necessary for image segmentation. The textons are defined as a set of blobs or emergent patterns or shape features sharing a common property all over the image. Textons are defined which are having a close relationship with image features and local distribution. Textons are considered as texture primitives and are located with certain placement rules. The different textons may form various image features. If the textons in the image are small and the tonal difference between neighboring textons is large, a fine texture may result. If the textons are larger and concise of several pixels, a coarse texture may result. If the textons in image are large and consists of a few texton categories, an obvious shape may result. If the textons are greatly expanded in one orientation, pre-attentive discrimination is somewhat reduced. If the elongated elements are not jittered in orientation, the texton gradients at the texture boundaries are increased.

Feature extraction: The feature is a function of one or more measurements, each of which specifies some quantifiable property of an object, and is computed such that it quantifies some significant characteristics of the object. Features such as shape, histogram, texture, color, etc. are used to describe the content of the image.

Color features (color moment): Color moment is a compact representation of the color feature to characterize a color image. It has been shown that most of the color distribution information is captured by the three low-order moments. The first-order moment (μ) captures the mean color, the second-order moment (v) captures the variance and the third-order moment capture standard deviation(s). These three low-order moments (μ, v, and σ) are extracted for each of the three color planes (R G B), using the following mathematical formulation:

$$\text{Mean}(\mu) = \frac{1}{n}\sum_{i=1}^{n} x_i$$

$$\text{Variance (V)} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i-\mu)^2$$

$$\text{Std Dev }(\sigma) = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\mu)^2}$$

***Mean*:** It is nothing but the average i.e. adding up all the numbers. Where Σ represents the summation, xi represents pixel n, represents number of pixels

Variance: The variance of a data set is the arithmetic average of the squared differences between the values and the mean. Thus, the variance of a frequency distribution is given by

Where v-variance,∑=summation ,x_i=sample set of every term,μ=mean.

Standard deviation: the std dev is power of 2 to variance value, where σ= std deviation, Σ = Summation, which means the sum of every term in the equation after the summation sign, x_i =s ample observation this represents every term in the set , = mean, n-1 =pixel size.

Texture feature: Local Binary pattern is feature vector and is type of visual descriptor used for classification of an image which improves the detection of an image and it is found to be powerful feature for texture classification of a psoriasis images mainly with respect to the segmented border. Here it focus on extraction of a new texture based feature for edge detection. We validate the segmentation accuracy based on extracted features.

Step 3:

Local Binary Pattern(LBP) is evaluated on the quantized skin image for obtaining local information in a precise way. Local Binary Pattern (LBP) is based on the concept of texture primitives. This approach is a theoretically, computationally simple and efficient methodology for texture analysis. To represent the formations of a textured image, the LBP approach, models 3×3 neighborhood as illustrated in figure2. A 3×3 circular neighborhood consists of a set of nine elements, P = {pc, p0, p1… p7}, where pc represents the gray level value of the central pixel and pi (0≤i≤7) represent the gray level values of the peripheral pixels. Each 3×3 circular neighborhood then can be characterized by a set of binary values bi (0≤i≤7) as given in the following equation:

$$b_i = \begin{cases} 1 & \Delta p_i < 0 \\ 0 & \Delta p_i \geq 1 \end{cases} \quad [1]$$

Where $\Delta p_i = p_i - p_c$.

For each 3×3 neighborhood a unique LBP code is derived from the following equation:

$$LBP_{P,R} = \sum_{i=0}^{i=7} b_i \times 2^i \quad [2]$$

Every pixel in an image generates an LBP code. A single LBP code represents local micro texture information around a pixel by a single integer code.

LBP ∈ [0,255].

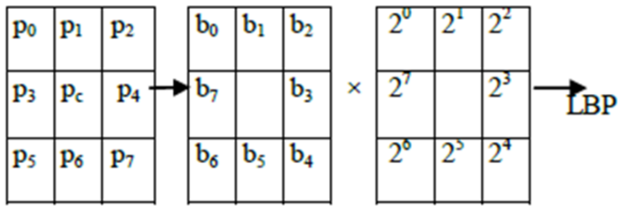

Fig. 2 Representation of LBP

The $LBP_{P,R}$ operator produces 2^P different output values, corresponding to the 2^P different binary patterns that can be formed by the P pixels in the neighbor set. Achieving rotation invariance, when the image is rotated, the gray values g_p will correspondingly move along the perimeter of the circle, so different $LBP_{P,R}$ may be computed. To achieve rotational invariance a unique identifier to each LBP is assigned in the present paper as specified in the following equation:

$$LBP_{P,R}^{ri}(x,y) = \min\{ROR(LBP_{P,R}, i)\} \quad [3]$$

Where i = {0, 1, 2, 3..,, P-1} and the superscript ‗ri‘ stands for rotation invariant. The function $ROR(LBP_{P,R}, i)$ performs a circular bit-wise right shift on the P-bit number $LBP_{P,R}$ i times to the right (|i| < P).

Step4:

Image segmentation refers to partitioning of an image into different regions that are homogeneous or "similar" in some image characteristics. It is usually the first task of any image analysis process module and thus, subsequent tasks rely strongly on the quality of segmentation. Identifies separate objects within an image and finds regions of connected pixels with similar properties, finds boundaries between regions and removes unwanted regions. Calculate accuracy rate of an images.

Step5:

Edge detection: The points at which image brightness changes sharply are typically organized into a set of curved line segments termed *edges*. The boundaries of object surfaces in a scene often lead to oriented localized changes in intensity of an image, called edges. Here the boundaries can be detected at image locations which encounter two opposite directions of flow in the stable state. This segmentation scheme helps to represent and organize the image information in a more efficient way.

Algorithm:
Step1: Read original color image
Step2: Conversion of gray image to color image using RGB quantization
Step3: Apply texton using LBP on dermoscopy image
Step4: Produces segmented regions
Step5: Edges are detected.

IV. RESULTS AND DISCUSSIONS

Data Collection

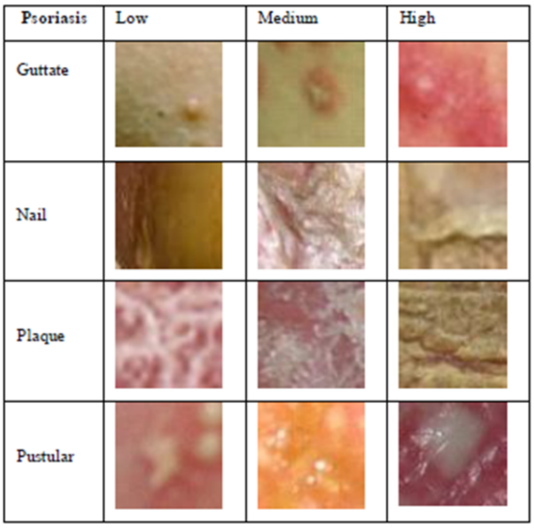

Fig. 3
Sample Database of Psoriasis

The Fig-3 shows input samples of psoriasis skin images that are considered in this paper. There are total 180 images of 4 types and each type of image is subdivided as low, medium, high severity.

Table I. Data Collected For Psoriasis Infected Skin Images

Sl.No.	Class	Total no. of images
1	Guttate Low	12
2	Guttate Medium	10
3	Guttate High	13
4	Nail Low	17
5	Nail Medium	13
6	Nail High	11
7	Plaque low	12
8	Plaque Medium	20
9	Plaque High	20
10	Pustular low	20
11	Pustular Medium	10
12	Pustular High	22
Total		180

Table I. presents the psoriasis image sample distribution with respect to type of psoriasis and severity. The database contains both real images which are captured from the digital camera of 8 megapixels. The preprocessing techniques are applied to crop the input image into 64*64 size pixels. The aim of preprocessing is an improvement of an image data input that suppresses unwanted distortions or enhances some features. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image.

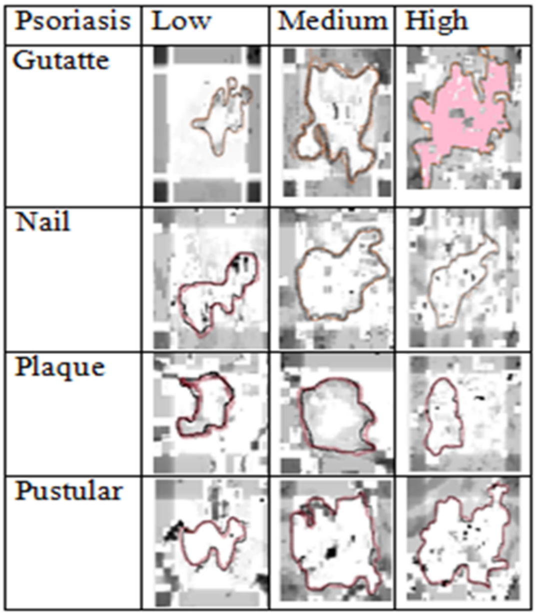

Fig.4 : Segmented Images Of Psoriasis

The figure4 gives result of segmented images of psoriasis type of images.

Guttate psoriasis appears in small red spots on the skin. It is the second most common form of psoriasis. The spots often appear on the torso and limbs, but they can also occur on the face and scalp. From figure4 it is observed that the segmented region is good and found more appropriate for diagnosis.

Nail psoriasis can cause nail pitting, grooves, discoloration, loosening or crumbling of the nail, thickened skin under the nail, and colored patches or spots under the nail. The segmented region formed is difficult for diagnosis because of small patches spread over of uniform color.

Plaque is characterized by thick red patches of skin, often with a silver or white layer of scale.

Pustular is characterized by white pustules surrounded by red skin. The pus inside the blisters is noninfectious. Scaling also occurs. The affected part is segmented with respect to edge detection.

CONCLUSION

The Figure5. Shows the graph for comparison of the identification rate for the different types of Psoriasis skin diseases with three severity levels. The diagnosis of skin disease is very long term and time consuming process. Conventional diagnostic test are painful to patients. Hence we have developed computer aided psoriasis disease diagnostic system using LBP algorithm which provides better accuracy and faster diagnosis than human physician. The color and texture feature plays important role in classifying particular disease.

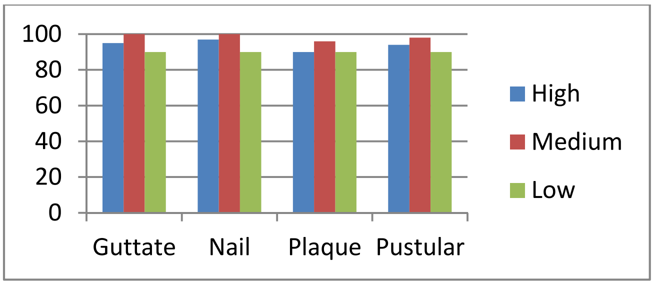

Fig. 5Analysis of Psoriasis infected Skin images

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