Survey of Texture Based Feature Extraction for Skin Disease Detection

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***Abstract*— Skin diseases are most common form of infections occurring in people of all ages. As the costs of dermatologists to monitor every patient is very high, there is a need for a computerized system to evaluate patient's risk of skin disease using images of their skin lesions. Many researchers have used different preprocessing, segmentation and classification techniques to determine whether a skin image suffers from diseases or not. Feature extraction is very important for predictive modeling applications. Feature extraction in image processing is a method of capturing visual content of images for indexing and retrieval. Primitive image features can be either general features, such as extraction of color, texture and shape or domain specific features. Texture based features are widely used in image analysis for medical diagnosis. This paper presents a comprehensive survey of texture based feature extraction for detection of skin diseases and proposes a system based on the findings.**

Keywords—Texture Features, GLCM,Skin Diseases

I. INTRODUCTION

Skin is the largest organ present in the human body. Skin diseases are very common among people of all age groups. In 2013, with prevalence rate of 10 percent, the population affected across India from skin disease was estimated at nearly 15.1 crore. It was estimated that at a CAGR of 12 percent about 18.8 crore people were likely to suffer from skin disease by 2015. At present, there are about 6,000 dermatologists catering to a population of over 121 crore[1]. This means that for every 100,000 people, only 0.49 dermatologists are available in India as compared to 3.2 in many states of the US. So there is high need for a computerized system to evaluation of these diseases. Detection of skin diseases is a relatively well researched field and many authors have used different data mining, statistics and machine learning algorithms in past. Neural networks, Support Vector Machine (SVM) are widely used in literature. Feature extraction is very important to these types of classification problems.

Data is normally represented by a fixed number of features which can be binary, categorical or continuous. Feature is synonymous of input variable or attribute. Finding a good data representation is very domain specific and related to available measurements. For example, in medical diagnosis, the features may be symptoms, that is, a set of variables categorizing the health status of a patient (e.g. fever, glucose level, etc.). Although feature selection is primarily performed to select relevant and informative features, it can have other motivations, including general data reduction, feature set reduction, performance improvement and data understanding [2].

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations.

When the input data to an algorithm is too large to be processed and it is suspected to be redundant, then it can be transformed into a reduced set of features [3]. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits 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.

Generally speaking, textures are complex visual patterns composed of entities, or sub patterns that have characteristic brightness, colour, slope, size, etc. Thus texture can be regarded as a similarity grouping in an image [4]. Texture analysis aims in finding a unique way of representing the underlying characteristics of textures and represent them in some simpler but unique form, so that they can be used for robust, accurate classification and segmentation of objects [5]. Texture based features are widely in image analysis for medical diagnosis. This paper presents a comprehensive survey of texture based feature extraction for detection of skin diseases.

II. THE GRAY LEVEL CO-OCCURRENCE MATRIX (GLCM)

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. GLCM method is a way of extracting second order statistical

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texture features. The approach has been used in a number of applications. Third and higher order textures consider the relationships among three or more pixels. These are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty.

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, Θ) contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (Θ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, Θ). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in fig 1 for four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbor). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbor pixel) falls to the right of another pixel with grey level 0(reference pixel)[6].

Ref pixel/ Neigh. Pixel	0	1	2	3
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

Fig. 1. GLCM Calculation

GLCM has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Haralick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. These features are Angular Second Moment (ASD), Contrast, Correlation, Sum of Squares, Inverse Difference Moment (IDM), Sum Average, Sum Variance, Sum Entropy, Entropy, Difference Variance, Difference Entropy, Information Measures of Correlation and Maximal Correlation Coefficient [4]. Formulas for some of the features are given in table I.

Image analysis techniques have played an important role in several medical applications. These features are widely used in skin disease detection by many researchers.

TABLE I. TEXTURE FEATURE FORMULAS

Feature Name	Formula
Entropy	$\sum_i \sum_j P(i,j)\log(P(i,j))$
Energy	$\sum_i \sum_j P^2(i,j)$
	i j
Contrast	$\sum_i \sum_j (i-j)^2 P(i,j)$
Homogeneity	$\sum_i \sum_j P(i,j)/(1+\lvert i-j\rvert)$
Correlation	$1/(\sigma i \,.\sigma j) \sum_i \sum_j (i-\mu i)(j-\mu j)\, Pi,j$

III. REVIEW OF USE OF TEXTURE FEATURES FOR SKIN DISEASE DETECTION

[6] explains extraction of GLCM features form a image in detail.

[7] uses contrast, correlation, energy, intensity and homogeneity features and shows these can be correlated with skin symptoms.

In [8] authors have used GLCM feature extraction technique to detect melanoma skin cancer. They have used Fisher score ranking to select most important features out of total of 23 features that can be computed based on GLCM technique. Following 12 features were selected based on score Contrast, Correlation, Cluster Prominence, Dissimilarity, Homogeneity, Difference variance, Difference entropy, Information measure of correlation 1,Information measure of correlation 2,Inverse difference homogenous (INV), Inverse difference normalized (INN) and Inverse difference moment normalized. They have reported accuracy of 92% using Traditional MLP on test dataset.

The work in [9] uses 5 GLCM based features Variance, Energy, Correlation, Homogeneity and Entropy for detection of melanoma skin cancer in digital images. Authors have used SVM for the classification of skin lesions as malignant and benign lesions with the accuracy of 95%.

4 GLCM based features Entropy, Energy, Contrast and Homogeneity are used by [10] for Psoriasis detection. Along with these texture features color features like first-order moment the mean color(μ_c), the second-order moment the standard deviation (σ_c) and the third-order moment skewness (θ_c) of color were used. Further back propagation neural network was used for classification of skin samples with or without psoriasis.

[11] also used textual features for of an image for detection of Psoriasis. First Region of Interest (ROI) of image was extracted using active contour method. Energy, Entropy, Contrast in each color channel RGB were considered as features along with other features Mean and Standard Deviations of ROI of 3 color channel of diseased skin, distribution (scattering of the ROI-s). Neural network with backpropagation was used as classifier for detection.

[12] shows that textual features Contrast, Correlation, Energy, and Homogeneity for skin cancer detection can be used.

The work presented in [13] uses these features for skin cancer detection. Additional features like Entropy, Solidity, Majoraxislength, Minoraxislength, Equivdiameter, Perimeter, Mean, Standard Deviation, Convexarea Area, Euclidean Distance, Manhattan Distance, Minkowski Distance and Hamming Distance are used. All these features are given to

neural network for classification of an image as cancerous or non-cancerous.

[14] Shows use of texture and fractal features for skin cancer detection. Fractal analysis is the analysis of the geometrical figures, density, contours, etc in an image. Energy, Entropy, Contrast, Correlation, and Homogeneity were extracted from GLCM. SVM was used for decision purpose.

In [15] textual features Contrast, Correlation, Homogeneity, Entropy and Energy of an image were used for Skin Cancer Detection along with Area, and Perimeter of object of interest. Support Vector Machine (SVM) was used for classification of an image as cancerous or non-cancerous. These authors have also used Back propagation neural network to classify a skin image as normal or melanoma image for 3 types of skin cancer along with additional features Mean Intensity, Standard Deviation of an image [16]. With back propagation they recorded results as close as 100%.

Similar work was presented in [17] where input image was classified as melanoma cancerous or non-cancerous. The authors used Energy, Contrast, Inverse Difference Moment, Dissimilarity, Entropy, Maximum Probability and Inverse textual features.

In work presented in [18] Contrast, Correlation, Energy, Homogeneity, standard deviation, eccentricity, and perimeter these features are passed to SVM classifier. Two skin cancer types melanoma and basal cell carcinoma were the two target classes.

These authors extended their work [19] where they used more GLCM features autocorrelation, contrast, correlation, cluster prominence, cluster shade, energy, entropy, homogeneity, dissimilarity, maximum probability, sum average, sum variance, variance, sum entropy, difference variance, difference entropy, information measure of correlation, inverse difference, inverse difference normalized, inverse difference moment normalized. The authors also compared results of SVM and KNN classifiers for classifying an image with skin cancer type as melanoma or basal cell carcinoma or other skin allergy. They showed SVM outperforms KNN.

Authors of [20] used Mean, Standard deviation, Skewness, Kurtosis, Contrast, Energy and Homogeneity GLCM features for Skin cancer detection. Authors have also found 3 stages of skin cancer depending upon the area of the lesion and type of cancer (Melanoma and Non-Melanoma) depending upon the color variation.

Approach discussed in [21] uses Autocorrelation, Contrast, Energy, Entropy, homogeneity textual features of an image for skin cancer classification. Multiclass SVM was used for classifying an image into four types of skin cancers as Melanoma, Basal-cell Carcinoma, Actinic Keratosis, Squamous-cell Carcinoma.

In their work in [22] authors have used contrast, energy, homogeneity, correlation along with other statistical parameters such as mean, skewness, and kurtosis extracted from GLCM for skin cancer detection. These authors extended their work by adding dermoscopic features such as Asymmetry, Border, Color and Diameter (ABCD) of skin lesion for detection of skin cancer [23]. Accuracy of classification was increased from 88% to 92% by addition of dermoscopic parameters.

In [24] two types of features have been used, color and texture for Skin Cancer detection. For texture features, GLCM and Local Binary Patterns (LBP) have been used. From GLCM features Entropy, Energy, Contrast and Homogeneity are considered. Authors have shown that only GLCM features may not do well. But GLCM along with LBP produces better results. Even adding Color features further increases accuracy of detection.

[25] shows use of GLCM features Energy, Correlation, Contrast and Entropy from for detection of skin cancer using SVM.

[26] shows experiments using GLCM as a feature extraction method and neural network as a classifier for classification of only two classes-cancerous and non-cancerous. Contrast, Correlation, Energy, Mean, and Homogeneity are used as GLCM based features.

[27] uses of 13 textual features along with 16 image quality analysis features for detection of three skin diseases as Benign Skin Cancer, Malignant Skin Cancer and Warts. Image segmentation is carried out using C-Means Algorithm and Watershed Algorithm. Watershed algorithm proved to be better than C-means algorithm.

In [28] authors have used 3 GLCM features Contrast, Homogeneity and Energy for detection of three skin diseases Atopic dermatitis, Eczima and Urticaria. These features were calculated along four directions as horizontal ($\theta = 0^{o}$), vertical ($\theta = 90^{o}$), right diagonal ($\theta = 45^{o}$) and left diagonal ($\theta = 135^{o}$). Average of these 4 directional was considered as final feature value for overall estimation of a feature.

Most of the research work in this area focus on detecting whether a skin lesion is malignant or not and ignore other benign lesions. [29] presents extensive work on classification of non-melanoma skin lesions into 5 classes based on a novel hierarchical K Nearest Neighbors (K-NN) classification. Color and texture features were extracted from skin lesions. Two sets of texture features are extracted from GCMs calculated over the lesion area of the image, as well as over a patch of healthy skin of the same image. Differences and ratios of each of the lesion and normal skin values were also calculated for further processing.

All this work is presented in concise form in table II which also lists additional features, evaluation parameter etc. for comparison.

IV. METHODOLOGY

Fig. 2 shows block diagram of proposed skin disease detection system. Initially different skin disease affected images will be collected from authentic sources. Such images can be collected from hospital under the supervision of expert doctors.

TABLE II. SUMARY OF WORK ON TEXTUAL FEATURES FOR SKIN DISEASE DETECTION

Work cited	Disease	Classifier	GLCM Features	Additional Features	Dataset	Evaluation Measure
8.	Melanoma Skin Cancer	Neural Network	Contrast, Correlation, Cluster Prominence, Dissimilarity, Homogeneity, Diff variance, Diff entropy, Info measure of corr 1,Info measure of corr 2,Inv diff homogenous (INV), Inv diff normalized (INN) and Inv diff moment normalized-total 12	---	Total images - 102,51 - melanocytic nevi,51 – melanomas	Accuracy-92%
9.	Melanoma skin cancer	SVM	Variance, Energy, Correlation, Homogeneity and Entropy	---	Total -20 images, 10 -benign 10 - malignant	Accuracy 95%
10.	Psoriasis	Neural Network	Entropy, Energy, Contrast and Homogeneity	mean color (μ_c), standard deviation (σ_c) and skewness of color	24 images 12- Psoriasis 12- others	Sum Square Error (SSE) $< 10^{-6}$
11.	Psoriasis	Neural Network	Energy, Entropy, Contrast for each channel of RGB	Mean and Std Devs of ROI of RGB , distribution of the ROI-s	Total -20 images, 10 -diseases 10 – normal	Accuracy 100%
12.	Skin Cancer	Neural Network	Contrast, Correlation, Energy, and Homogeneity	---	---	---
13.	Skin Cancer	Neural Network	Contrast, Correlation, Energy, and Homogeneity	Entropy , Solidity, Majoraxislen, Minoraxislen, Equivdia, Perimeter, Mean, Std Dev, Conarea Area, Eucli Dist, Man Dist, Min Dist, Ham Dist	40 cancerous 19 Non-cancerous test images	Accuracy 97.5% and 96.67% for cancer and Non-Cancer Classes
14.	Skin Cancer	SVM	Contrast, Correlation, Energy, Entropy, and Homogeneity	Fractal features	---	---
15.	Skin Cancer	SVM	Contrast, Correlation, Energy, Entropy and Homogeneity	Area, and Perimeter of object of interest	Total -10 images, 05 -cancer 05-noncancer	---
16.	Skin Cancer	Neural Network	Contrast, Correlation, Energy, Entropy and Homogeneity	Area, Perimeter Mean Intensity, Std Dev of an image	Total - 50 Normal - 25 Skin Cancer 1 - 8, Skin Cancer2- 8 , Skin Cancer 3 -9	Accuracy Over 87.5%
17.	Skin Cancer	Neural Network	Energy, Contrast, Inv Diff Moment, Dissimilarity, Entropy, Maximum Probability and Inverse	---	---	Accuracy 97.5%
18.	Melanoma, basal cell carcinoma Skin Cancer	SVM	Contrast, Correlation, Energy, Homogeneity, std dev , eccentricity, perimeter	---	---	---
19.	Melanoma, basal cell carcinoma Skin Cancer, Skin Allergy	SVM and KNN	Autocorr, contrast, corr, cluster prominence, cluster shade, energy, entropy, homogeneity, dissimilarity, maximum probability, sum average, sum variance, variance, sum entropy, diff variance, diff entropy, info measure of corr, ID, ID normalized, IDM normalized-total 19		Total- 85 images Melanoma-35, basal cell carcinoma-30, Skin Allergy-20	---
20.	Skin Cancer	Neural Network	Mean, Standard deviation, Skewness, Kurtosis, Contrast, Energy and Homogeneity	---	Training-90 images Testing-30	Accuracy 86.66%
21.	Skin Cancer (4 types)	Neural Network	Autocorrelation, Contrast, Energy, Entropy, homogeneity	--	Total- 359 images 77, 84,101 and 101 for different cancer types	Accuracy 81.43%
22.	Skin Cancer	Neural Network	Energy, Correlation Homogeneity, Contrast, Skewness, Kurtosis and mean	---	60-total images, 39 –Cancerous, 31-Non cancerous	Accuracy 82%
23.	Skin Cancer	Neural Network	Energy, Correlation Homogeneity, Contrast, Skewness, Kurtosis and mean	Area, Border, Color, Diameter	Total- 60 Cancerours-40 Noncancerous-19	Accuracy 92%
24.	Skin Cancer	SVM	Entropy, Energy, Contrast and Homogeneity	Local Binary Pattern Color Features-Moment1-Moment4	69- total images melanoma - 43 and non-melanoma- 26	Accuracy 90.32 % Sensitivity-85.84%

						Specificity-93.97%
25.	Skin Cancer	SVM	Energy, Correlation, Contrast and Entropy	---	Total- 60 30 -benign, 30-malignant	Accuracy 91.66%
26.	Skin Cancer	Neural Network	Contrast, Correlation, Energy, Mean, Homogeneity	---	Total-50 images	Accuracy 82%
27.	Benign Skin Cancer, Malignant Skin Cancer and Warts	Neural Network	Mean, Std Dev, Entropy, Root Mean Square, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Energy, and Homogeneity	Image Quality Assessment	45 digital skin images	Accuracy 96-98%
28.	Atopic dermatitis, Eczima, Urticaria	Neural Network	Contrast, Homogeneity and Energy along four directions	---	Total- 225 images, 75 each for 3 disease conditions	Accuracy 66.66%
29.	Actinic Keratosis(AK) , Basal Cell Carcinoma(BCC) , Mole (ML), Squamous Cell Carcinoma(SCC), Seborrhoeic Keratosis(SK)	KNN	energy, contrast, correlation, entropy, homogeneity, inverse difference moment, cluster shade, cluster prominence, max probability, autocorrelation, dissimilarity and variance- total 12	mean colours RGB, covariance matrix of RGB	960 lesions, 45 AK, 239 BCC, 331 ML, 88 SCC, 257 SK	Accuracy 74.3%

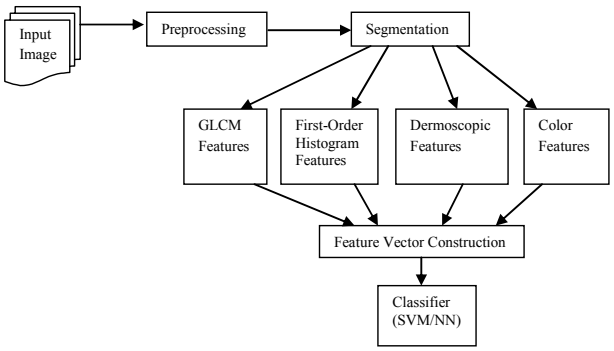

Fig 2. Block Diagram of Skin Disease Detection System

A. Pre-Processing

The input images can be preprocessed for intensity adjustment, noise removal. Some kind of filtering can be used for hair removal. Generally preprocessing reduces processing time and increases performance.

B. Segmentation

Segmentation is one of the important steps in skin disease detection. It is used to separate human skin form non-skin areas. An accurate segmentation of skin images can help the diagnosis to define well the affected skin region from input image.

C. Feature Extraction

As discussed in section II different types of features can be used for skin disease detection. Four major types of features can be used in general.

1) GLCM Features: GLCM based features like Contrast, Correlation, Energy, Entropy and homogeneity which are widely used can be considered here.

2) First-Order Histogram Features: Features like Mean, Skewness, Energy computed form First-order histogram can be considered.

*3) Dermo*scopic Features: dermoscopic features such as Asymmetry, Border, Color and Diameter (ABCD) of affected skin regions can be used.

4) Color Features: mean color (μ_c), standard deviation (σ_c) and skewness of color can be used.

All these features together forms a feature vector for each training image.

D. Classification

This feature vector can be passed as an input to some classification algorithm like neural networks with back-propagation or Support Vector Machine (SVM) for classifying an input image in one of the predefined disease classes.

V. CONCLUSION

Computerized detection of skin diseases may be very helpful for medical practitioners as the people across the globe are suffering from different skin diseases. Texture is a very interesting image feature that has been used for classification of images in medical image analysis. Texture analysis has been an active area of research in pattern identification. In this paper, work on texture based features derived from GLCM matrix used for the detection of skin diseases is discussed and consolidated. Texture features proved to be very promising for classification of images in the past. Many researchers have used additional features along with texture based features to

improve accuracy of classification. Most of the work is carried out detection of skin cancer but other diseases like psoriasis, warts, moles, eczema are also considered in some of the works. Classification of an image as having a disease or not is most carried by classifiers like neural networks and SVM. Most the research shows overall accuracy around or above 90%. Top five features used in all this work are Contrast, Correlation, Energy, Entropy and homogeneity. Skin Disease Detection System based on these findings is proposed.

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