Diagnosis of Melanoma Skin Cancer from Digital Images using Texture Distinctiveness with Neural Network

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***Abstract*: Incidence rate of skin cancer are increasing day by day. Skin cancer is one of the deadliest forms of cancer but detected earlier can save the life time of the human being. An automated screening system is introduced to identify the presence of skin cancer in advance. In this paper, texture distinctiveness lesion segmentation algorithm is used. Experience and training-based characteristics of back propagation neural network is used with texture distinctiveness lesion segmentation algorithm, for identifying the normal and abnormal portions of skin .The most commonly occurring skin cancer is Melanoma. The proposed system is to diagnose the presence of this skin cancer and its probability of risk as low, medium, high.**

Keywords: Melanoma, segmentation, skin cancer, texture, neural network.

I.INTRODUCTION

Cancer is a life threatening disease caused primarily by genetic instability and accumulation of multiple molecular alternations [1] [2].Present diagnostic and prognostic classifications are insufficient to make prediction for successful treatment and patient outcome [3] [4].Among many types of cancer, Skin cancers are the most common form of cancers in human [5]. The common types of skin cancers are melanoma, basal and squamous cell carcinoma, and Actinic Keratosis [6].Digital Dermoscopy is widely considered as one of the most cost effective method to identify and classify skin-cancer. The rate of detection of melanoma using Dermoscopy is higher than detection only with unaided observation [7]. The diagnostic accuracy of Dermoscopy is also depending on the training of the dermatologist. So that automatic diagnosis is essential tool for less experienced physicians. In order to achieve an effective way to identify skin cancer at an early stage, digital images of skin lesions have been investigated. The proposed method comprises at first pre-processing the images to remove impulse noise using adaptive median filter. Secondly extract the lesion from the digital image by TDLS algorithm. Thirdly classify the lesion as a melanoma or non-melanoma and its probability of risk by using back propagation algorithm in neural network. The majority of proposed segmentation algorithms are only applicable to Dermoscopy images, which has better contrast between the lesion and surrounding skin area for certain types of lesions. Before extracting features from the skin lesion and classifying the lesion as melanoma or non-melanoma, the location of the lesion border must be identified using a segmentation algorithm. It is important that the skin lesion segmentation algorithm is accurate, because resulting segmentation is used as an input to feature extraction and cancer classification algorithms. Segmenting skin lesions from digital images is a problem due to illumination variation. The presence of illumination variation can have a negative impact on segmentation and classification. Segmentation algorithms are required to perform illumination correction. In this approach the process of segmenting skin lesions uses textural information, because normal skin and lesion areas have different textures. Different texture information in an image is extracted and textures from different regions are compared. Stocker et al. [7] analysed texture in skin images using basic statistical approaches, such as the gray level co-occurrence matrix. They found that texture analysis could accurately find the dissimilarities between the texture distributions of a skin images. Texture-based segmentation algorithms have been applied to Dermoscopy images. The algorithm proposed by Xuet al. [8] learns a model of the normal skin texture using pixels in the four corners of the image, for identifying the particular skin lesion region. Hwang and Celebi [9] use Gabor filters to extract texture features and use a g-means clustering approach for segmenting the lesion. In this paper, a TD segmentation algorithm is used to locate the texture of skin lesions [10]. TD captures the dissimilarity between different texture distributions. Regions in the image are classified as being part of lesion and skin based on TD metric. Dermatologists diagnose malignancy in skin lesions based on their extensive training, experience from previous diagnoses. Their diagnosis is based on looking at a set of features, since a single feature alone cannot determine malignancy in the lesion. Experience and training-based learning is an important characteristic of neural networks that makes it ideal for diagnosis applications[11]. Neural network is proposed for accurate segmentation of skin cancer images.

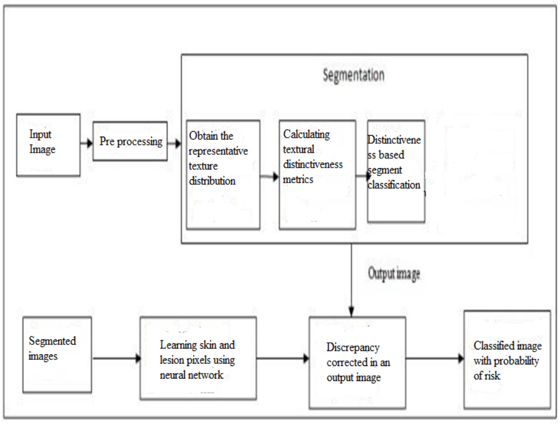

Figure 1:Block diagram of the system

II.PROPOSED SYSTEM

Our method for detecting melanoma and non-melanoma lesions involves three steps:pre-processing,TDLS segmentation, and neural network classification. Figure. 1 illustrates the overall architecture of the system.

1) Pre-processing

The digital forms of images are degraded by optic lens in a digital camera. This leads to compilation in human perception, in which the features of digital images are very complex. The process involves improvement on enhancement of image, which includes noise removal,hair removal,making acute.The pre-processing step clear away the unwanted parts,regulate the image skew ,expel noise and impulse noise from the image by using median filter. This filter is used for eliminating the impulse noise which performs well in case of spatial noise density in which the values of noisypixels were replaced by median pixel values. Segmentation of skin lesion becomes difficult in the presence of shadows and bright areas caused by illumination variation. Therefore illumination correction should be done as a pre-processing step.

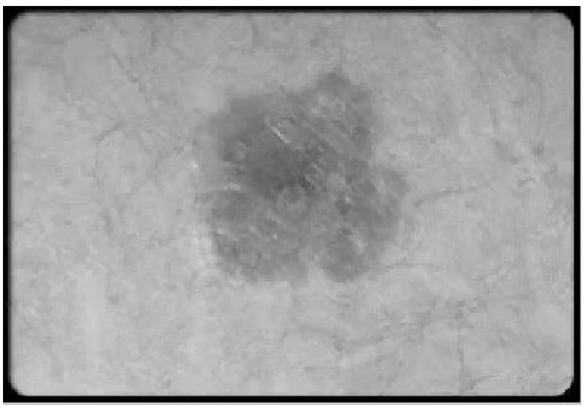

Figure 2: output of Pre- processing

2) Segmentation

The segmentation is the most important stage for analysing image properly since it affects the accuracy of the subsequent steps. Segmentation removes the healthy skin from the image and finds the region of interest. However, proper segmentation is difficult because various types of lesions have different skin properties, texturesshapes, sizes, and colours.Image segmentation is the process of partitioning an image data into disjoint regions that exhibit within group resemblance according to some prefixed norm and exhibit between group dissemblance .In additions, some lesions have irregular boundaries and in some cases there is smooth transition between the lesion and the skin. To address this problem, several algorithms have been proposed.

a) TDLS Algorithm

In the implementation of the TDLS algorithm, the image is converted into XYZ colour space. Terrillon et al. [12] found that the XYZ colour space is an efficient colourspace which is to segment the skin region of human faces. Next step is to find local texture vector for each pixel in the image. The texture vector contains pixels in the neighbourhood of size n centered on the pixel of interest s. In the case of a multiple channels, **t**A, s is the texture patch centered at pixel s and corresponding to channel A. The texture vector is constructed by grouping each **t**A,s corresponding to the same pixel across all channels. For an image of size N × M, we have a set of N × Mtexture vectors.$T = tsj1 \leq j \leq N \times M$ (1) after extracting texture vectors, a two-step clustering algorithm is used. This is done by running a k-means clustering algorithm followed by a finite mixture model to find$K$ clusters of texture data. One limitation with k-means clustering is that it does not take any probabilistic values. In finite mixture model clustering, a Gaussian distribution is assumed for all clusters and the model parameters are the distribution mean μ and distribution covariance Σ. To measure similarity of two texture distributions, the metric,is defined in (2). It gives the probability that the mean of one texture distribution is a realization of the mean of the other texture distribution. Let tjr and Σj are the mean and covariance of distribution. The measure of similarity L,given in (3) is the average of $lj\ ,k$ and $lk\ ,j$.(2)$Lj\ ,k\ =12lj\ ,k\ +\ lk,j$ (3)We are interested in finding distinct texture distributions. Because the lesion texture distributions are dissimilar from the normal skin texture distributions and also from other texture distributions, due to colour variation. The metric d, given in (4) is the probability that a texture distribution is distinct from another texture distribution. $dj\ ,k\ =\ 1 - Lj\ ,k$ (4) A TD metric Dj given in (5) is used to capture the dissimilarity of texture distribution Tjr from other texture distributions.$PTkrI$ is the probability of occurrence of a pixel being associated with a texture distribution Tkr .$Dj\ =\ dj\ ,kKk=1\ PTkrI$ (5)In the case of normal skin texture distributions, thedissimilarity of one skin texture distribution from other skin texture distributions is very small. The TD metric for skin texture distributions is low. Lesion texture distributions are dissimilar from other skin and lesion texture distributions. The second main step in the TDLS algorithm is to find and classify regions in the

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input image as being part of the lesion based on the sparse texture distributions and their associated TD metric.A TD metric D is calculated for each texture distribution based on the probability of it being similar to other texture distributions. This information is combined with the contents of each region to determine a regional TD metric, DR. DR represents the average TD across region R (6), where $PTjrR$ is the probability of a pixel being associated with the j^{th} texture

Distribution in region R, =, k=1 $PTjrR$ (6) each region is classified as lesion or skin based on TD metricDR. The classification step is illustrated in (7), where y is the resulting segmentation map. It is 1 for lesion and 0 for normal skin. The threshold is denoted by τwhich*is* defined to identify the set of representative texture distributions as normal skin and lesion based on the TD metrics. It is determined by Otsu's threshold. yR =1, $DR \geq \tau 0$ (The output of TDLS algorithm is a binary image in which brighter pixels corresponds to lesion and darker pixels corresponds to skin. The output of TDLS may not accurate due to thresholding. So it is given to neural network for testing. Based on the classification result of neural network, output of TDLS is corrected. Final output will be the more accurate segmented image.)

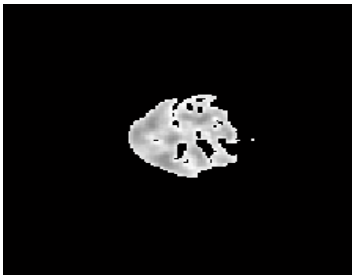

Figure 3 :(a) segmented image

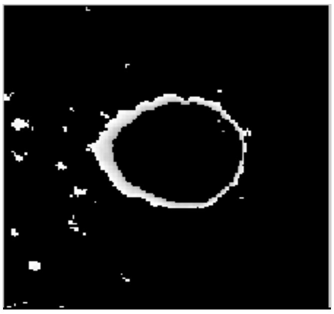

Figure 3:(b) segmented image

3) Neural Networks

Neural network is an information processing system that has certain performance characteristics in common with biological neural networks.Neural network is characterized by (i) its pattern of connections between the neurons(architecture),(ii)its method of determining the weights on the connections(training,learningalgorithm),(iii)its activation function.The structure ofneural network is given in figure

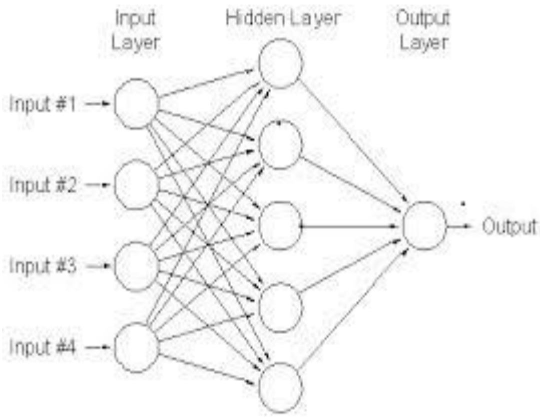

Figure 4: Structure of Neural Network

Neural network consists of large number of simple processing elements called neurons.Each neuron is connected to every other neuron by means of directed communication links, each with an associated weight. Neural networks are organized as layer, input layer, two orthree hidden layers and an output layer. Elements or patterns are given to the network via the input layer, which is connected with one or more hidden layers. The actual processing is done in the hidden layers by a system of weighted connections which is given to the output layer. The output layer provides the outcome of the processing or classification[13]. Neural networks contain some kind of learning function, which helps to modify the weights of the connections for getting the desired output.The individual neurons are trained with patterns. Structure of neural network is similar to the classification methodology of human brainwhich makes an ideal system for medical diagnosis. The neural network learns the XYZ values of each pixel in the skin and lesion regions from the set of segmented images. Thenetworkresponses in the output neuron and produces the 1 for lesion and 0 for skin.

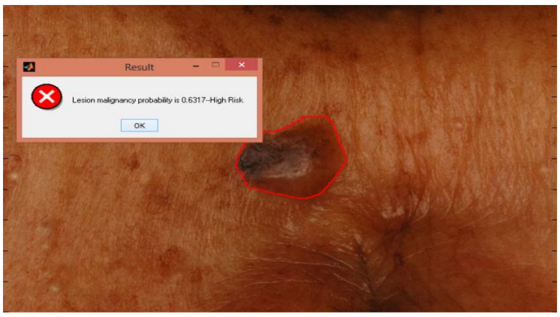

Figure 5:(a) output of neural network

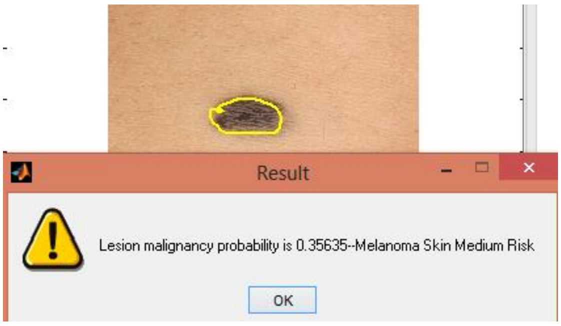

Figure5:(b) output of neural network

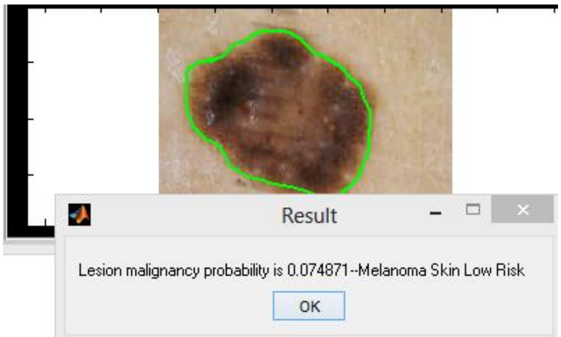

Figure 5:(c) output of neural network

III. EXPERIMENTAL RESULTS

The main purpose of this project is to diagnose the presence of melanomaskin cancer and its probability of risk using TDLS algorithm. Backpropagation neural network differentiate lesion and normal skin region by means of training with neural network,simulation results shows the probability of risk factor for given input images in terms of high,medium,low.Thus accurate results can be obtained in neural network classification.

IV. CONCLUSION

In summary, Texture distinctiveness (TD) lesion segmentation algorithm is used. It captures dissimilarity between the textures

Distribution by dividing an image into smaller regions and classified as lesion or skin based on TD map. Distinctiveness is high for lesion region and low for Skin region. The output of TDLS may not accurate due to thresholding. So it is given to neural network for correcting the discrepancyin the segmented output of TDLS. Experience and training-based learning is an important characteristic of neural network.From the segmented images neural network learns normal and lesion skin pixel values. The skin lesion region is identified from the classified neural network output. Thus proposed framework achieves higher segmentation accuracy.

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