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Segmentation of Skin Lesions from Digital Images using Texture Distinctiveness with Neural Network

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Abstract: Melanoma is the deadliest form of skin cancer. Incidence rates of melanoma have been increasing, but survival rates are high if detected early. Inorder to reduce the costs for dermatologists to screen every patient, there is a need for an automated melanoma screening system. In this paper, texture distinctiveness lesion segmentation algorithm is used. Dermatologists diagnose malignancy in skin lesions based on their extensive training, experience from previous diagnoses, and their access to vast amounts of medical research. Experience and training-based learning is an important characteristic of neural networks. Therefore a back propagation neural network is used with texture distinctiveness lesion segmentation algorithm. The proposed framework shows higher segmentation accuracy.

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

I. INTRODUCTION

Melanoma is the most deadly form of skin cancer and its incidence has been rapidly increasing over the last few decades. In the United States, the lifetime risk of getting melanoma is 1 in 49 [1]. Due to the increase in incidence rates, early detection of melanoma is essential. To reduce costs of screening melanoma, an automated melanoma screening algorithms have been proposed.

A dermatoscope is a special device for assessing the risk of skin lesions [2]. Images acquired through a digital dermatoscope are known as dermoscopy images. Early work on automated systems to assess the risk of melanoma used dermoscopy images. There is a need for a segmentation algorithm for dermoscopy images of skin lesions. 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 lesionsBefore extracting features from the skin lesion and classifying the lesion as malignant or benign, 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 melanoma 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.

Many segmentation algorithms have been proposed for the melanoma images. A recent summary by Celebi *et al.* [3] reviews the existing segmentation algorithms for dermoscopy images. The majority of segmentation algorithms includes simple thresholding, active contours [4], and region merging [5]. Most of the algorithms only use features from pixel color to drive segmentation.

Another approach to segment skin lesions is to use textural information, because normal skin and lesion areas have different textures. Different texture information in an image are extracted and textures from different regions are compared. Stoecker *et al.* [6] analyzed texture in skin images using basic statistical approaches, such as the gray-level cooccurrence matrix. They found that texture analysis could accurately find regions with a smooth texture and that texture analysis is applicable to segmentation of dermatological images.

Texture-based segmentation algorithms have been applied to dermoscopy images.The algorithm proposed by Xu *et al.* [7] learns a model of the normal skin texture using pixels in the four corners of the image, which is later used to find the lesion. Hwang and Celebi [8] use Gabor filters to extract texture features and use a *g*-means clustering approach for segmenting the lesion.

In this paper, a segmentation algorithm based on texture distinctiveness (TD) is used to locate skin lesions in photographs. This algorithm is referred to as the TD lesion segmentation (TDLS) algorithm [9]. TD captures the dissimilarity between different texture distribution. Regions in the image are classified as being part of lesion and skin baed on TD metric.

Dermatologists diagnose malignancy in skin lesions based on their extensive training, experience from previous diagnoses, and their access to vast amounts of medical research. 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 [10]. In this paper TDLS algorithm with back propagation neural network is proposed for accurate segmentation of melanoma images.

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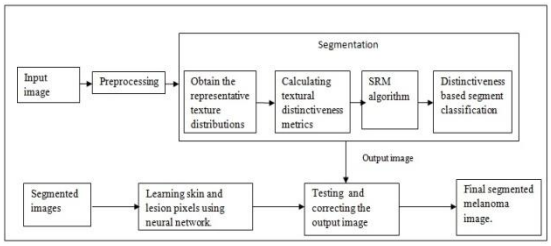

Fig.1 Architecture of the system

II. PROPOSED SYSTEM

Our method for detecting melanoma lesions involves three steps: preprocessing,TDLS segmentation,and neural network classification. Fig. 1 illustrates the overall architecture of the system.

A. Preprocessing

Segmentation of skin lesion becomes difficult in the presence of shadows and bright areas caused by illumination variation. Without the correction for illumination variation, these algorithms tend to identify areas with shadows as part of the skin lesion. Therefore illumination correction should be done as a preprocessing step.

B. TDLS Algorithm

In the implementation of the TDLS algorithm, the image is converted into XYZ color space. Terrillon et al. [11] found that the XYZ color space is an efficient color space in which 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 neighborhood 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 concatenating 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 × M texture vectors.

$$T = \{t_{sj} \,|\, 1 \le j \le N \times M\} \tag{1}$$

After extracting texture vectors, a two-step clustering algorithm is used. First, a *k*-means clustering algorithm is run, which is followed by learning a finite mixture model. *K*-means clustering finds *K* clusters of texture data. One limitation with *k*-means clustering is that it does not take into account any probabilistic information. Therefore, the second step is to apply finite mixture model clustering. In this implementation, 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 $l_{j,k}$ 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 t_j^r and Σ_j are the mean and covariance of distribution T_j^r. The metric $l_{j,k}$ is asymmetric, because when comparing most pairs of distributions, $\Sigma_i \neq \Sigma_j$. The measure of similarity $L_{j,k}$ given in (3) is the average of $l_{j,k}$ and $l_{k,j}$.

$$l_{j,k} = \frac{1}{\sqrt{(2\pi)^{n\times n\times a}|\Sigma_j|}} \exp\left(-\frac{1}{2}\left(t_j^r - t_k^r\right)^T \Sigma_j^{-1} \left(t_j^r - t_k^r\right)\right) \tag{2}$$

$$L_{j,k} = \frac{1}{2}\left(l_{j,k} + l_{k,j}\right) \tag{3}$$

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 color variation. The metric $d_{j,k}$ given in (4) is the probability that a texture distribution is distinct from another texture distribution.

$$d_{j,k} = 1 - L_{j,k} \tag{4}$$

A TD metric D_j given in (5) is used to capture the dissimilarity of texture distribution T_j^r from other texture distributions.$P(T_k^r|I)$ is the probability of occurrence of a pixel being associated with a texture distribution T_k^r.

$$D_j = \sum_{k=1}^{K} d_{j,k}\, P(T_k^r|I) \tag{5}$$

In the case of normal skin texture distributions, the dissimilarity of one skin texture distribution from other skin texture distributions is very small. The TD metric for skin texture distributions is small overall. Lesion texture distributions are dissimilar from other skin and lesion texture distributions, so the textural distinctiveness metric is large.

The second main step in the TDLS algorithm is to find and classify regions in the input image as being part of the lesion based on the sparse texture distributions and their associated TD metric. The corrected lesion image is divided into a large number of regions using statistical region merging (SRM) algorithm[12]. SRM contains two main steps: a sorting step and a merging step. In the first step, SRM sorts pixels in an image to determine the order in which pixels are compared. In the second step, SRM merges pairs of pixels into regions based on their similarity. The output of SRM is large number of regions.

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, D_R. D_R represents the average TD across region *R* (6), where $P(T_j^r|R)$ is the probability of a pixel being associated with the *j*th texture distribution in region *R*,

$$D_R = \sum_{k=1}^{K} d_{j,k}\, P(T_j^r|R) \tag{6}$$

Each region is classified as lesion or skin based on TD metic D_R. 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 τ and it represents the decision boundary between the normal skin and lesion class. The threshold τ is defined to divide the set of representative texture distributions into two classes, normal skin and lesion, and is also based on the TD metrics. It is determined by Otsu's threshold.

$$y(R) = \begin{cases} 1, & D_R \ge \tau \\ 0, otherwise \end{cases} \tag{7}$$

C. Neural Network

Neural network, often referred to as Artificial Neural Network (ANN) is a computing system made up of

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processing elements called neurons which process the information by their dynamic state response to external inputs. Neural networks are organized as layers – one input layer, one or more hidden layers and an output layer. Hidden layers are made up of a number of neurons. Features/patterns are given to the network via the input layer, which are connected to one or more of the hidden layers. The actual processing is done in the hidden layers through a system of weighted connections. The hidden layers are connected to the output layer. The output layer provides the outcome of the processing or classification [13].

Most neural networks contain some kind of learning function, which modifies the weights of the connections according to the training pattern presented to it. The individual neurons are trained with patterns, which is very

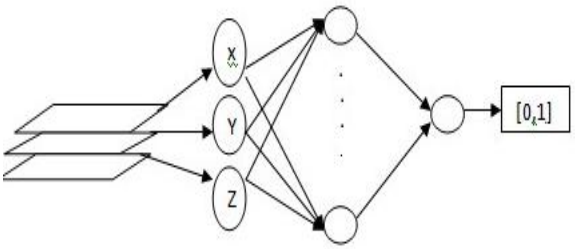

Fig.2. Structure of neural network

similar to how the human brain learns to classify. This aspect of the neural networks makes an ideal system for medical diagnosis, where learning to recognize patterns is the key to accurate diagnosis.

In this research, a back propagation neural network with one hidden layer is implemented to get the advantages of experience. The neural network learns the XYZ values of each pixel in the skin and lesion regions from the set of segmented images. The network responses in the output neuron and produces the 1 for lesion and 0 for skin. The structure of neural network is given in fig 2.

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.

Fig 3(b) shows the TD map of original image.It is corrected with neural network classification as shown in fig 3(c). The final segmented image is shown in fig 3(d).

III. EXPERIMENTAL RESULTS

The objective of this experiment is to measure sensitivity, specificity, and accuracy of TDLS and TDLS with learning after the algorithms classify each pixel as belonging to the normal skin class or lesion class. A set of 30 images are used to test the segmentation and 70 images are used to train the neural network. Each algorithm is applied to the corrected images and the resulting segmentation is compared to the manually drawn segmentation acting as ground truth. The metrics used to compare to the ground truth are sensitivity, specificity, and accuracy. Their formulas are given in (8), (9), and (10), where TP is the number of true positive pixels, FP is the number of false positive pixels, TF is the number of true negative pixels, and FN is the number of false negative pixels.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP}+\text{FN}} \quad (8)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}} \quad (9)$$

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FN}+\text{TN}+\text{FP}} \quad (10)$$

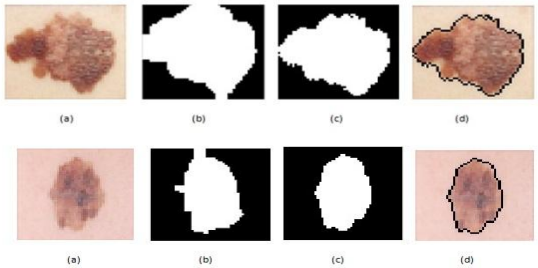

Fig.3. (a) original image (b) textural distinctiveness maps (c)corrected textural distinctiveness maps (d) segmented image

TABLE I
SEGMENTATION ACCURACY RESULTS FOR MELANOMA IMAGES

Segmentation Algorithm	Sensitivity	Specificity	Accuracy
L-SRM[14]	89.4%	92.7%	92.3%
Otsu-R[15]	87.3%	85.4%	84.9%
Otsu-RGB[16]	93.6%	80.3%	80.2%
TDLS	88.89%	98.04%	96%
TDLS with Neural network	93.18%	99.51%	98.40%

Table 1 shows the average sensitivity, specificity and accuracy for entire set of images on different segmentation algorithm. The first algorithm (L-SRM) is designed for dermatological images, but can be applied to lesion photographs as well. Otsu-R finds the Otsu threshold using the red color channel. The second method Otsu-RGB uses all three RGB color channels and finds Otsu thresholds for each channel.Otsu-RGB algorithm has better sensitivity. Table 1 infers that TDLS algorithm with neural network is able to perform well in all three metrics.

IV. CONCLUSION

In summary, a novel lesion segmentation algorithm using the concept of learning is proposed. Texture distinctiveness lesion segmentation algorithm is used. It captures dissimilarity between the texture distribution. Then image is divided into smaller regions and classified as lesion or skin based on TD map. Distinctiveness for lesion region is high. Skin region will have low distinctiveness. Experience and training-based learning is an important characteristic of neural networks that makes

it ideal for diagnosis applications. From the segmented images neural net work learns skin and lesion pixel values. Any incorrectness in the segmented output of TDLS is corrected with neural network. The proposed framework achieves higher segmentation accuracy.

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