International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online)), Volume 2, Special Issue 3, February 2014)
International Conference on Trends in Mechanical,Aeronautical,Computer,Civil,Electrical and Electronics Engineering (ICMACE14)

Detection of Skin Lesions in Dermoscopic Images

J.Junitha Persi Rajam[1], A.A.Haseena Thasneem[2]

[1]P.G Student, Electronics and Communication Engineering, National College Of Engineering,Tirunelveli, TamilNadu,India

[2]Asisstant Professor, Electronics and Communication Engineering, National College Of Engineering,Tirunelveli TamilNadu,India

[1]junithapersirajam@gmail.com

[2]haseenajmal@gmail.com

***Abstract* - Melanoma is the most dangerous and deadly type of skin cancer. However, if it is diagnosed in an early stage there is a high probability of being cured. In this regard, several imaging techniques have been explored to improve the diagnosis accuracy of skin lesions. Dermatoscopy is one of the most relevant of such diagnosis techniques, it allows the *in vivo* observation and inspection of skin lesions and hence a better visualization of their morphological structures. This paper proposes segmentation of skin lesion from the surrounding skin in the dermoscopic images by using Neural Network segmentation algorithm. It also analyses and compares the performance of this technique using three different metrics namely sensitivity, accuracy and border error with two other segmentation techniques namely Adaptive Thresholding and K-Means clustering.**

***Keywords* — Melanoma, Dermoscopy, Adaptive Thresholding(AT), K-Means clustering, Neural Network(NN).**

I. INTRODUCTION

Skin lesion is a part of the skin that has an abnormal growth or appearance compared to the skin around it. Some lesions have irregular boundaries and in some cases there is a smooth transition between the lesion and the skin. Malignant Melanoma is a type of skin cancer, if identified early it can be cured. Dermatoscopy is the examination of skin lesions with a dermatoscope. Dermoscopy images of pigmented lesions are taken at x10 magnification under lighting at a low angle of incidence. Accurate skin lesion segmentation from the background skin is important for diagnosis. The standard approach in automatic dermoscopic image analysis has usually three stages: 1) image segmentation 2) feature extraction and feature selection and 3) lesion classification. Due to different shapes and colors of dermoscopic images, segmentation is the most important stage of all. This paper focuses on segmenting dermoscopic images for skin lesions. Comparison of the segmented outputs by calculating accuracy, sensitivity and border error is also performed.

II. SEGMENTATION METHODS

Adaptive Thresholding(AT), K-Means clustering and Neural Networks(NN) techniques are used to segment the skin lesions in dermoscopic images. The following sections describe each of the segmentation techniques in more detail

2.1. Adaptive Thresholding (AT)

Different threshold is used for different regions in the image. Adaptive thresholding establishes the threshold level for converting dermoscopic image into binary image. Skin lesion segmentation can be obtained by comparing the color of each pixel with a threshold T [1]. The pixel is classified as lesion if it is darker than the threshold value T. The output of Adaptive Thresholding is a binary image. The color component selection is based on the entropy of the color component *i.*

$$S(i) = -\sum_{k=0}^{L-1} - h_i(k) \log[h_i(k)] \quad (1)$$

Where $h_i(k)$ is the histogram of the color component. Assume that the image varies in the range {0 to 255}. Color plane with highest entropy can be selected by using the following equation,

$$i^* = \arg\max_c S(i) \quad (2)$$

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online)), Volume 2, Special Issue 3, February 2014)
International Conference on Trends in Mechanical,Aeronautical,Computer,Civil,Electrical and Electronics Engineering (ICMACE14)

Threshold value T is automatically computed from the histogram of the selected color component $h_i(k)$. If the histogram consists of two major components then the threshold value can be easily chosen from the local minima between the maxima plus a small offset to account for quantization issues.

$$T = T_{valley} + T_1 \quad (3)$$

If the histogram consists of a single component then the threshold value is obtained from the smallest intensity value plus an offset.

$$T = T_{min} + T_2 \quad (4)$$

The offset values of T_1 and T_2 were established empirically.

Adaptive Thresholding is based on the fact that the values of pixels that belong to a skin lesion differ from the pixel values of the background. Selecting an upper and a lower value, it is possible to separate those pixels that have values within this range[2].

2.2. K-Means Clustering

The K-Means clustering method is applied to segment the dermoscopic images. K-Means clustering is a partitioning method[3]. K-Means Clustering refers to the process of grouping samples, that are similar within each group. These groups are called clusters. The K-Means clutering is a non-hierarchical clustering technique that follows a simple procedure to classify a given data set through a number of K clusters. The K-Means clustering algorithm updates the space partition of the input data iteratively, where the elements of the data are exchanged between clusters based on a predefined metric (typically the Euclidian distance between the cluster centers) in order to satisfy the criteria of minimizing the variation within each cluster and maximizing the variation between the resulting K clusters [3]-[4].

The pixel assignment is performed only by evaluating the color information in a certain color space.

The connections between the data point under evaluation and its neighbors is not taken into account, a fact that will lead to a partition of the input data into regions that are not related to the scene objects [5]-[6]. K-Means clustering is convergent and its aim is to optimize the partitioning decisions based on a user-defined initial set of clustering that is updated after each iteration. K-Means clustering algorithm produces accurate segmentation results only when applied to images defined by homogenous regions with respect to texture and color. K-Means clustering method is numerical, unsupervised, non-deterministic and iterative. Hierarchical clustering is also widely employed for image segmentation.[7][8].

2.2.1 K-Means clustering algorithm

The K-Means clustering algorithm is an iterative technique that is used to partition an image into K clusters[9].

The algorithm is:

• Place K points into the space represented by the objects that are being clustered.

• Assign each object to the group that has the closest centroid.

• When all objects have been assigned, recalculate the positions of the K centroids.

• Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters).

2.3.Neural Networks

Artificial Neural Networks or Neural Networks also called as connectionist systems, parallel distributed systems or adaptive systems, because they are composed of series connections of interconnected processing elements that operate in parallel. Segmentation removes the healthy skin from the dermoscopy image and finds the region of interest[10].

After segmentation, the output is a binary image. Neural Network based Segmentation is accomplished by scanning the whole image pixel by pixel and labelling each

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online)), Volume 2, Special Issue 3, February 2014)
International Conference on Trends in Mechanical,Aeronautical,Computer,Civil,Electrical and Electronics Engineering (ICMACE14)

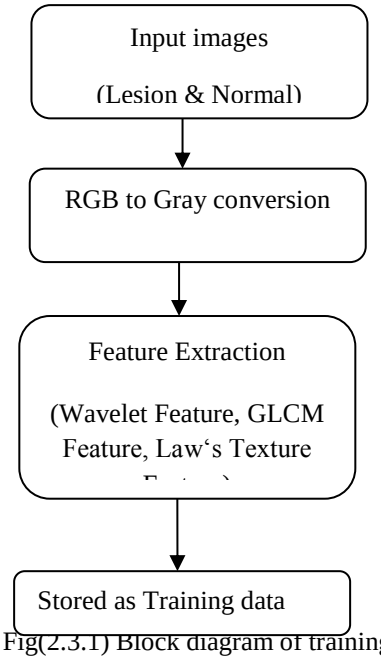
pixel as object or background. Also NN has an added advantage that it can be used for noisy and complex data.
NN is used for segmentation, classification, noise reduction and prediction. Activation functions are applied to the weighted sum of the inputs of a neuron (node) to produce the output.In this paper we used sigmoid activation function for segment the dermoscopic images.
Neural Network consists of two stages:

- Training stage
- Testing stage

Various back propagation algorithms are used to train the NN. In this paper the Levenberg-Marquardt back propagation algorithm is used to train the feed forward neural network. The Levenberg-Marquardt algorithm is very sensitive to the initial network weighs.

2.3.1 Training stage

In the training stage, various features namely Wavelet Feature, GLCM Feature and Law's Texture Features are extracted.



Fig(2.3.1) Block diagram of training stage

In the training stage, Normal and Lesion images are given to the network.

2.3.2 Feature Extraction

Wavelet feature, GLCM(Gray Level Co-occurrence Matrix) feature and Law's Texture features are extracted from the input image.

2.3.2.1 Wavelet feature

Wavelet feature selection algorithm is based on statistical dependence[11]. This algorithm is improved by combining the dependence between wavelet feature and the evaluation of individual feature component.

Wavelet Transforms enable the decomposition of the image into different frequency sub bands, similar to the way the human visual system operates. This property makes it especially suitable for the segmentation and classification of texture images.

For texture classification, absolute features need to be extracted to obtain a representation that is as discriminative as possible in the transform domain. A widely used wavelet feature is the energy of each wavelet sub band.

The 2D discrete wavelet transform is applied to the image. 2D-DWT performs a single level two-dimensional wavelet decomposition. Then Low Low(LL), Low High(LH), High Low(HL) and High High (HH) values from the wavelet decomposed image is stored.

2.3.2.2 GLCM feature

The Gray Level Co-ocurrence Matrix (GLCM) method is a way of extracting second order statistical texture features from the image. GLCM method is widely used in many texture analysis .

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image[12].

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'.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online)), Volume 2, Special Issue 3, February 2014)
International Conference on Trends in Mechanical,Aeronautical,Computer,Civil,Electrical and Electronics Engineering (ICMACE14)

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 the large dimensionality of the image, the GLCM's are sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels can be reduced.

Entropy

The entropy of a dermoscopic image can be defined as a measure of the uncertainty associated with a random variable.

Entropy quantifies, in the sense of an expected value, the information contained in an image. Entropy shows the amount of information of the image that is needed for the image compression.

Entropy measures the loss of information or message in a transmitted signal and also measures the image information.

$$\text{Entropy} = \sum_i \sum_j C_{ij} \log C_{ij} \quad (5)$$

C - GLCM matrix

Energy

Angular second moment is also known as Uniformity or Energy. It is the sum of squares of entries in the GLCM. Angular second moment measures the image homogeneity.

Angular second moment is high when image has very good homogeneity or when pixels are very similar.

$$\text{Energy} = \sum_i \sum_j C^2_{ij} \quad (6)$$

Homogenity

Homogenity can measure the closeness of the distribution of elements in GLCM to the GLCM diagonal.

$$\text{Homogenity} = \sum_i \sum_j \frac{C_{ij}}{1+|i-j|} \quad (7)$$

These are the Gray Level Co-occurence Matrix(GLCM) features extracted from the input image during the training stage.

2.3.2.3 Law's Texture feature

Laws observed that certain gradient operators such as Laplacian and Sobel operators accentuated the underlying microstructure of texture within the dermoscopic image. This is the basis for a feature extraction scheme based on a series of pixel impulse response arrays obtained from combinations of 1-D vectors shown in Figure (2.3.2).

The entropy of a dermoscopic image can

Each 1-D array is associated with an underlying microstructure and labeled using an acronym accordingly. The arrays are convolved with other arrays in a combinatorial manner to generate a total of 25 masks, typically labeled as L5L5 for the mask resulting from the convolution of the two L5 arrays.

Level L5 = [1 4 6 4 1]

Edge E5 = [-1 -2 0 2 1]

Spot S5 = [-1 0 2 0 -1]

Wave W5 = [-1 2 0 -2 1]

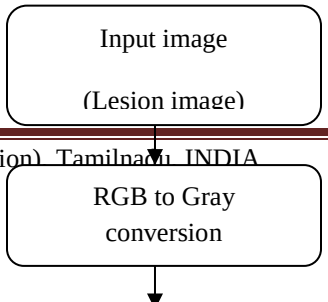
Ripple R5 = [1 -4 6 -4 1]

Figure(2.3.2). Five 1-D arrays identified by Laws

These masks are subsequently convolved with a texture field to accentuate its microstructure giving an image from which the energy of the microstructure arrays is measured together with other statistics.

2.3.3 Testing stage

In the testing stage, lesion image is given to the trained neural network as input image. The trained network identifies the input image as lesion image by comparing the features in the training data set and segment the lesion. The segmented output is taken out from the Neural Network.



International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online)), Volume 2, Special Issue 3, February 2014)
International Conference on Trends in Mechanical,Aeronautical,Computer,Civil,Electrical and Electronics Engineering (ICMACE14)

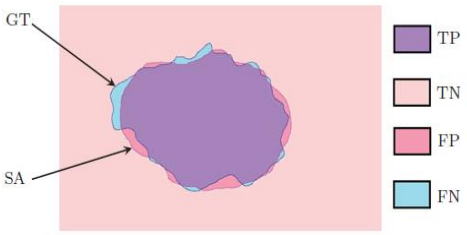


Fig (4.1) Measurement method based on four parameters

- TP (True Positive) - TP is the number of pixels that were classified both by GT and SA as lesion pixels.
- TN (True Negative) - TN is the number of pixels that were classified both by GT and SA as non lesion pixels.
- FP (False Positive) - FP is the number of pixels where a non lesion pixel was falsely classified as part of a lesion by SA.
- FN (False Negative) - FN is the number of pixels where an lesion Pixels was falsely classified as non lesion by SA.

Table I segmentation performances on 10 images

Techniques	Sensitivity	Accuracy	Border error
Adaptive Thresholding	82.89%	94.20%	36.38%
K-Means Clustering	88.82%	95.73%	26.26%
Neural Networks	91.80%	96.93%	15.3%

For each segmentation algorithm the median value are given.

Figure(2.3.3) Block diagram of testing stage

III. Evaluation Of Results

The segmented output of each technique is analysed using three metrics namely sensitivity, accuracy and border error. The following figure clearly illustrates the parameters namely TP,TN,FP and FN as well as the method of measurement.GT(Ground Truth) is obtained from dermatologist.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online)), Volume 2, Special Issue 3, February 2014)
International Conference on Trends in Mechanical,Aeronautical,Computer,Civil,Electrical and Electronics Engineering (ICMACE14)

IV. Conclusion

Three segmentation techniques were applied to the dermoscopic images to segment the skin lesions and evaluated with 3 different metrics, namely sensitivity, accuracy and border error. Segmentation performance shows that Neural Network based lesion segmentation has high sensitivity, accuracy and less border error. Hence it can be said that the NN algorithm segments the lesion boundary properly.

V. References

[1] M. Silveria, J. C. Nascimento, J. S. Marques, A. R. S. Marcal, T. Mendonca, S. Yamauchi, J. Maeda, and J. Rozeira, "Comparison of segmentation methods for melanoma diagnosis in dermoscopy images," IEEE Trans. Signal Process., vol. 3, no. 1, pp. 35–45, Mar. 2009.

[2] Maglogiannis, S. Pavlopoulos, D. Koutsouris, "An Integrated Computer Supported Acquisition, Handling, and Characterization System for Pigmented Skin Lesions in Dermatological Images," IEEE transactions on information technology in biomedicine, vol. 9, no. 1, march 2005.

[3] Wei Sun and Yaonan Wang, "Segmentation Method of MRI Using Fuzzy Gaussian Basis Neural Network Neural Information Processing", Letters and Reviews, Vol.8, No.2, August 2005, pp.19-24.

[4] Ibrahiem M. M. El Emary, "On the Application of Artificial Neural Networks in Analyzing and Classifying the Human Chromosomes", Journal of Computer Science, vol.2(1), 2006, pp.72-75.

[5] Bouchet A, Pastore J and Ballarin V, "Segmentation of Medical Images using Fuzzy Mathematical Morphology", JCS and T, Vol.7, No.3, October 2007, pp.256-262.

[6] Wilson, E., D.W. Sutter, and R.W. MahThe Application of Watershed in Segmentation of Overlapping Cells.. 2004. Honolulu, HI, United States: Acta Press, Anaheim, CA, United States.

[7] A.M Uso,F.Pla,P.G Sevila," Unsupervised Image Segmentation using a Heirarchical Clustering Selection Process".Structural Syntactic and Statistical Pattern Recognition Vol 4109,pp.799-807,2006.

[8] A.Z Arifin,A.Asano,"Image Segmentation by histogram thresholding using hierarchical cluster analysis"Pattern Recognition Letters,Vol.27,no.13,pp. 1515-1521,2006.

[9] H.S.Prasantha et. al. / (IJCSE) International Journal on Computer Science and Engineering Vol. 02, No. 04, 2010, 1209-1218 Medical Image Segmentation H.S.Prasantha, Dr.Shashidhara.H.L Dr.K.N.B.Murth Madhavi Lata.G PES Institute of Technology, Bangalore, Karnataka, India.

[10] Dr. J. Abdul Jaleel, Sibi Salim, Aswin.R.B Dept. of Electrical & Electronics Engineering, TKM College of Engineering, Kollam, Kerala, India. Artificial Neural Network Based Detection of Skin Cancer International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering Vol. 1, Issue 3, September 2012 .

[11] Ke Huang and Selin Aviyente, Member IEEE,Wavelet Feature Selection for Image Classification. IEEE Transactions On Image Processing, Vol. 17, No. 9, September 2008.

[12] P. Mohanaiah, P. Sathyanarayana, L. GuruKumar Image Texture Feature Extraction Using GLCM approach. International Journal of Scientific and Research Publications, Volume 3, Issue 5, May 2013.