An Automated SVM Based Skin Lesion Segmentation and Classification System for Tumor Diagnosis

N. Rajesh Kumar*
Assistant Professor, Dept. of ECE
SACS MAVMM Engineering College
Madurai, Tamilnadu, India

M. Vignesh Babu
Assistant Professor, Dept. of ECE
SACS MAVMM Engineering College
Madurai, Tamilnadu, India

***Abstract*—Medical image processing plays an important role in computer aided automatic cancer detection and diagnosis process. This paper proposes an efficient screening methodology for skin cancer segmentation using Support Vector Machine (SVM) classifier. The proposed method consists of the following stages as preprocessing, feature extraction, feature training and classification. Median filter is used as preprocessing stage to smooth the regions in skin image. Further, texture features are extracted from the preprocessed image and then these features are trained and classified using SVM classifier. The performance of the proposed skin cancer segmentation methodology is compared with ground truth images to analyze its performance in terms of sensitivity, specificity and accuracy.**

***Keywords*—skin cancer; median filter; feature extraction; classifier; texture features**

I. Introduction

Skin cancer is the second most common cancer type in women and it is the third most cancer type in men, as per Global Cancer Statistics Report (2015) [1].Skin cancer is more common in people with light coloured skin who have spent a lot of time in the sunlight. Skin cancer can occur anywhere on our body, but it is most common in places that have been exposed to more sunlight, such as our face, neck, hands, and arms.

Skin cancer can look many different ways. The most common sign of skin cancer is a change on the skin, such as a growth or a sore that won't heal. Sometime there may be a small lump. This lump can be smooth, shiny and waxy looking, or it can be red or reddish brown. Skin cancer may also appear as a flat red spot that is rough or scaly. Not all changes in the skin are cancer, but we should see a doctor if we notice changes in our skin.

Melanoma is a disease of the skin in which cancer (malignant) cells are found in the cells that colour the skin (melanocytes). Melanoma usually occurs in adults, but it may occasionally be found in children and adolescents. The skin protects our body against heat, light, infection, and injury. It is made up of two main layers: the epidermis (the top layer) and dermis (the inner layer). Melanocytes are found in the epidermis and they contain melanin, which gives the skin its colour. Melanoma is sometimes called cutaneous melanoma or malignant melanoma.

II. Proposed Methodology

The proposed skin cancer detection system uses SVM classifier to detect the cancer lesions. The various stages in this system include preprocessing, feature extraction, segmentation by k-means and classification of lesions. The flow of proposed method is depicted in Fig. 1.

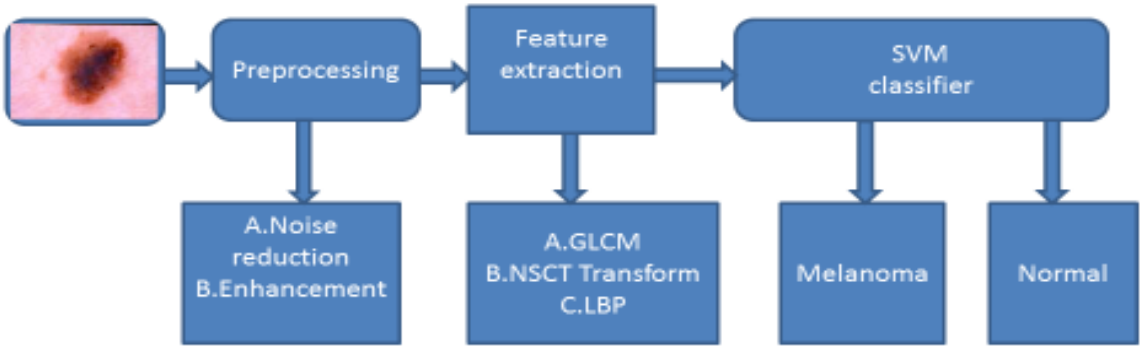


Fig. 1. Overall flow of proposed skin cancer detection system.

A. Preprocessing

In the preprocessing stage, the skin images are enhanced sing the median filters. The median filters preserve the edges of the image. Images commonly involve removing low-frequency background noise, normalizing the intensity of the individual particles images, removing reflections, and masking portions of images. Image preprocessing is the technique of enhancing data images prior to computational processing. The procedure done before processing by correcting image from different errors is preprocessing. This has to be done before image enhancement .Image processing in electrical engineering and computer science, image processing is any form of signal processing for which the input is an image, such as photographs or frames of video; the output of image processing can be either an image or a set of characteristics or parameters related to the image.

III. Feature Extraction

Features are able to differentiate the normal brain image from abnormal brain image. In this paper, the features as GLCM, Gabor and DWT are extracted from the approximate sub band of the NSCT transform.

A. GLCM features

The gray level co-occurrence matrix (GLCM) is a method of extracting second order statistical texture features depending on the number of gray levels used. The GLCM matrix is constructed in any one of the orientations as 0^0,45^0,90^0 and 180^0. In this paper, the GLCM matrix is constructed in the orientation of 45^0. GLCM features are the spatial features which are extracted from the co-occurrence matrix. The co-occurrence matrix is constructed in 45° from the enhanced skin image. The features as Contrast, Dissimilarity, Homogeneity, Entropy, Mean, Variance, Correlation and Angular Second Moment are extracted to increase the classification accuracy which is used to classify the given brain image into either normal or abnormal, as stated below.

$$Contrast = \sum_{i,j=1}^{N} P_d\,(i-j)^2 \quad (1)$$

$$Homogeneity = \sum_{i,j=1}^{N} \frac{P_d}{1+|i-j|} \quad (2)$$

$$Entropy = \sum_{i,j=1}^{N} P_d\,(-\ln P_d) \quad (3)$$

Mean: $\mu_i = \sum_{i,j=1}^{N} i(P_d)$

$$\mu_j = \sum_{i,j=1}^{N} j(P_d) \quad (4)$$

Variance: $\sigma_i = \sum_{i,j=1}^{N} P_d\,(i-\mu_i)^2$

$$\sigma_j = \sum_{i,j=1}^{N} P_d\,(j-\mu_j)^2 \quad (5)$$

$$Correlation = \frac{\sum_{i,j=1}^{N}(i-\mu_i)(j-\mu_j)P_d}{\sigma_i\sigma_j} \quad (6)$$

$$AngularSecondMoment = \sum_{i,j=1}^{N} P_d \quad (7)$$

Where, i, j - Co-ordinates in the co-occurrence matrix,

P_d - Co-occurrence matrix value at the coordinates i, j and

N - Dimension of the Co-occurrence matrix.

B. DWT features

A discrete wavelet transform (DWT) is based on wavelets. DWT analyzes the image on different resolution scales and splits the image into various frequency components, i.e. multi-resolution image. This permits to view the spatial and frequency attributes of the image simultaneously. Wavelets are small waves and are mathematical functions that represent scaled and shifted copies of a finite-length waveform called the *mother wavelet*.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (8)$$

where, a is the scaling parameter and b is the shifting parameter.

Firstly, wavelet transform is applied to each row and secondly to each column of the resulting image of the first operation. The resulting image is decomposed into four sub-bands: LL, HL, LH, and HH sub-bands. (L=Low, H=High). The LL-sub-band contains an approximation of the original image while the other sub-bands contain the missing details. The LL-sub-band output from any stage can be decomposed further. When using a wavelet transform to describe an image, an average of the coefficients-in this case, pixels-is taken. Then the detail coefficients are calculated .Another average is taken, and more detail coefficients are calculated. This process continues until the image is completely described or the level of detail necessary to represent the image is achieved. As more detail coefficients are described, the image becomes clearer and less blocky. Once the wavelet transform is complete, a picture can be displayed at any resolution by recursively adding and subtracting the detail coefficients from a lower-resolution version. This technique is used by iterated systems.

C. Moment Invariant Features

Moment invariants have been frequently used as features for image processing, remote sensing, shape recognition and classification. Moments can provide characteristics of an object that uniquely represent its shape. Invariant shape recognition is performed by classification in the multidimensional moment invariant feature space. Several techniques have been developed that derive invariant features from moments for object recognition and representation. These techniques are distinguished by their moment definition, such as the type of data exploited and the method for deriving invariant values from the image moments. It was Hu (Hu, 1962), that first set out the mathematical foundation for two-dimensional moment invariants and demonstrated their applications to shape recognition. They were first applied to aircraft shapes and were shown to be quick and reliable (Dudani, Breeding and McGhee, 1977).

These moment invariant values are invariant with respect to translation, scale and rotation of the shape. Hu defines seven of these shape descriptor values computed from central moments through order three that are independent to object translation, scale and orientation. Translation invariance is achieved by computing moments that are normalized with respect to the centre of gravity so that the centre of mass of

the distribution is at the origin (central moments). Size invariant moments are derived from algebraic invariants but these can be shown to be the result of a simple size normalization. From the second and third order values of the normalized central moments a set of seven invariant moments can be computed which are independent of rotation

IV. K-MEANS SEGMENTATION

The tumor regions are segmented from the abnormal skin image using K-means method, which is an unsupervised algorithm that characterizes the input information into various classes in view of their inherent separation from one another. A cluster is a gathering of objects which are similar between them and are not at all like the objects having a place with different groups. The points are clustered around centroids.

K-means clustering is an algorithm which gathers objects in view of attributes into k number of gatherings where k is a positive integer. The gathering (clustering) is finished by minimizing the Euclidean separation between the information and the comparing cluster centroid. For a given image, the cluster means 'm' is computed by,

$$m = \frac{\sum_{f.c(i)=k} x_i}{N_k} \quad ; \; k = 1, \ldots K \qquad (9)$$

The steps involved in k-means segmentation are described as follows:

1. Choose the number of clusters k with initial cluster centroid v_i ; i =1,2, ..., k.
2. Split the input data points into k clusters by assigning each data point x_j to the closest cluster centroid $v_i$using the Euclidean distance , d_{ij}

$$d_{ij} = \|x_j - v_i\| \qquad (10)$$

Where, X={x_1, x_2, ….x_n} is the input dataset.

3. Calculate a cluster assignment matrix *U* to define the data points partition with the binary membership value of the j[th] data point to the i[th] cluster, such that $U = |u_{ij}|$, where $u_{ij}$is {0, 1} for all i, j.

$\sum_{i=1}^{k} u_{ij} = 1$for all j and $0 < \sum_{j=1}^{n} u_{ij} < n$ for all i.

4. Re-calculate the centroid using the membership values using,

$$v_i = \frac{\sum_{j=1}^{n} u_{ij} x_j}{\sum_{ij=1}^{n} u_{ij}} \text{for all } i. \qquad (11)$$

5. If there is no change in cluster centroid or assignment matrix from the previous iteration, stop the process or go to step 2.

V. SVM CLASSIFICATION

It is otherwise called as binary classification algorithm. The binary SVM algorithm has been classified as linear and non-linear SVM. The training set for the case of normal linear SVM classifier is represented as,

$$T_{nor} = \{x_1, x_2, x_3, \ldots . x_i\}$$

where, x_i represents the extracted features and 'i' represents the number of features extracted.

It should satisfy the following conditions as,

$$Minimize \left\{\frac{1}{2}|W|^2 + C\sum_{i=1}^{l} \varepsilon_i\right\} \qquad (12)$$

Where, W is the optimal hyperplane parameter, ε_i represents slack variable which has the value greater than '0' and C represents the penalty value,

$$Maximize \left\{\sum_{i=1}^{l} d_i - \frac{1}{2}\sum_{j=1}^{l} \alpha_i \alpha_j\right\} \qquad (13)$$

Where, α_i and α_j represents the kernel function of the SVM classifier, and $C \geq \alpha_i \geq 0$

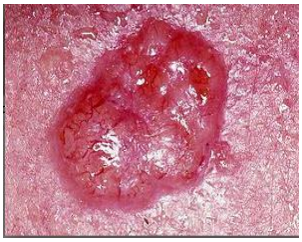
The SVM classification is mapped into,

$$Maximize \left\{\sum_{i=1}^{l} d_i - \frac{1}{2}\sum_{j=1}^{l} \alpha_i \alpha_j . \exp(\gamma \|x_i\|^2)\right\} \quad \text{and} \quad 0 \leq \gamma \leq 1 \qquad (14)$$

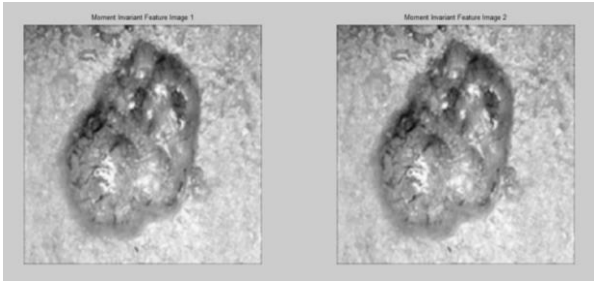
Where, γ is the smoothness parameter.

VI. RESULTS AND DISCUSSION

In this paper, 50 skin tumor affected images (Normal case: 10, abnormal case: 20) from the open access dataset is used for evaluation. These skin images are categorized into training and testing set. The training set contains 10 normal images and 20 abnormal images. The testing dataset contains 10 normal images and 20 abnormal images. MATLAB R2013 is used in this paper for simulation. The proposed system classifies 9 normal images as normal and 19 abnormal images as abnormal. Hence, this proposed skin tumor detection system achieves classification accuracy rate of 90% and 95% for both normal and abnormal skin images, respectively. The average classification accuracy rate of the proposed system is about 92.5%.



(a)



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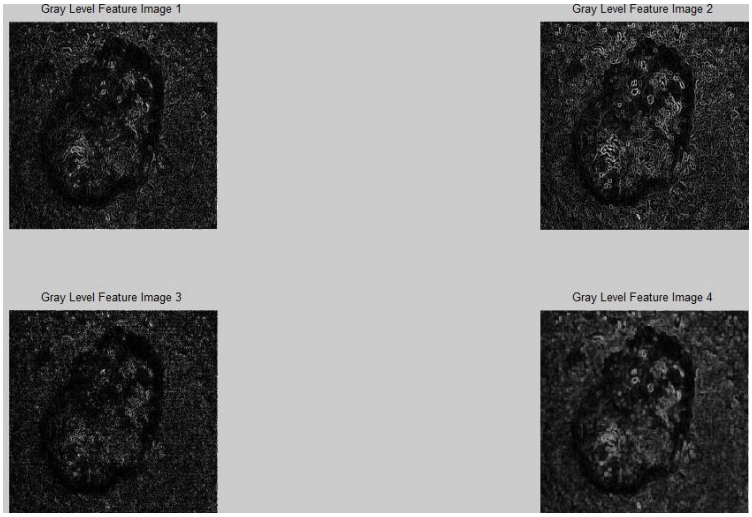
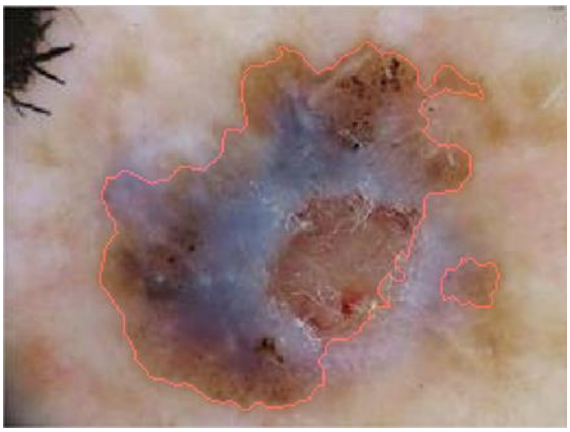


(c)



(d)

Fig. 2. (a) Original skin image, (b) Moment invariant output, (c) Gray level features, (d) SVM classified image.

VI. Conclusion

A computer aided fully automatic detection system for the detection of skin cancer has been proposed in this paper. The method is used to classify the preprocessed skin lesion images into normal and abnormal images. And it also defines what type of cancer it is. This method is proposed to reduce the manual segmentation time and increases the accuracy than that segmented by a physician.

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