Abstract- Melanoma a potentially fatal form of cancer has many diagnostic approaches. But they still lacks in efficiency due to factors like complex visual patterns, streaks, presence of hair and cost of dermatological examining. This paper describes a method that differentiates a normal skin from that of a malignant type. With the acquired image, pre-processing is done by converting them to gray scale and dull razor algorithm is applied to remove fine hair, small glows and noises. Features are extracted by acquiring the darker pixels found on the surface following which the radial distance between each dark spot is calculated. Segmentation is done using textural distinctiveness algorithm that calculates the local texture vectors by TD metrics and by computing the regional TD metrics the resultant map is acquired. Finally, classification of the segmented image is done with the use of support vector machine, where dataset is trained and their feature vectors are used to deduct generic equations, when a new dataset is tested in the system it predicts if the acquired image is melanoma or non-melanoma.

Keywords: Melanoma, Skin Lesion, Textural Distinctiveness, Image processing.

I. Introduction

Image processing is a vast domain which consists of technique to enhance raw images received from cameras, sensors, space probes or pictures taken from our day-to-day life for various purposes. One such application is in Medical Science, where images are acquired, processed, detected and recognized that are later used for clinical analysis. Cancer is a life threatening disease known to human. They are not just one disease but many diseases, where abnormal cells multiple without control. There are many types of cancer that occur internally and externally, with the latter known as skin lesion.

A typical lesion can occur in any part of the body and can cover very small or large area, single or multiple layers, confined to one specific spot or distributed widely. Thus with the type of origin and characteristics they are categorized into twelve names. Figure 1 shows example of dermatological photographs of a lesion diagnosed with melanoma and a benign pigmented lesion. This paper concentrates on malignant melanoma, the most deadly form of skin cancer but also has the highest chance of survival rate if found at early stage.
According to the World Health Organization (WHO), it is incident that both non-melanoma and melanoma skin cancer have been increasing rapidly. Currently 2-3 million non-melanoma cases and 132,000 melanoma cases are found globally each year. The following graph shows the occurrence of melanoma under different age groups found in both genders for the last 25 years.

**Figure 2 Occurrence of Melanoma for different age groups**

*Source: Adyar Cancer Institute, Chennai*

Dermoscope is device that is used to evaluate pigmented skin lesions; these dermoscopic images have great potential when diagnosed at early stage. The standard approach in automatic dermoscopic image analysis has usually the following methodology: 1) image acquisition; 2) pre-processing; 3) feature selection and extraction; 4) segmentation and 5) classification. The segmentation is an important phase as it deals with accuracy; however it is difficult due to various factors like lesion shapes, sizes, color along with different skin types and textures.

This paper is organized as follows. Related works are described in Section II, following which the system architecture and proposed system is explained in Section III. Experimental results are shown in Section IV with conclusion and future works in Section V followed by the references.

**II. Previous work**

K. Fergani et al (2014) [9] proposes a hybrid structural and texture distinctiveness vector field convolution approach, where both are incorporated into a multifunctional vector field convolution model. Here texture distinctiveness is used to enable automatic initialization and is incorporated with intensity variation to improve and accelerate convergence towards the object boundary. Experimental results show 90.64% of accuracy in using this method.

Maryam Sadeghi et al (2013) [18] extends a method to identify the presence and absence of streaks in skin lesion by analyzing the appearance of detected streak lines, and perform a three way classification for streaks. Features are extracted the directional pattern of detected lines is analyzed to extract the orientation features to detect the underlying pattern. Using the proposed method, the valid streaks along with color and texture features of the entire lesion are acquired, with an accuracy of 76.1%.

Ning Situ et al (2007) [20] proposed an evolutionary strategy based segmentation algorithm to identify the lesion area by an ellipse. Evolutionary Strategy is a random search based optimization technique. This approach can detect the lesion automatically without setting the parameters manually. Their future enhancement is to incorporate some edge and textural information in order to improve the system’s segmentation accuracy.
Huiyu Zhou et al (2010) [12] introduce snake model technique to improve segmentation accuracy, especially in medical imagery. This paper proposes a mean shift based gradient vector flow (GVF) snake algorithm, which drives the internal/external energies towards the correct direction. The proposed segmentation method incorporates a mean shift operation within the standard GVF cost function. Experimental result shows segmentation accuracy with 81%.

Christian Scharfenberger et al [9] gives a novel statistical textural distinctiveness approach for robustly detecting salient regions in natural images. Extractions are made by rotational-invariant neighborhood textural representations, and are used to learn a set of representative texture atoms. A sparse texture model is constructed by a weighted graph that characterizes the statistical textural distinctiveness between all atom pairs. Finally saliency of each pixel is computed based on the probability of occurrence of textural atoms. Experimental results show that the proposed system is efficient and has strong potential.

Vamsi K. Madasu et al (2009) [25] propose a Fuzzy Co-Clustering Algorithm for Images technique to segment medical images based on colors. Further, textural features are included as a clustering parameter for detecting blotches in the lesion. In order to get image specific values to the parameter, bacterial foraging algorithm is used to optimize the objective function. Experimental result show that the detection of malignant blotches are successful with low segmentation error rate.

Alexander Wong et al (2011) [2] gives an automatic method for segmenting skin lesion by a novel iterative stochastic region-merging approach. The region merging likelihood function is based on the regional statistics, to determine the merger of regions in a stochastic manner. Experimental results show that the proposed system achieves an overall segmentation error under 10%. Future enhancement is to use textural information in region merging to improve accuracy.

Jose Fernandez et al (2009) [17] describes an automatic system for the diagnosis of skin lesion in pigmented skin, further more the system uses a decision support component. This combines the outcome of the classified image with context knowledge such as skin type, age, gender and affected body part. The proposed system gives an accuracy of 86%, with a sensitivity of 94%, and specificity of 68%.

### III. Proposed System

#### A. System Architecture

This paper shows a system that takes clinical images as the input for diagnosis. The images are pre-processed; features are extracted and segmented in order to be classified as malignant or non-malignant type of skin lesion. The following figure 1 shows the overall system architecture, it depicts the four major modules that intend to process this system.

![Figure 3. System Architecture](image)

#### B. Pre-Processing

The overall system functions as follows: initially the dermatological images are fed as the input to the system. They are pre-processed for the removal of fine hairs, small glows and glitches. This is done with
the use of dull razor technique, where the images are converted into gray scale and dark hair locations are identified by the use of morphological closing operator. In this technique a structuring element (SE) is used as a reference for the dilation and erosion of the input image, where the thin and long hair structures are located and removed. The removed hair pixels are to be smoothed which is done by bilinear interpolation, where the hair pixels are replaced with the surrounding pixels’ intensity value.

Figure 4 shows a dermoscopic image of melanoma skin which has hair structures on it. Figure 5 shows the extraction of thin and long hair structures from the foreground, while Figure 6 shows the preprocessed image with hair being removed and overall image smoothed.

C. Feature Extraction

Features are defined on the basis of color or spatial distribution over the pixels of the image. Features are extracted from the pre-processed images. First the weighted centers of dark pixels found on the lesion surface are extracted. Thus the lesion centers are calculated with respect to the position of dark spots. In order to find the weighted average, specific number of dark pixels (depending on the input) are considered and calculated of their weighted average with respect to their coordinates by equation (1).

$$x_c = \frac{1}{N} \sum_{i=1}^{N} x_i \quad y_c = \frac{1}{N} \sum_{i=1}^{N} y_i$$

(1)

Where, $$(x_c, y_c)$$ is the centroid of the dark pixel. To calculate the radial distance computed for every pixel based on its distance from the calculated center point, Euclidean distance between the center point and the pixel is given by equation (2).

$$D_{x,y} = \sqrt{(x - x_c)^2 + (y - y_c)^2}$$

(2)

Where, $$D_{x,y}$$ is the radial distance computed for the pixel in the position (x,y). It is calculated for every pixel in the sub-image by finding the Euclidean distance between the corresponding pixels and the extracted center. Thus we include distance as a feature to obtain a more closed space for segmenting the lesion area.
D. Segmentation

In this paper, we propose a segmentation algorithm based on textural distinctiveness (TD) to recognize the skin lesion. It is known as Textural Distinctiveness Lesion Segmentation (TDLS) algorithm as it uses textural characteristics to locate skin lesion from a normal type. It consists of two steps, initially the local texture vectors \( t \) for the area of interest are found. It contains information describing an object’s important character. In case there are multiple channels of texture vectors we need to concatenate each of them \( t_A \), where \( A \) is the channel. By equation (3) the texture vector \( T \) for an image of size \( N \times M \) is found,

\[
T = t_{sj} \quad 1 \leq j \leq N \times M \tag{3}
\]

Thus, texture vectors are extracted for each cluster and fixed centroids are implemented by k-means clustering algorithm, since each cluster has different texture data causing different results. Gaussian distribution is assumed for each cluster with parameters as mean \( \mu \) and covariance \( \sigma \). To find similarity between two textural distributions is computed by a metric \( l_{j,k} \), shown in equation (4), which depicts the probability of mean of one textural distribution to that of the other.

\[
L_{j,k} = \frac{1}{2} (l_{j,k} + l_{k,j}) \tag{4}
\]

The metric \( L_{j,k} \) is calculated for asymmetry where, \( \sigma_i \) and \( \sigma_j \) are the mean and covariance of the textural distribution. While comparing most pairs the distribution ends up with \( \sigma_i \neq \sigma_j \) as the structure of the lesion area are not symmetrical. Further textural distributions are found distinctively as the texture of skin varies widely to that of the lesion. This is computed by the metric as follows in equation (5),

\[
d_{j,k} = 1 - L_{j,k} \tag{5}
\]

Where the probability for any distribution is 1 and finding the probability of a distinct textural distribution is by the metric \( d_{j,k} \) (5). The overall dissimilarity of textural distribution \( D_j \) in equation (6) is given by \( P(T^r_k | l) \) the probability of occurrence of a pixel with a specific texture distribution \( T^r_k \).

\[
D_j = \sum_{k=1}^k d_{j,k} P(T^r_k | l) \tag{6}
\]

In case of normal skin the dissimilarity is very small. The second part is to find the region and classify them based on their textural distribution along with the TD metric. The lesion image are divided into large number of regions, thereby sorted and merged accordingly. In the sorting step, pixels of the image are sorted to determine the order in which they are compared. In merging step, the system combines the pairs of pixels based on their similarity into regions. Thus for each region the textural distribution \( D \) in equation (7) is calculated and combined with every consecutive region as regional TD metric \( D_R \).

\[
D_R = \sum_{k=1}^k d_{j,k} P(T^r_k | R) \tag{7}
\]

Where \( D_R \) represents the average textural distribution across a region \( R \) with the probability of each pixel being associated. Finally a resulting segmentation map \( Y(R) \) found by equation (8) is formed where threshold \( \tau \) is used to provide the boundary between normal skin and lesion skin in an image.

\[
Y(R) = \begin{cases} 
1, & D_R \geq \tau \\
0, & \text{otherwise}
\end{cases} \tag{8}
\]

It is represented Otsu’s threshold where 1 represents the presence of lesion and 0 represents the presence of normal skin.

E. Classification

Once the images are segmented they need to be trained and classified by the system. This paper uses support vector machine classifier which is a supervised learning model used for classifying data. The
decision function is fully specified by a subset of training samples. The training data set is labeled as \( \{x_i, y_i\} \) where \( i=1,\ldots,l \). Similarly the training data set satisfies anyone of the constrains in equation (9) and (10);

\[
x_i \cdot w + b \geq +1 \quad \text{for} \quad y_i = +1; \quad (9)
\]

\[
x_i \cdot w + b \leq -1 \quad \text{for} \quad y_i = -1; \quad (10)
\]

The newly found data are predicted into one of the category by the trained system.

IV. Experimental Result

Each algorithm applied with its dataset is compared with that of the proposed system and are showcased as follows. The proposed system is applied on the dataset acquired with melanoma and non-melanoma images with sensitivity, specificity and accuracy as the metrics being calculated.

Figure 7 and 8 are the input dataset given for the system to compute.

Figure 9, 10 and 11 shows the comparison of different methods for the diagnosis of both melanoma and non-melanoma skin types. As seen, it is clear that with the use of...
of textural information for the diagnosis of lesion the rate of accuracy is higher than that of other method such as Otsu’s RGB analysis or Statistic region merging algorithm.

V. Conclusion and Future Work

This paper focuses on the segmentation accuracy while processing a dermoscopic image for skin lesion. Textural distinctiveness lesion segmentation algorithm is proposed and compared with that of other methods and found to be higher in accuracy. Presence of hairs, blotches and uneven lighting are few difficulties faced which are addressed in this paper. The system can be further extended in terms of undertaking a larger dataset and also finding a probabilistic difference between other forms of skin lesion to that of melanoma.

REFERENCES