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A Survey on Melanoma Diagnosis using Image Processing and Soft Computing Techniques

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ABSTRACT

The study presents a review on different methodologies to diagnose the melanoma, a deadly skin cancer. Melanoma is a type of skin cancer which arises on the outer layer of skin. Major cause of this type of skin cancer is over exposure of skin to UV radiation and also severe sun burns. It is the cancer which grows rapidly and has higher chances of death. There are many clinical diagnosis techniques are available, but the exact and accurate results of melanoma is acquired by analyzing the skin lesion image with the emerging image processing and soft computing techniques. ABCD analysis is the process used to differentiate the melanoma skin lesions with the other type of skin diseases. The same is used in the processing of the skin lesion image using image processing techniques and the results are optimized using soft computing techniques. This study narrates the procedure and methodologies of image processing and soft computing techniques used to diagnose the melanoma with better accuracy.

Key words: Malignant melanoma, asymmetry, border, color and diameter

INTRODUCTION

Melanoma skin lesions are analyzed by ABCD analysis which predicts the disease with its features such as asymmetry, border, color and diameter. Many researchers have been conducted based on each feature to diagnose the melanoma accurately and also at as early stage as possible. The basic operation or process to diagnose the melanoma is to separate the melanocytic lesion from the skin with clarity and without noises. It makes the further procedure to be implemented easily. For skin detection many procedures are developed to achieve the result with more clarity and exactness. The next step is to preprocess the image so that the image can be in the format, from which some significant features can be derived. Those features will be used in diagnosis of melanoma at proliferation stage. Next using the four parameters of ABCD analysis, the inputted skin lesion can be identified whether it is melanoma or other types of skin cancer. Each parameter is subjected to quantification such that the measures will be used to predict which type of skin cancer it is:

- Image acquisition
- Preprocessing

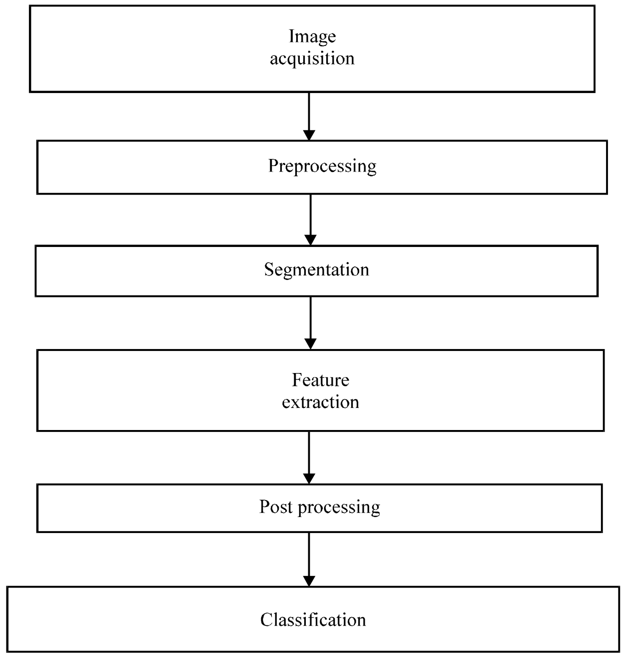

Fig. 1: Diagnosing or classifying melanoma using image processing

- Segmentation
- Feature extraction
- Post processing
- Classification

The above said steps are used to diagnose a skin lesion and classify whether it is malignant or benign as shown in the Fig. 1. There are many researches took place on all the major parameters to diagnose the melanoma at very early stage, so that the patient can be given proper treatment. The study is comprised of a survey based on various aspects of diagnosing melanoma using its well known features of asymmetry, border, color and diameter. Before classification, the affected skin lesion should be separated from the normal skin. Different methodologies to classify a skin lesion is presented in this study as a step by step procedure.

STEPS INVOLVED IN MELANOMA DIAGNOSIS

Image acquisition: Images of melanoma are captured using the technique dermoscopy or epiluminance microscopy. It uses an equipment called dematoscope to observe and capture the skin lesion closely.

Preprocessing: Preprocessing is a mandatory task to be done on the images acquired using dermoscopy. It is required because the captured image may not be clear in resolution. Human skin surface will be accumulated by hairs, scars and skin tone differences. Hence, the images should be preprocessed to access the affected skin lesion accurately. An image can be preprocessed in multiple number of ways. They are: Hair removal, noise filtering, black frame removal, equalization, contrast enhancement etc., these techniques are narrated as below:

- Celebi *et al.* (2008a) used black frame removal technique for preprocessing. The darkness of the pixel is determined with the help of HSL color space's lightness component (Eq. 1):

$$L = \frac{\max (R, G, B) + \min (R, G, B)}{2} \tag{1}$$

If value of lightness of the pixel is less than 20 then it is considered to be black. The image scanning is done row by row beginning from top based on this criterion. If a particular row contains 60% black pixels, then it is marked as a portion of the black frame. When the row with value lesser than the percentage of the threshold of the pixel is sited, top to bottom scan is terminated. Automatic Color Equalization technique (ACE) was used in Schaefer *et al.* (2011). Two main stages of ACE are dynamic tone reproduction scaling and spatial adjustment or chromatic. In the spatial adjustment stage color normalization is performed to enhance the image contrast, whereas the second stage is accountable for accurate lightness constancy and tone mapping. Hair removal technique was used in Capdehourat *et al.* (2011) and Schmid-Saugeon *et al.* (2003). Automatic hair removal algorithm is used to remove hair. Hair detection and image impainting are the essence of this algorithm. Image segments are identified using this algorithm which approximates the structure of the hair. Finally the regions that enclose these segments are interpolated with the help of information of the surrounding pixels. Since luminance components are best suited for hair and dark pigment differentiation the L*u*v* color space is chosen. A constant threshold is sufficient to produce satisfactory results since hair is a light absorbent body. Hair and pigmented structures were differentiated using luminance component L*. Median Filtering technique was used in Messadi *et al.* (2009) and Celebi *et al.* (2008b, 2009). A nonlinear filter which replaces the median value of each pixel by neighboring one. For skin tumor images this filter is used. Presence of trace amount of noise depicting some hair traces, adversely affect the segmentation quality. Artifacts in dermoscopy images can be eliminated easily with the help of median filters, with appropriate mask size. To obtain optimal results, mask size and image size should be proportional. For an M×N image, n should be (Eq. 2):

$$n = \text{floor}\left(5.\sqrt{\frac{M}{768}.\left(\frac{N}{512}\right)}\right) \tag{2}$$

Dull Razor technique was used in Messadi *et al.* (2009). An artifact removal technique, that deals well with hair and other artifacts. Dull Razor algorithm is illustrated as follows:

Dull Razor algorithm
Step 1: To remove the small details, dilate the image then erode
Step 2: Compute the dissimilarity between the obtained and the original one
Step 3: To remove noise first dilate and then the mask of difference is eroded
Step 4: A Boolean mask is created for artifacts location; and
Step 5: Replace the mask covered pixels by original image's pixel

Karhunen-Loe've Transform (KLT) technique was used in Messadi *et al.* (2009). A preprocessing step that facilitates segmentation process by enhancing edges. Principal component analysis (PCA) is commonly used method to attain the reduction without much loss of information. KLT's purpose is to find M orthogonal vectors set from data space which takes better interpretation of their variance (Eq. 3-4):

$$mx = \frac{1}{M}\sum_{k=1}^{M} X_k \tag{3}$$

$$C_x = \frac{1}{M}\sum_{k=1}^{M} (X_k.X_k^T - m_x.m_x^T) \tag{4}$$

Where:

M = No. of data
m_x = Image's average vector
A = Matrix, whose lines are eigen vectors of C_x matrix, ordered by the decrease in eigen values

KLT of X can be defined as Eq. 5:

$$y = A.(x\text{-}m_x) \tag{5}$$

Gaussian filter technique was used in Schmid (1999) and Celebi *et al.* (2009). Original image is filtered using Gaussian filter with impulse response (Eq. 6):

$$g(m,n) = (1 \div 2\pi.\sigma^2).\exp\,(-(m^2 + n^2/2\square^2)) \tag{6}$$

Region boundaries are blurred when this method is used. This is the disadvantage of Gaussian filter. Morphological filter technique was used in Schmid (1999). This method produces kind of pre-segmented image. Image is altered much when using this filter. These are the disadvantages of morphological filter. Pseudorandom filter technique was used in Hance *et al.* (1996). This filter possess many necessary properties similar to median filter. Length 5 pseudomedian is defined as Eq. 7:

$$\begin{aligned}\text{PMED}(a,b,c,d,e) = (\,1/2)\text{MAX}(\text{MIN}(a,b,c),\ \text{MIN}(b,c,d),\ \text{MIN}(c,d,e)+\\ (1/2)\text{MIN}(\text{MAX}(a,b,c),\ \text{MAX}(b,c,d),\ \text{MAX}(c,d,e))\end{aligned} \tag{7}$$

Average of 2 parts of the equation cancels out the biases. Pseudomedian is defined as Eq. 8:

$$\text{PMED}\,\{SL\} = (1/2)\ \text{MAXIMIN}\,\{SL\}+(1/2)\ \text{MINIMAX}\,\{SL\} \tag{8}$$

$\{S_L\}$ = Sequence of elements $s_1, s_2, s_3 \ldots\ s_L$

Non skin masking technique was used in Hance *et al.* (1996) to know whether the color is either skin or non-skin. This algorithm uses set of heuristics. The pixel samples in the red plane is compared to that of blue and green planes on the basis of brightness level. To determine whether the pixel is non skin, predefined threshold values are used. Color space transform technique was used in Celebi *et al.* (2009). RGB image is converted into scalar image using any one of the methods below:

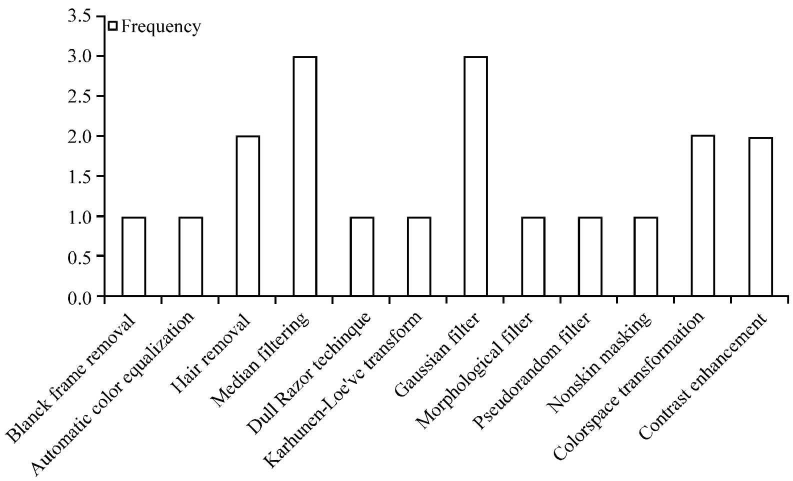

Fig. 2: Comparison chart of preprocessing techniques

Table 1: Preprocessing techniques

Methods	References
Black frame removal	(Celebi *et al*., 2008a)
Automatic color equalization	(Schaefer *et al*., 2011)
Hair removal	(Capdehourat *et al*., 2011; Schmid-Saugeon *et al*., 2003)
Median filtering	(Messadi *et al*., 2009; Celebi *et al*., 2008b, 2009)
Dull Razor technique	(Messadi *et al*., 2009)
Karhunen-Loe've transform	(Messadi *et al*., 2009)
Gaussian filter	(Schmid, 1999; Celebi *et al*., 2008b; Morar *et al*., 2012)
Morphological filter	(Schmid, 1999)
Pseudorandom filter	(Hance *et al*., 1996)
Non skin masking	(Hance *et al*., 1996)
Color space transformation	(Celebi *et al*., 2009)
Contrast enhancement	(Celebi *et al*., 2009)

- Only blue channel is retained
- Luminance transformation is applied:

$$\text{Luminance} = 0.299\times\text{red}+0.587\times\text{green}+0.114\times\text{blue}$$

- Channel with highest variance is retained using Karhunen-Loe've transform

Contrast enhancement technique was used in Celebi *et al*. (2009). Lesion and background skin are separated maximally by transforming original RGB into de-correlated color space linearly. Figure 2 presents a comparative analysis on preprocessing and Table 1 gives the list of techniques used in the literature.

Segmentation: The process of dividing an image into number of sub images which are meaningful is known as Segmentation. Each segment of an image will infer us various details of about an image. In melanoma diagnosis, the exact segmentation is needed to segment the affected skin lesion area from normal skin. If the lesion area is segmented, then the appropriate features can be easily extracted from segmented region. There are several types (Celebi *et al*., 2009) of segmentation which can be used to segment the affected lesion from normal skin.

First is the histogram thresholding (Tobias and Seara, 2002). One or more threshold values are determined to separate the objects from background. In the valley region, optimum threshold must be located to segment the image using histogram thresholding. The gray scale image should be bimodal or nearly bimodal for the histogram technique to work well. Second one is clustering (Palus and Bogdanski, 2003). Pixels from an image are grouped together based on calculated similarity. Dense clusters in the color space are created by dominant colors. Unsupervised clustering algorithms are used to partition color space into homogeneous regions. Third one is edge based (Uemura *et al*., 2011). Edges of the image pixel are identified by using edge based techniques. Edges between the regions are detected using edge operators. Fourth category is region based. Using region merging or splitting pixels are grouped into homogeneous region. Fifth one is morphological (Sarker *et al*., 2008). It is generally applied to gradients of the image. The image is over-segmented and this is the problem in morphological segmentation. This method involves object contour detection from predetermined seeds with the help of watershed transform. Sixth category is model based (Freedman *et al*., 2005). This method is used to model the images as random fields and various optimization procedures are used to determine the parameters. Segmenting deformable objects is a difficult task. Seventh one is active contours (snake and their variants, (Morar *et al*., 2012; Xiang *et al*., 2006). These methods use curve evolution techniques to detect the object contours. The stopping curve is particularly related to the segmentation of the image and does not depend on the image gradient. Evolving curve is used to detect boundary of the objects. Last category is soft computing (Kaur and Banga, 2011; Singh *et al*., 2011), a technique which includes evolutionary computation, fuzzy logic, neural networks are taken for the classification of pixels. Soft Computing techniques are used to reduce the complexity of segmentation. Iterative segmentation technique was used in Schaefer *et al*. (2011) and Rajab *et al*. (2004). Intensity mapping is one of the steps in iterative segmentation which achieves less redundancy than color mapping. The appealing feature of this step is that seven different smoothening kernels can be chosen dynamically based on the noise. Value of optimal threshold T of an image can be determined by using Isodata algorithm. For an image I, R_i denotes the ith n regions from the image (Eq. 9-10):

$$T_{i,\,k+1} = \frac{\mu Ri,\, k + \mu Ri + 1,\, k}{2} \tag{9}$$

$$\mu_{Ri,\,k} = \frac{\sum m,\, n \in Ri,\, k^{1}\,(m,\, n)}{NRi,\, k} \tag{10}$$

Where:

- $T_{i,k+1}$ = Optimal threshold separating pixel
- $R_{i,k}$ = Mean pixel value
- $Nr_{i,k}$ = Number of pixels

Object outlining adapts a simple logic rule stating that the foreground pixel is left unchanged when at least one background pixel in 3×3 neighborhood is present, else foreground is changed to background color. Cooperative neural network segmentation technique was used in Schaefer *et al.* (2011) and Rajab *et al.* (2004). Neural network detects the object boundaries and also recognizes edge patterns in noisy lesions, intensity variations in surrounding lesions are less likely recognized. Low level feature extraction is applied after convolving the template of weights for each output node at the hidden layer with the original image. For each network output, maximum threshold is used to fuse threshold outputs for summing up various edge maps. Prototype noisy edge patterns are memorized by neural network when an image contains similar noisy patterns to those included. Adaptive threshold technique was used in Silveira *et al.* (2009). By performing color comparison of each pixel with a threshold T, segmentation of lesions can be obtained. A pixel is said to be active, if it is darker than the threshold value. Then, holes are filled using morphological post processing and largest connected component is selected. Based on entropy value (as in equation below) an automatic color component selection method is used (Eq. 11):

$$S(i) = -\sum_{k=0}^{L-1} hi(k)\log(hi(k)) \tag{11}$$

Color plane is selected for which the entropy value is high (Eq. 12):

$$i^* = \text{argmax} S(i) \tag{12}$$

The computation of threshold value is done from the color component which is selected from the histogram. Gradient Vector Flow (GVF) technique was used in (Silveira *et al.*, 2009). Elastic contour is used for approximation of object boundary (Eq. 12):

$$x(s) = (x(s), y(s)), s\in(0, 1) \tag{13}$$

Heuristic criteria or the user initializes contour in the image domain and based on the differential equation, it is modified. Towards the object boundary, the contour's long range attraction is allowed by GVF field (v), which is the regularized version of the image. Adaptive snake technique was used in Silveira *et al.* (2009). Edge linking is used by this technique to detect contour segments in the image. Based on EM (Expectation-Maximization) theorem a robust elimination algorithm is used for subset approximation. Two steps process is done to detect the strokes. HSV (Hue, Saturation and Value) color space is used for intensity transition detection along the set of radial direction. A simple continuity criterion is adopted to perform edge linking. FBSM (Fuzzy Based Splitting and Merging) technique was used in Silveira *et al.* (2009) to extract texture and color from original image. The color features used are L*, a*, b* and the texture features used are Statistical Geometrical Features (SGF). Execution of split and merge technique undergoes 4 stages like boundary refinement, global merging, local merging and simple splitting. Similarity is estimated through fuzzy among last 3 stages. Fuzzy rules used are:

- **Rule 1:** If SGF difference is SMALL, then HOMOGENEOUS (HO); else NOT_ HOMOGENEOUS (NHO)
- **Rule 2:** If L*a*b* difference is SMALL, then PROBABLY_HOMOGENEOUS (PHO); else PROBABLY_NOT_ HOMOGENEOUS (PNHO)

Finally, centroid defuzzification is applied. Fuzzy C-Means technique was used in Hance *et al*. (1996) and Schmid (1999). According to safety margin specified by the user, number of valid classes are determined. The pixels which are classified according to safety margin are allocated to a valid class. Result of segmentation will be more accurate, if value of safety margin is large. Spherical coordinates technique was used in Hance *et al*. (1996). RGB data is transformed into spherical transform domain using this algorithm. Image is mapped to color space exemplified by one dimensional intensity space and 2 angles A and B. Equation 14-16 are for conversion:

$$L = \sqrt{(R^2+G^{2+}B^2)} \tag{14}$$

$$\text{Angle A} = a\cos\frac{B}{L} \tag{15}$$

$$\text{Angle B} = a\cos\left(\frac{r}{L x \sin(\text{Angle} A)}\right) \tag{16}$$

Midpoint between maximum and minimum is found out by dividing the color space using center split. Principal component transform/median cut technique was used in Hance *et al*. (1996). This is based on PCT technique. The components of resulting vectors are uncorrelated because Eigen vectors of covariance matrix are been used as linear transform matrix. Equation of new vector is (Eq. 17):

$$\begin{bmatrix} X1 \\ X2 \\ X3 \end{bmatrix} = \begin{bmatrix} E11 & E12 & E13 \\ E21 & E22 & E23 \\ E31 & E32 & E33 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{17}$$

Four phases of color quantization task:

- For color statistics the original image is sampled
- On the basis of color statistics a color map is chosen
- The original colors are mapped to the neighbors in the color map
- The original image is quantized and redrawn

Region fusion based technique was used in Yuan *et al*. (2009). In this technique, Chan Vese prototype is used to segment an image into small regions with strong edge and homogeneity. Based on gradient information and the intensity of the centroid, small regions are merged together which belongs to the same homogeneous cluster. Each segmented region is applied with active contour iteratively in the initial stage. Further the regions are segmented with lower and higher intensity and terminate the process as soon as the count of pixels located in the region is lesser than minimum area percentage of all the pixels in the image. In the second stage, merging of overlapping and non-overlapping regions is done. If edge strength of outer region is less than the edge strength of inner region, then those two regions are merged. Narrow band graph partitioning technique was used in Yuan *et al*. (2009). Three steps are adopted in this technique. In the first step reinitialisation procedure is adopted. Here local reinitialisation of level set function of each pixel to a signed distance function is done. Within (ebs+ubs) layers of pixels approximation of level

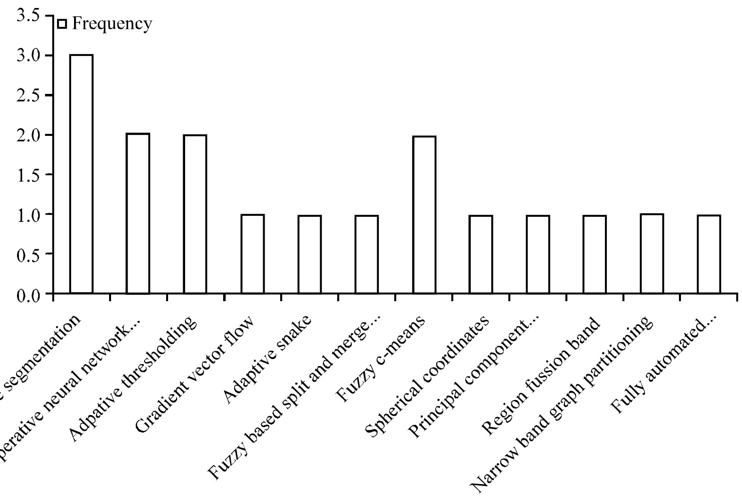

Fig. 3: Comparison chart of segmentation techniques

set function is done. The value of the level set functions on zeroth layer is zero. First layer is formed by connecting four neighbors on both directions of the pixel. Four connected neighbors that do not belong to second layer but lie on first layer form the second layer. Until (ebs+ubs)th layer is formed this procedure continues. The pixels which are present in these regions are all active. In the second step, the curve is updated by examining each pixel of the active pixel and updating its level function. The curve is extracted after updating all level set functions. Convergence control is the third step. The extraction of final curve is done once after the completion of curve evolution based on the conditions of attaining the maximum iteration or by achieving the non-motile state of the curve. Fully automated segmentation algorithm was used in Zortea *et al.* (2014). Fully automated algorithm selects the small seed regions which corresponds to the models of the skin and lesions. From segmented lesion the features of interest are calculated. An iterative binary classification setting is used to treat the lesion segmentation problem. Figure 3 presents a comparative analysis on segmentation techniques and Table 2 gives the list of techniques used in the literature.

Feature extraction: Feature extraction is an important phase where the features necessary to diagnose melanoma are extracted to infer some useful information. These features can be extracted from the segmented skin lesion. Each feature follows the ABCDE rules (Safi *et al.*, 2012) of skin cancer:

- **Asymmetry (A):** Generally the normal moles are symmetric and the skin cancer moles are asymmetric
- **Border (B):** Melanocytic lesions are usually found with blurry or jagged edges
- **Color (C):** Different colors are found inside the mole of the melanocytic lesion
- **Diameter (D):** Normal diameter of the lesion is around 6 mm, which becomes suspicious when extended
- **Elevation (E):** It is suspicious when the mole is found in elevated form

Feature vector technique was used in (Cheng *et al.*, 2008). Feature vectors are standard techniques which are used for classifying objects, where an attribute set defines each object of the

Table 2: Segmentation techniques

Methods	References
Types of segmentation	(Celebi *et al*., 2009) (Tobias and Seara, 2002; Palus and Bogdanski, 2003; Uemura *et al*., 2011; Sarker *et al*., 2008; Freedman *et al*., 2005; Morar *et al*., 2012; Xiang *et al*., 2006; Kaur and Banga, 2011; Singh *et al*., 2011)
Iterative segmentation	(Schaefer *et al*., 2011; Rajab *et al*., 2004; Palus and Bogdanski, 2003)
Cooperative neural network segmentation	(Schaefer *et al*., 2011; Rajab *et al*., 2004)
Adaptive thresholding	(Silveira *et al*., 2009; Morar *et al*., 2012)
Gradient vector flow	(Silveira *et al*., 2009)
Adaptive snake	(Silveira *et al*., 2009)
Fuzzy based split and merge algorithm	(Silveira *et al*., 2009)
Fuzzy c-means	(Hance *et al*., 1996; Singh *et al*., 2011)
Spherical coordinates	(Hance *et al*., 1996)
Principal component transform/median cut	(Hance *et al*., 1996)
Region fusion band	(Yuan *et al*., 2009)
Narrow band graph partitioning	(Yuan *et al*., 2009)
Fully automated segmentation algorithm	

feature space. It is a vector with n dimension that comprises of the measurements corresponding to an object in the image of selected feature. SRM (Statistical Region Merging) algorithm for border detection was used in Celebi *et al*. (2008a). It is a segmentation technique for color image on the basis on merging and region growing. SRM is based on 2 major components similar to other region growing algorithms like merging the predicate and the order which is followed for testing that predicate. Definition of predicate is Eq. 18-19:

$$P(R, R') = \begin{cases} \text{true if } \forall\alpha \in \{R, G, B\} \,|\, \overline{Ra'} - \overline{Ra} \,| \leq \sqrt{b^2(R) + b^2(R')\,|} & \\ \text{false} & \text{otherwise} \end{cases} \tag{18}$$

$$b(R) = g\sqrt{\frac{1}{2Q\,|R\,|} \ln(6\,|\,I\,|^2 R_{|R|})} \tag{19}$$

Where:

R', R = Tested regions
R_a = Color channel's observed average
$R_{|p|}$ = Set of p pixel's regions

SI, is a set of adjacent pixel's pair on the basis of 4-connectivity in the image. In the image I, p' and p be pixels, R (p) is the current portion where the p pixel is present. Based on function f (p, p') the sorting of pairs is done in increasing order by the SRM algorithm. The order is traversed once after sorting, by carrying out a merging test P(R(p), R(p')) for the couple of pixels p, p' where R(p)≠R(p'), combining R(p') and R(p), if true is returned. Radial Search Technique was used in Zhang *et al*. (2000). In the first round, this technique finds the seed border points. During the second round, border is tracked based upon the nearest neighbor border point. Absolute color feature technique was used in Celebi *et al*. (2008a) and Ballerini *et al*. (2012). Chromatic

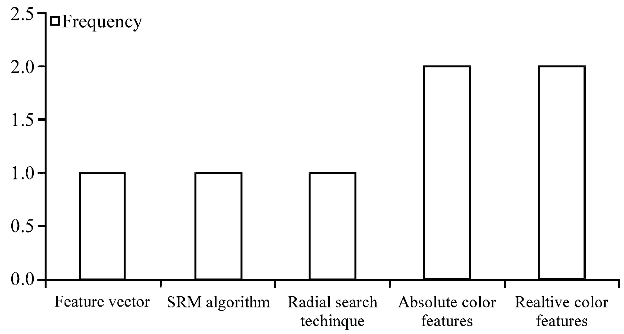

Fig. 4: Comparison chart of feature extraction techniques

Table 3: Feature extraction techniques

Methods	References
Factors	(Safi *et al*., 2012)
Feature vector	(Cheng *et al*., 2008)
SRM algorithm	(Celebi *et al*., 2008a)
Radial search technique	(Zhang *et al*., 2000)
Absolute color features	(Celebi *et al*., 2008b; Ballerini *et al*., 2012)
Relative color features	(Celebi *et al*., 2008a; Ballerini *et al*., 2012)

coordinates of a particular pixel is used to quantify its absolute color. Major advantage of the coordinates is that it is invariant to intensity and illumination direction. Relative color feature technique was used in Celebi *et al*. (2008b) and Ballerini *et al*. (2012). It refers to lesion pixel color in comparison to the average background skin color. Major advantages of relative color features are, variations in the images are compensated, equalization in the variation is done and it is more natural. Figure 4 presents a comparative analysis on feature extraction methods and Table 3 gives the list of techniques used in the literature.

Post processing: Post processing is a technique done after the features are extracted from the melanoma skin lesion. Following are some of the literature, where post processing is used in determining some specific features. Color technique was used in (Celebi *et al*., 2008a). The mean value of R, G and B corresponding to the pixels is computed from the corners of the image of size 20×20 pixels. The background skin color is estimated with the help of this mean color. The portions that come under light colored category, that is, portions with less than 60 mean colored distances to that of non-lesion skin color are discarded. Added rectangular bordered regions and those that touch the image frame are removed. Initially, result for border detection is acquired by merging the left out regions after eliminating the regions that are isolated. Morphological tool technique was used in Schmid (1999). The following iterative expression is used for extraction purpose:

$$X_k = (X_{k-1} \text{ XOR B})\text{intersection A} \quad (20)$$

The algorithm converges when $X_k = X_{k-1}$ and let $Y = X_k$. The implementation of the algorithm takes place in recursive manner and the segmented image pixel is taken as input. If the surrounding pixel and latter have the same value, then it is given as input. Regional merging technique was used in Celebi *et al*. (2009). Two regions are produced by segmentation procedure:

Lesion and background skin. These regions are partitioned into multiple sub regions by segmentation procedure because they are rarely homogeneous. The sub regions which are part of lesion region should be identified and merged to obtain single lesion region. This can be done in many ways:

- The sub regions with similar color to the background skin is eliminated, leaving only the sub regions of the lesion part by estimating the background skin color from corners of the image
- To differentiate the regions of lesion and background skin, various color and texture features are extracted from each region and classifiers are used to determine the features which discriminate effectively

Island removal technique was used in Celebi *et al.* (2009). Binary area opening filter is used to remove the islands (i.e small isolated regions) in the label image. Border smoothing technique was used in Celebi *et al.* (2009). Ragged borders are produced by segmentation methods. Many filtering methods such as Morphological filter and curve fitting are used to obtain natural borders. Border expansion technique was used in Celebi *et al.* (2009). Computer detected borders were contained within the dermatologist detected borders. To reduce this discrepancy, computer detected borders are expanded using several techniques like morphological filtering, euclidean distance transform and iterative region growing. Figure 5 presents a comparative analysis on post processing and Table 4 gives the list of techniques used in the literature.

Classification: Classifying of feature vector in two classes, malignant and benign, is the ultimate aim of classification. Decision tree technique was used in Capdehourat *et al.* (2011) and Masood and Al-Jumaily (2013). Decision trees combination via adaptive boosting stood as the most promising classification process by providing very successful result. Weights to the training data are assigned and they are modified at the end of each classifier by incrementing the weight of

Table 4: Post processing techniques

Methods	References
Color	(Celebi *et al.*, 2008a)
Morphological tool	(Schmid, 1999)
Region merging	(Celebi *et al.*, 2009; Palus and Bogdanski, 2003)
Island removal	(Celebi *et al.*, 2009; Morar *et al.*, 2012)
Border smoothing	(Celebi *et al.*, 2009)
Border expansion	(Celebi *et al.*, 2009)

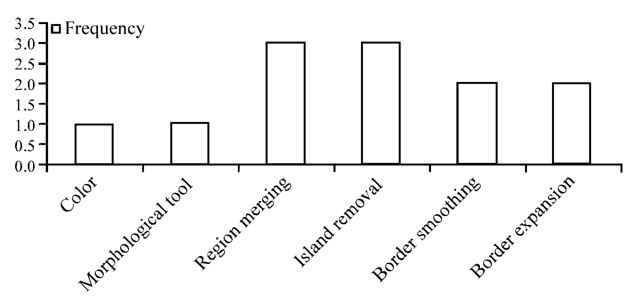

Fig. 5: Comparison chart of post processing techniques

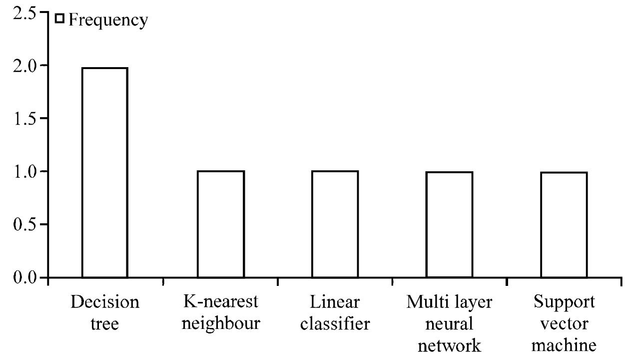

Fig. 6: Comparison chart of classification techniques

Table 5: Post processing techniques

Methods	References
Color	(Celebi *et al*., 2008b)
Morphological tool	(Schmid, 1999)
Region merging	(Celebi *et al*., 2009; Palus and Bogdanski, 2003)
Island removal	(Celebi *et al*., 2009; Morar *et al*., 2012)

misclassified samples and weight of correctly classified instances is decremented. K-nearest neighbor technique was used in Masood and Al-Jumaily (2013). It is one among the nonparametric pattern recognition techniques, where the class containing unclassified sample is represented by the majority of K closest neighbor. It allows the direct comparison of known and unknown lesions. Linear classifier technique was used in Schmid-Saugeon *et al*. (2003). This classifier finds the hyper plane parameters with the help of gradient descent approach with minimal misclassification error. Multi-Layer neural network technique was used in Messadi *et al*. (2009). In this technique the neurons take a major part. Here layers of neurons and the first layer neurons are connected to external source and act as the receptor for the input vector. An object's characteristic vector is passed to the first layer neurons. Each layer's output is transmitted to the next layer through the neurons. Other than the output layer all the other layers are hidden. The network's overall performance depends on the various arbitrary parameters like number of iterations and the hidden layers. Support vector machine classification technique was used in Safi *et al*. (2012). SVM supports linear classification of data. With the help of specific polynomial kernels it does linear classification of data in high dimensional feature space which is non-linearly related to the input space. PCA (Principle Component Analysis) technique is applied for the input data's dimension reduction. Using magnitude as the parameter, the outcome of the feature vector which contains the eigen values is sorted in decreasing order. The most relevant component is represented by the highest eigen value. Figure 6 presents a comparative analysis on preprocessing and Table 5 gives the list of techniques used in the literature.

RESULTS AND DISCUSSION

Various image processing methods involved in diagnosing melanoma are reported in the study. Out of the techniques stated above, for border detection before applying the SRM algorithm, techniques like image smoothing and black frame removal were applied in the preprocessing stage.

This SRM algorithm shows a good performance even in the presence of few complicating factors like skin lines, blood vessels are present. When iterative segmentation method was applied to the original image, the average error rate obtained for R, G, B is 0.51, 0.22, 0.15, but when the same method is applied to the image which was preprocessed using automatic color equalization the average error rate was reduced to 0.36, 0.13, 0.11 which clearly states that applying segmentation procedure to preprocessed image yields better results. For segmenting the synthetic lesions the IS (Iterative Segmentation) method is considered to be the most effective one. Similarly when cooperative neural network was applied to the original image, the average error rate obtained for R, G, B is 0.56, 0.24, 0.19, but when the same method is applied to the image which was preprocessed using automatic color equalization the average error rate was reduced to 0.24, 0.16, 0.17 which clearly states that applying segmentation procedure to preprocessed image yields better results. When the preprocessing techniques like median filtering and Dull Razor were used along with PCA method, noise removal was effective and frequency of each color was reduced to great extent. Fuzzy c-means segmentation algorithm offers best possibility to dermatologists to accept the result without any supervision and reduces time to change the clusters. Among the following segmentation techniques AT, GVF, AS, FBSM, the AS gives the best result and it stands as the robust one. Region based active contours performs well when compared with thresholding, clustering-based, edge-based method. When relative color feature algorithm used with neural network model yield best results, with success rate 79% of classification process including 70% of benign and 86% of melanoma. Among the three segmentation techniques: Fuzzy c-means, spherical coordinates and PCT/median cut, the latter yielded low average error rate and for further algorithm development it served as a most promising technique. When the radial search border detector is used on model images, borders were detected more accurately with 97% with less error.

CONCLUSION

In this study, we have discussed various methodologies for the melanoma diagnosis. Compared to clinical diagnosis, combination of image processing and soft computing techniques yielded more accurate results to detect melanoma. The process of melanoma diagnosis is carried out in various stages like preprocessing, segmentation, feature extraction, post processing and classification which employ sophisticated techniques for getting accurate results. Based on the survey performed, when a clinical image is processed with median filtering/Gaussian filter techniques in the preprocessing stage, with the iterative segmentation technique in the segmentation stage, by choosing color as a feature along with island removal post processing technique, with decision tree as classifier, best results can be obtained with more accuracy. When these techniques are combined together and performed on a chosen clinical image, detection of melanoma in the initial stage itself can be achieved.

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