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Segmentation And Automatic Classification Of Skin Lesion Using Neural Networks

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Abstract— *Melanoma is a lethal disease often impossible to cure if detected at later stages. To save a person, it is necessary to detect melanoma at earlier stages because melanoma treatment is detected at prior stages. Due to several reasons, there is a need for an automated system to detect melanoma. An automated system for the segmentation and the skin lesion classification is proposed using the artificial neural network. Image segmentation is carried out to bifurcate input image into different clusters. In this proposed methodology, the Fuzzy C Means algorithm is used for the pre-segmentation, and then Gaussian Mixture Model is used for the modeling. The results of the Gaussian mixture model are not as efficient up to the desired level. Artificial Neural Networks are used to achieve the highest accuracy, and their accuracy is checked by using the parameters of sensitivity and specificity.*

Keywords — *Skin Cancer, Melanoma, Gaussian Mixture Model, Artificial Neural Network, Innovation.*

I. INTRODUCTION

Skin cancer is a deadly disease, and its accurate detection plays a vital role in the diagnosis. Among all skin cancers, melanoma is the most challenging form of skin cancer [1]. Melanoma is found mostly in white-skinned persons from age 15-34[2]. Ultraviolet rays, mainly UVA and UVB rays, are the utmost reasons for melanoma growth [2]. The first instance of melanoma was noticed in 1930 in the United States [3]. After that, the graph of melanoma diagnosis increased day-by-day. Undoubtedly, the growth of melanoma is very slow, and if detected early, the person's survival rate increases to 95% for five years. Many publications reported the automated diagnosis of skin cancer by image processing due to the reasons that dermatological results are not as accurate as well as require a lot of training to dermatologists. The dermatoscopic criteria use the formula of ABCD(E) to differentiate between a benign and melanoma.

Asymmetry (A) represents moles that are not symmetrical when divided into two halves. B represents borders moles that are notched, uneven, or blurred. C represents color, and in melanoma, the moles appear to be uneven shades of black, brown and tan, and white or blue. D represents the diameter, and melanomas are usually large in diameter, often greater than 6 mm. E represents evolving in ABCD and enlargement and other morphological changes in ABCD-E (DI), when a mole changes in size, shape, color, or appearance and spreads, leading to symptoms such as bleeding or itching. The skin has a giant biological structure. The skin chores are protection from microbes, balancing of body temperature, permits the sensations of touch, heat, and cold reduces harmful effects of UV radiation, and produces vitamin D. The coatings of the skin may be categorized as the Epidermis, the Dermis, and hypodermis.

The outer coating of skin is known as the epidermis. It is soft, and it repeatedly regenerates. The thickness of the epidermis varies on distinct parts of the body. The thickness ranged between 0.5 and 4 mm and comprised different types of cells known as keratinocytes, corneocytes, and melanocytes. It acts as a physical barrier between the body and the environment. It also prevents excessive water loss. The inner or lower layer of the two main layers of cells that make up the skin is known as the dermis. The main functions of the dermis layer are producing sweat and temperature balancing of the body. The main purpose of these layers is the protection of skin. Figure 1 represents the process of automated diagnosis of melanoma; first of all, input of the suspicious image is given. Then shadows are removed from the background by applying various techniques in the process of background compensation. After that, division of regions in the image is done in the segmentation.

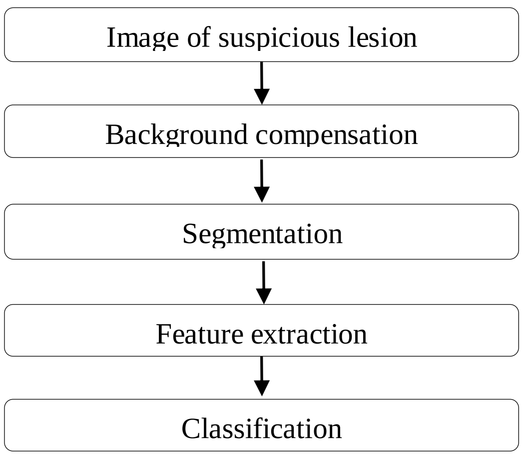


Figure 1: Automated melanoma diagnosis

Segmentation:

In image analyzing, viewing objects, visualizing, and processing tasks, separating them into meaningful structures, and separating images is always an important step. In the location of objects and borders, the use of image segmentation. The primary objective of segmentation is to turn the input images into relevant and simple to analyze [4]. Segmentation is a vital process in which partitioning and grouping are done. Partitioning: Partitioning is done according to relevant internal properties. Grouping: In grouping, identifying sets of relevant tokens in the image [5] is done.

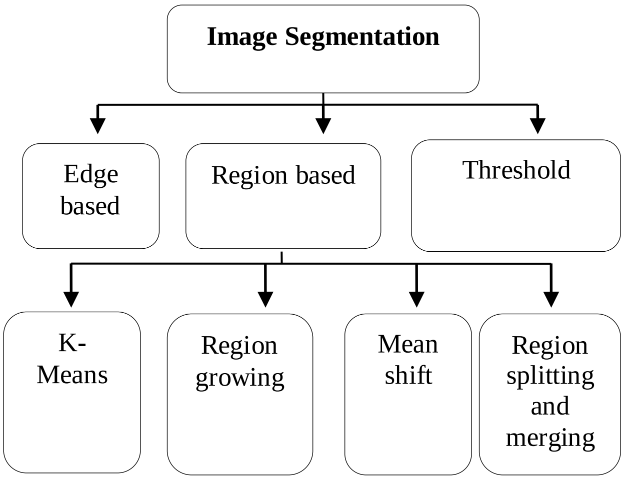


Figure 2 Types of segmentation

Various types of segmentation are represented in figure 2. The main types of segmentation are threshold, edge-based and region-based. Threshold-based segmentation: Threshold segmentation is also known as intensity-based segmentation. The common techniques of threshold-based segmentation are histogram and slicing techniques. These techniques can be applied directly, but sometimes, the preprocessing and the post-processing techniques are also used.

The major advantages of thresholding may be considered as easy to implement, the process of thresholding is also fast, and also it performs best on several types of images like documents and controlled lighting.

The only disadvantage of the thresholding is that there is no assurance of the coherence of the object. The results may contain holes or extraneous pixels.

To overcome this problem, morphological operators can be used for post-processing. Edge-based segmentation**:** In this technique, detection of the edges in the images is used to represent the objects' boundaries and is also used to identify these objects. Common problems in Edge Based Detection:- False Detections: Sometimes, there is an edge in the image even when there was no border [6]. Missed Detections: Many times, there was no edge detection even when there a real border exists.

Region-based segmentation is the opposite of edge-based segmentation. This segmentation starts in the middle of the object and then grows outwards until it meets its boundaries. Advantages of region-based segmentation: These techniques perform very better in noisy images where there is difficulty detecting the borders. Disadvantages of region-based segmentation: Its biggest disadvantage is that its output is over segmented or under segmented.

II. LITERATURE REVIEW

In the year 1999, the screening algorithm of melanoma had been described [2]. It shows the early signs of melanoma and the people having a higher risk of melanoma. JMahbod described the type of skin cancer. et al. [7]. They also explained the treatment options available at that time, like surgery, mono chemotherapy, combination therapy, and immunotherapy, were described. In 2010, the use of dermatoscopy by the US dermatologists [8]. It gives a brief view of the use of dermatoscopy and the limitations of dermatoscopy due to the reasons of lack of training and interest.

In 2011, a new method was discovered to classify the pigmented skin lesions by using the standard cameras [7]. Standard cameras took the images. After that, each image went through a series of processes such as (1) Preprocessing, (2) Segmentation, (3) Feature extraction (4) Lesion Classification. In the preprocessing, shadows were removed, then segmentation was performed, and in feature extraction, the quantitative representation for the lesion area was generated, and at classification, the distinction between benign or melanoma was done.

In July 2013, a method was introduced to increase the efficiency and correct the illumination variation named MSIM, i.e., Multistage Illumination modeling [9]. In the proposed algorithm, Monte Carlo sampling was done to determine the non-parametric model of the illumination, and after that, the reflectance component of the photograph was calculated. The specificity, sensitivity, and accuracy of the output images were quite high.

In this paper, automatic melanoma recognition was done using multi-stage neural networks [10]. A gaussian mixture model was used for image smoothening, and neural networks were used for automatic classification.

III. PROPOSED ALGORITHM

The proposed algorithm's main objective is to obtain automatic image annotation using an Artificial Neural Network and undertake a large skin cancer set and achieve the highest possible accuracy. The steps which are followed to achieve the mentioned objectives are

1. *Inputting the RGB image.*
2. *Then conversion of RGB image is done into L*a*b color space.*
3. *After that, texture matrices are obtained, and texture representatives are obtained.*
4. *GMM modeling and posterior matching of pixels is done.*
5. *Finally, classification is done using ANN.*
6. *At last, the accuracy assessment of the algorithm is done by checking the sensitivity and specificity.*

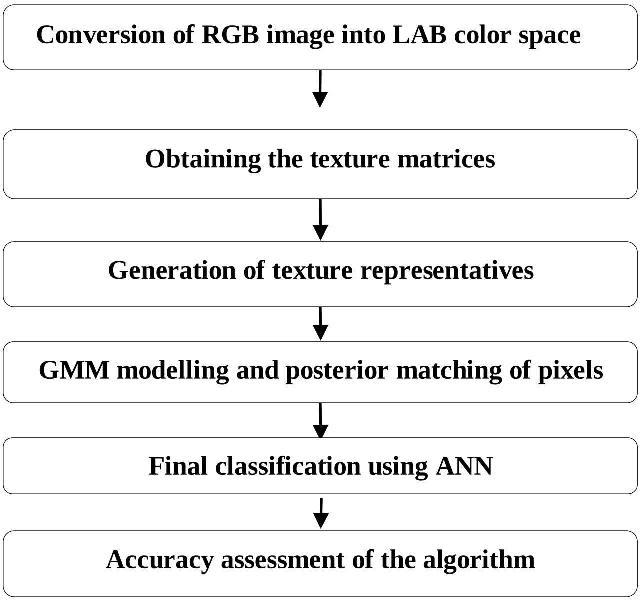
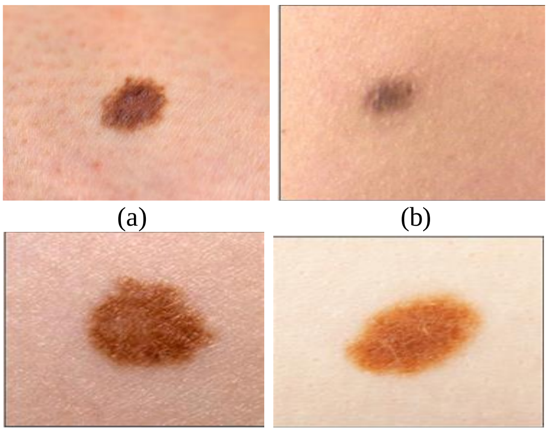


Figure 3 Block diagram of the proposed algorithm

The block diagram explains the operation of the proposed algorithm in fig. 3. First of all, the RGB image is converted into the XYZ color space, and then the XYZ color space is converted into the Lab color space because Lab color space is easy to visualize by the human perception. After that, texture matrices are obtained, and then texture representation is done using the Fuzzy C Means algorithm. Then the Gaussian mixture models are used, and the posterior matching of the pixels is done. Then the artificial neural networks are used for the final classification. Before using artificial neural networks, first of all, they are trained to get the desired results. At last, sensitivity and specificity are checked.

IV. RESULTS



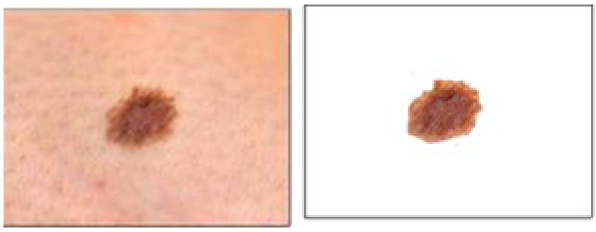
(a) (b) (c) (d)

Figure 4 Images of melanoma taken for experiments

Schematic of the proposed work

A. Inputting the image in MATLAB

In this step, the melanoma image's input is provided, and its ground truth is obtained.



(a) (b)

Figure 5 In the image (a) there is the original image (b) ground truth image of the original image

*B. Conversion of RGB image into L*a*b color space*

L*a*b color and * a seed area part are used for the region's algorithm. The color space capabilities of the LAB allow it to draw global color characteristics from a digital image. Thus, the analyzed RGB images are translated to LAB format. On the axis, L, which is perpendicular to a pile of "ab" levels, every one containing every possible color for a certain light [11], the characteristic called luminance or intensity is described. Transformation steps into the color space of L*a*b [11]

1. Initially, image transformation from RGB to XYZ color space is carried out.
2. XYZ values are transformed into L*a*b values of the CIE 1931 lab color space.

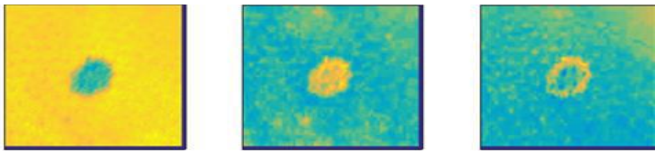


Figure 6 Original image divided into three channels R, G, and B

C. Obtaining the texture matrices

The texture vector includes pixels in a pixel-centered neighborhood of size n. Let s be in the image a position in pixels (x, y). Then the ts vector displays $n \times n \times a$ pixel-centric texture layer.

For each channel, a texture vector is extracted and linked sequentially by means of multiple channels with a separate vector. In the proposed algorithm, a matrix of 25 pixels is made, and the center point is taken as 3, and two-two neighboring pixels are taken to make a matrix. A texture vector is obtained from the matrix.

D. Generation of texture representatives

In this step, fuzzy clustering has been used on a single channel, which converts the whole image into a fixed number of clusters. One can vary the number of clusters to get better results according to the images' content [12]. First of all, all clusters are taken separately in which a pixel has been chosen as texture representative of that cluster. One can choose any pixel from that cluster, but getting pixel automatically, we use the center of the cluster as texture representative. This selection's importance is that the pixel chosen will always come from the center of the cluster and not the boundary region of the cluster.

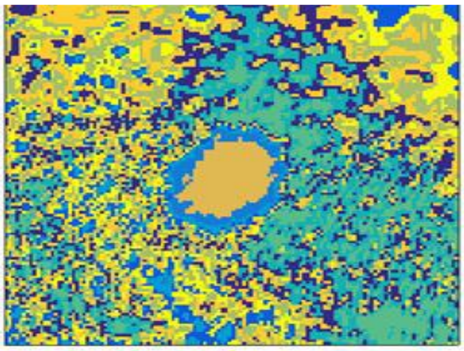


Figure 7 Input image is decomposed into fixed clusters

In fig. 7, the input image is decomposed into a predetermined number of clusters. A unique value is assigned to each cluster.

	$c(2 \leq c \leq n)$ $\mu(1 < \mu < \infty)$	1

This is a linguistic overview of the FCM algorithm that Fuzzy Logic implements

1. Select the number of clusters c ($2 \leq c \leq n$), exponential weight $\mu(1 < \mu < \infty)$, initial partition matrix U^0, and the termination criterion ϵ. Also, set the iteration index l to 0.

2. Calculate the fuzzy cluster centers $\{v_i^l \mid i=1, 2, ..., c\}$ by using U^l.

3. Calculate the new partition matrix U^{l+1} using $\{v_i^l \mid i=1, 2, ..., c\}$.

4. Calculate the new partition matrix $\Delta = \|U^{l+1} - U^l\| = \max_{i,j} |u_{ij}^{l+1} - u_{ij}^l|$. If $\Delta > \epsilon$, then set $l = l + 1$ and go to step 2. If $\Delta \leq \epsilon$, then stop.

After applying FCM on the 'L' channel of L*a*b color spaced image, we take the center of mass of each cluster as texture representative, and then GMM modeling has been done for them.

E. GMM modeling and posterior matching of pixels

Mixture models come under the classification of the density models. These models are encompassed of component functions, mainly Gaussian functions. Multimodal densities are formed by the combination of these functions. They are employed to model the texture vectors of chosen texture representatives to perform final improved segmentation tasks. After generating these models, every pixel's texture vector has been compared with all the GMM's using posterior maximum log-likelihood, which puts every pixel to the closest texture Gaussian model.

Following the Gaussian modeling of the entire figure in two regions, one is an area of the mere lesion while the other is an area of the skin. This is found in the deepest areas of the skin lesion according to strongly negative log probability values. Our results are also obtained from the Gaussian mixture model, but they are not so accurate.

Afterward, RGB values are individually combined and prepared for feeding to neural networks for training processes in two adjacent groups.

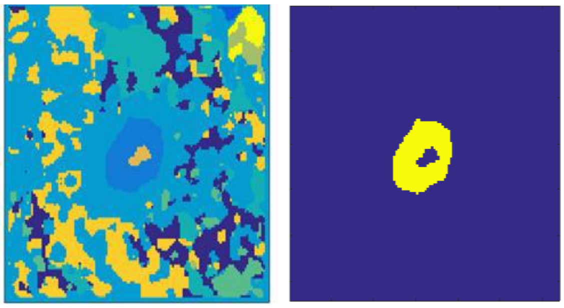


Figure 8 Result of images after applying GMM

F. Final classification using ANN

After the feature vector's extraction, which comprises two element classes: lesion and the normal skin, the proposal of the neural object recognizer was done to learn the relationship between the 3-layered artificial neural network system, Error Back Propagation Algorithm learns the patterns.

A neural network consists of 3 layers: the input layer, hidden layer, and output layer. There are 3 input units, 1 hidden unit, and 2 output units.

After training, the neural network can be tested for the whole image results in the final classification.

Figure 9 Results after applying ANN.

G. Accuracy assessment of the algorithm

The objective of this algorithm is to measure sensitivity and specificity.

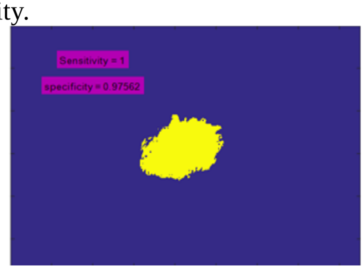


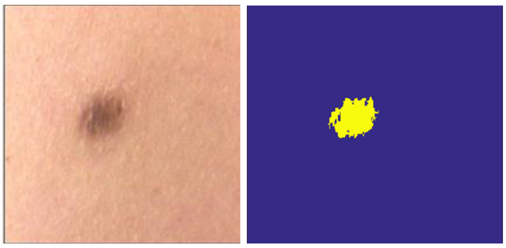
Figure 10 Sensitivity and Specificity results

The following formulas are given when T is the number of real positive pixels, F is the number of false pixels, N is the number of true negative performance pixels, and W is the number of false-negative pixels.

Sensitivity = (T/(T+W))
Specificity= (N/(N+F))

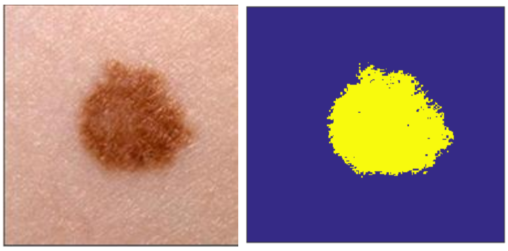
H. RESULTS OF IMAGES

In this section, the results of the various images undertaken are shown. The results are quite clear after applying the ANN.



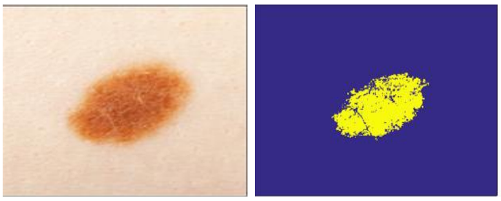
(a) (b)

Fig. 11 (a) is the original image, whereas (b) results after applying ANN



(a) (b)

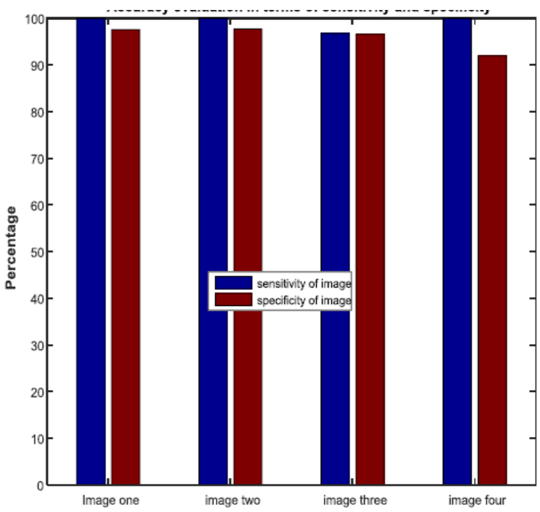
Fig. 12 (a) is the original image (b) results after applying ANN



(a) (b)

Fig. 13 (a) is the original image (b) results after applying ANN

I. GRAPH OF ALL IMAGES



VI. CONCLUSION

In this paper, a novel technique is applied for the detection of skin cancer. The facts of the applied scheme:

- The results of the applied technique are very accurate.
- 100% sensitivity is achieved.
- The proposed algorithm can be applied to large data sets.

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