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Lesion Segmentation in Dermoscopic Images Using Decision Based Neuro Fuzzy Model

Binamrata Baral[#1], Sandeep Gonnade[*2], Toran Verma [~3]

[#] *M.Tech. Scholar, C.S.E. Department, MATS School of Engineering and IT, MATS University, Raipur, C.G., India.*

[*] *Asst. Professor, C.S.E. Department, MATS School of Engineering and IT, MATS University, Raipur, C.G., India.*

[~]*Asst. Professor, C.S.E. Department, R.C.E.T, Bhilai, C.G., India.*

Abstract— **This paper presents a novel approach for segmentation based on Neuro-Fuzzy model using decision making. We know that segmentation is done based on some feature values of images. These features work as parameters. There are many segmentation techniques available presently based on different approaches. Many of them require parameter selection which is done manually by observation. This can be performed on those data which are having easily differentiable values. But images such as skin lesion images have very marginal or not-differentiable data of lesion and skin which cannot be easily analysed. This makes parameter selection and assigning parameter value task very difficult. Hence, to solve this problem, we are presenting a novel approach for segmentation problem that uses decision making. We have evaluated this approach by applying it on different dermatological images containing skin lesion which results in good quality segmentation of skin lesion.**

Keywords— **Color Images, Image Segmentation, Fuzzy, CART, Decision Tree, ANFIS, Medical Images.**

I. INTRODUCTION

The applications of computerized automatic image analysis for detection of skin lesion is an active research area recently as this provide help in early diagnosis of skin cancer [3]. Often, visual inspection of the skin lesion is not adequate for early detection of cancerous properties, which can be assisted by computer-aided diagnosis for increasing the survival rate. The computer-aided diagnosis of skin lesion consists of these general steps – image acquisition, pre-processing, segmentation, post processing (optional), feature extraction, and classification [4][9]. First of all, a digital dermoscopic image have to be acquired which has to be pre-processed to remove noise or unnecessary artifact such as hairs, reflections, etc. After this we have to perform segmentation which is very significant step in skin lesion diagnosis as accuracy in skin lesion border detection affects the later successive phases. If required, post processing is done to improve the segmented image. After segmentation is performed, features are extracted from the segmented lesion area and this is used for classifying the given input as whether the lesion is in beginning phase or malignant phase.

A segmentation technique is said to be fine if it segments the required region accurately and without any over segmentation. To achieve this, a number of different types of segmentation techniques have been developed based on clustering as in [19],[21],[22],[23], threshold based fuzzy logic as in [20], neural network as in [24],[26], genetic algorithm as in [1],[10], weighted graph as in [2],[25], evolutionary computation as in [18] etc.

In this paper, a new approach to perform targeted segmentation has been proposed which will be using a combination of decision making and neuro-fuzzy techniques. This approach works on each and every pixel in an image to perform segmentation. The proposed algorithm has been used to test on some medical images containing different lesion types and the output has been compared with existing methods.

The paper is organized as follows: the current section gives a brief overview about this paper, the next section contains the proposed methodology for segmentation of lesion images, Section III presents the result on the experimental dermatological images containing pigmented lesion and Section IV is the last section which concludes this paper and presents further future work possibilities.

II. METHODOLOGY

A. Proposed Approach

In this paper, a new algorithm has been proposed for more accurate detection of lesion using Neuro-Fuzzy model which is described as follows:

Algorithm : Proposed algorithm for segmentation of lesion

Step 1: Read the sample color images which are generally in RGB format.

Step 2: Convert the input sample images into CIE L*a*b color space which is a device independent format.

Step 3: Different features are extracted from the converted images. These features are:

a) Intensity Feature
b) Color Features.
c) Texture Features

Fig. 1. Conversion of Lesion Image from RGB colour space to CIE L*a*b* colour space showing the corresponding pixel values for different pixels of the same image in two different colour spaces.

Step 4: Classification and Regression Tree is used on the sample data to form a decision tree without any over-fitting.

Step 5: The decision tree generated is used for parameter selection as well as for the rules formation and designing of the fuzzy inference system.

Step 6: Takagi-Sugeno Fuzzy Inference System is to be used and is designed according the decision tree.

Step 7: The Adaptive Neuro Fuzzy Inference System is used on the designed Fuzzy Inference System to optimize the parameters which uses backpropagation algorithm for optimization.

The following sub-sections contain the detailed description of the real time working of the above mentioned algorithm.

*B. RGB to CIE L*a*b* Colour Space Conversion*

It is important to convert an image to a machine independent format. RGB color space format is device dependent whereas CIE L*a*b* color space format is device independent. The CIE L*a*b* color space [15], or CIELAB, is commonly used as an absolute color scale for analysis of skin [14]. But RGB color space format cannot be directly converted to CIE L*a*b* color space format. The International Commission on Illumination, also known as *Commission Internationale de l'Éclairage (CIE)*, studied color perception by human and developed a standard, called the CIE *XYZ in 1931*. This standard defined a three-dimensional space where a color is defined by three values, called tristimulus values. RGB color space format is first converted to CIE XYZ color space format which is then converted to CIE L*a*b* color space format as shown in Figure 2. The RGB to CIE XYZ conversion can be done using the following conversion matrix [16]:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

Although the tristimulus colorimeter can provide quantitative measurement of skin color and detect color differences, its practical usefulness is limited due to reasons given in [14]. The CIE created the *L*a*b** color space in 1976, to get a perceptually uniform color space that could be correlated with the visual appearance of colors. This color space format separates the intensity value of an image completely from its color component. L*a*b* consist of 3 components: Brightness, color a and color b. L represents Luminosity or brightness, color a represents color component between red/magenta and green where as color b represents color component between yellow and blue. The CIE XYZ to CIE L*a*b* conversion can be done using the following conversion formulas [16]:

$$\begin{aligned} L^* &= 116\, f(Y/Y_n) - 16 \\ a^* &= 500\, [f(X/X_n) - f(Y/Y_n)] \\ b^* &= 200\, [f(Y/Y_n) - f(Z/Z_n)] \end{aligned} \quad (2)$$

where

$$f(x) = \begin{cases} t^{1/3}, & t > \left(\frac{6}{29}\right)^3 \\ \frac{1}{3}\left(\frac{29}{6}\right)^2 t + \frac{4}{29}, & otherwise \end{cases} \quad (3)$$

here, X, Y and Z are the tristimulus values of CIE XYZ color space format and X_n, Y_n and Z_n are normalized X, Y and Z.

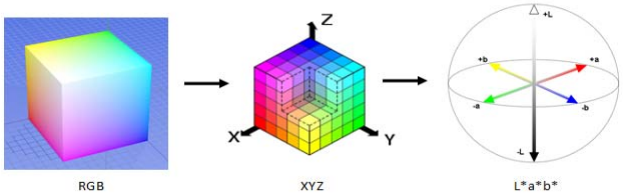

Fig. 2. Conversion of Image from RGB Color Space to CIE L*a*b* Color Space.

After applying the colour space conversion, skin lesion image appears as in Figure 1.

C. Texture Features

Texture of an image gives information about the spatial arrangement of color or intensities in the selected region of an image [11]. There are three principle approaches to describe the texture of a region: statistical, structural and spectral [12]. We have used statistical approach such as local entropy, local standard deviation and local range because of two reasons: 1) these texture analysis approaches works on each individual pixel of image and generates corresponding values and 2) statistical approach are one of the simple approaches that yield characterizations of structure such as smooth, coarse, grainy etc [12]. These texture analysis approaches are described in the following:

1) *Local Entropy*: It is a texture analysis approach which works on 9x9 neighboring pixels of the corresponding pixel to generate the average entropy in the output pixel using the following formula:

$$Entropy = -\sum_i \sum_j p[i,j] \log (p[i,j]) \qquad (4)$$

where $p[i,j]$ is the $[i,j]$th entry in a gray-tone spatial dependence matrix.

2) *Local Standard Deviation*: It is a texture analysis approach which works on 3x3 neighboring pixels of the corresponding pixel to generate the average standard deviation in the output pixel using the following formula:

$$Standard\ Deviation = \sqrt{\frac{\sum_{i=1}^{n} (Xi - \bar{X})^2}{n-1}} \qquad (5)$$

where Xi is the value of corresponding pixel, $\bar{X}$ is the mean of all pixel values in the image and n is the total number of pixels in an image.

3) *Local Range*: It is a texture analysis approach which works on 3x3 neighboring pixels of the corresponding pixel to generate the average range in the output pixel using the following formula:

$$Range\ Value = (Maximum\ Value) - (Minimum\ Value) \qquad (6)$$

D. Decision Tree

Decision Tree is a tool for supporting decision making which uses a graph representation in the form of tree like structure where each branch of the tree represents a test criteria and all the end nodes represents the outcome of the given test conditions. A path from root to a leaf node represents a classification rule and each node is acting as an AND operator. Decision tree contains two variables: predictor (P) and response (R), which can be represented as:

$$(P, R) = (P_1, P_2, \dots, P_n, R) \qquad (7)$$

where predictor are input variables and response are target variable according to which classification have to be done.

Decision trees are used when the amount of data to be analysed is a large and complex in nature as it simplifies the analysis for decision making process to create a flow-chart like structure.

We have used both classification method as well as regression method for decision making to identify rules for the fuzzy inference system (FIS). This is known as classification and regression tree (CART) which is used for the decision making process, using this; we can design and define rules for the FIS.

The intensity, colour and texture features extracted from the sample images are given input as predictors and the expected outcome are responses in the classification and regression tree (CART) function which generates a tree like model where each branches are the predictor conditions and the leaf nodes are the respective responses i.e. either skin or lesion. The generated model is used for the FIS structure designing and defining the rules. We have to stop the decision making process at a certain point so that over-fitting of data is not performed and an optimized decision tree is achieved. Hence, out of six extracted features only four features are chosen by the classification and regression tree, shown in Figure 3, which will be used for designing the fuzzy inference system for lesion segmentation.

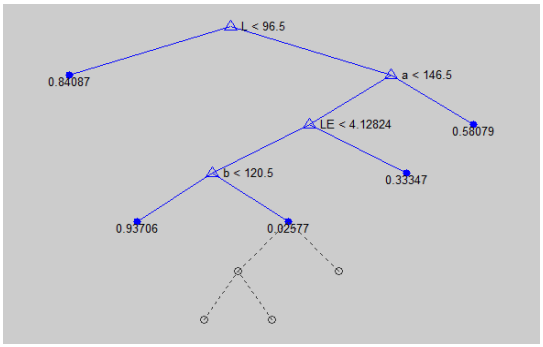

Fig. 3. Decision tree for the six extracted features of the sample data for lesion segmentation.

If we assume the lesion pixel value be 1 and skin and other region pixel value be 0 then after interpreting the decision tree we will take all the values less than 0.5 as value 0 i.e. representing skin and other region pixel and all the values equal to or above than 0.5 as value 1 i.e. representing lesion pixel. Therefore, we come up with 4 input and 5 rules for designing fuzzy inference system. The 4 inputs are luminosity (L), color a (a), color b (b) and local entropy (LE). The 5 rules according to our assumption and the decision tree are:

Rule 1. If L < 96.5 then output is Lesion pixel.

Rule 2. If L > 96.5 And a < 146.5 And LE < 4.12824 And b < 120.5 Then output is Lesion pixel.

Rule 3. If L > 96.5 And a < 146.5 And LE < 4.12824 And b > 120.5 Then output is Skin pixel.

Rule 4. If L > 96.5 And a < 146.5 And LE > 4.12824 Then output is Skin pixel.

Rule 5. If L > 96.5 And a > 146.5 Then output is Lesion pixel.

E. Fuzzy Inference System

Decision Tree Fuzzy Inference System (FIS) is an inference system which works on If-Then rule set to map the provided inputs to respective output. Fuzzy Inference Systems are of two types based on the method on which it works: Mamdani and Sugeno.

Takagi-Sugeno-Kang fuzzy inference method also known as Sugeno fuzzy inference method has been used. Sugeno method works same as the Mamdani method but generates either linear or constant outputs. The Sugeno type Fuzzy Inference System is designed with 4 different inputs, an output and rules based on the classification-regression decision tree analysis output structure. The Gaussian curve member function is used for inputs and constant membership function is used for the output. Gaussian membership functions are used for input values because Gaussian membership functions are most adequate in representing uncertainty in measurements [5]. A Gaussian membership function is a characteristic symmetric bell curve produced by bell function, which tend to fall towards zero. From [27], Gaussian function can be represented in the following form:

$$\mu_z(X_k, \gamma_k) = exp\left(-\frac{1}{2}.\frac{(X_k - center_k)^2}{\gamma_k{}^2}\right) \qquad (8)$$

with $\gamma_{k\neq 0}$ for any $k \in \{1, 2, \ldots, n\}$ and $center_k = \frac{u_k + U_k}{2}$

where U_k and u_k are curve controlling function of Gaussian membership function .

Table 1 shows the different ranges – low and high, for the input functions for fuzzy inference system which can be derived by decision tree represented. Using this we have defined input function which can be seen in Figure 4-7. Figure 8 shows the rules designed for the created fuzzy inference system which are according to the previous discussed 5 rules from decision tree representation. Initial weight for each rule is given the value 1 for scaling the output fuzzy set. Aggregation of all the outputs is done by simply the summing each rule's output set. Defuzzification of output is done by averaging weights.

TABLE I
RANGE OF INPUTS FOR FUZZY INFERENCE SYSTEM

Input	Low	High
Luminosity	0 – 96.5	96.5 – 200
Color a (a)	0 – 146.5	146.5 – 200
Color b (b)	0 – 120.5	120.5 – 300
Local Entropy (LE)	0 – 4.128	4.128 – 10

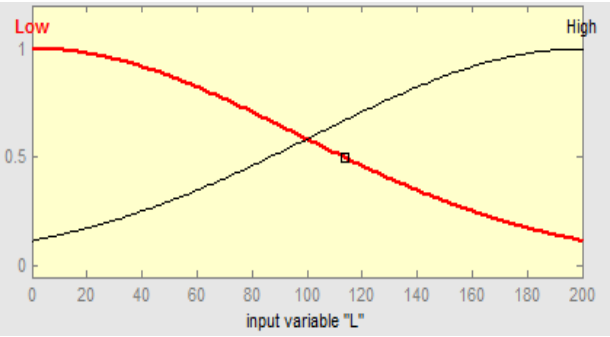

Fig. 4 : Functions for Luminosity (L)

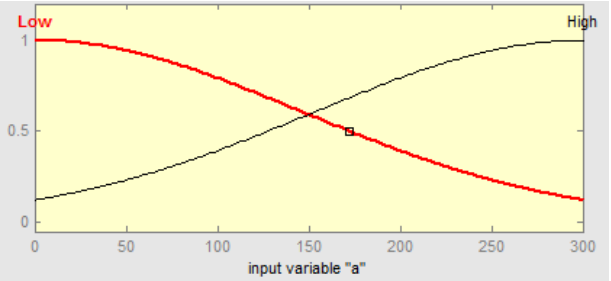

Fig. 5 : Functions for Color a (a)

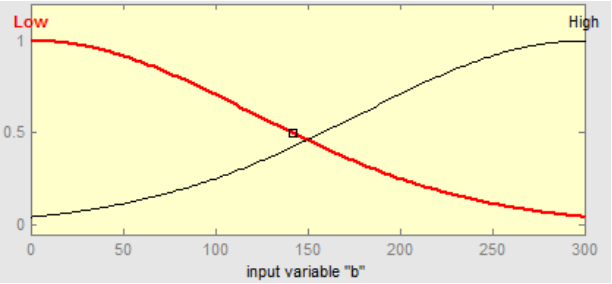

Fig. 6 : Functions for Color b (b)

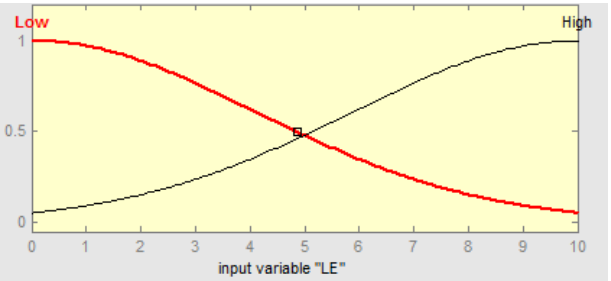

Fig. 7 : Functions for Local Entropy (LE)

1. If (L is Low) then (Output is L1) (1)
2. If (L is High) and (a is Low) and (b is Low) and (LEntropy is Low) then (Output is L2) (1)
3. If (L is High) and (a is Low) and (b is High) and (LEntropy is Low) then (Output is S1) (1)
4. If (L is High) and (a is Low) and (LEntropy is High) then (Output is S2) (1)
5. If (L is High) and (a is High) then (Output is L3) (1)

Fig. 8 : Rules for FIS

F. Neural Network

Artificial Neural Networks mimic the functioning of interconnected neurons in the central nervous system in animals that are capable of pattern recognition and machine learning. Neural network require prior knowledge for training but they are fast as they perform computation in parallel [9]. Artificial neural networks have layered structure where inputs are taken from input layer and output is generated at output layer but between the two layers, hidden layers are present which are trained and generate results. We have used ANFIS model of neural network to optimize the designed FIS.

G. Adaptive Neuro Fuzzy Inference System (ANFIS):

1) ANFIS Classifier

ANFIS is considered as universal estimator [7]. ANFIS provides a single framework where both the Fuzzy inference System and Neural Network works in combination. ANFIS works on simple If-Then rules which have learning capability. ANFIS works on Takagi-Sugeno fuzzy inference system. Hence, ANFIS is used to train the

fuzzy inference system. ANFIS uses supervised learning method to train the neural network. The fuzzy inference system design built is a normal feed-forward network having three layered architecture shown in figure 9 which is according to the rules given in figure 8.

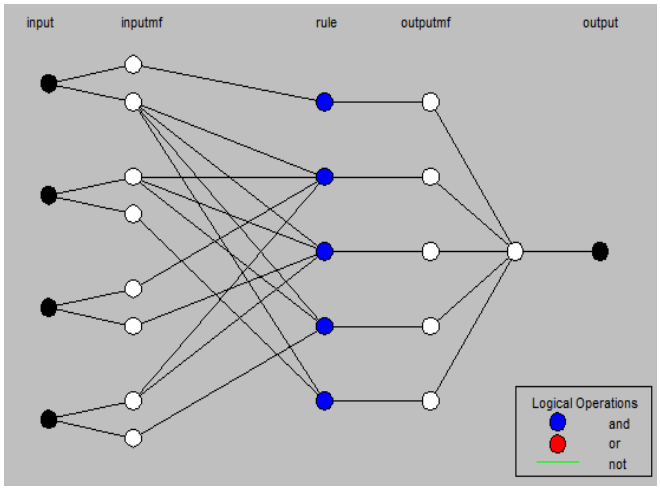

Fig. 9. Structure of Adaptive Neuro-Fuzzy Inference System.

2) Optimization of ANFIS Classifier

In this work, back-propagation learning algorithm is used to train the neural network and update the parameters. We have used 38996 data set to train the ANFIS from the sample images which have been downloaded from DermAtlas [17]. The back propagation algorithm works as follows. From [13], in the backpropagation algorithm, the net input to unit *i* in layer *k+1* is:

$$n^{k+1}(i) = \sum_{j=1}^{S_k} w^{k+1}(i,j).a^k(j) + b^{k+1}(i) \quad (9)$$

the output of unit *i* will be of unit *i* will be:

$$a^{k+1}(i) = f^{k+1}(n^{k+1}(i)) \quad (10)$$

and the system equation in matrix form for *M* layer network is given by:

$$a^0 = p \quad (11)$$

$$a^{k+1} = f^{k+1}(W^{k+1}.a^k + b^{k+1}), \quad (12)$$

where $k = 0,1,\dots,M-1$.

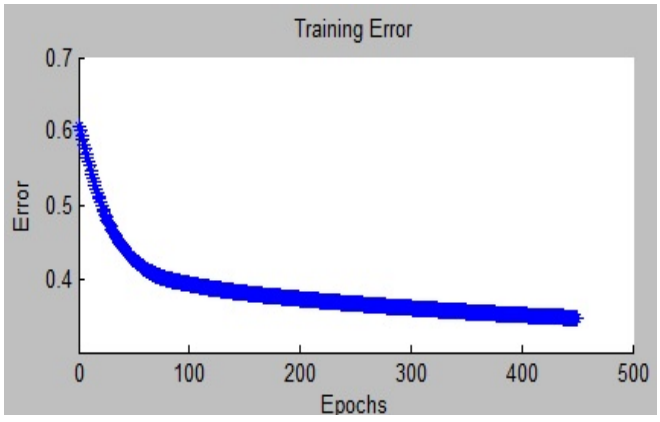

Fig. 10. Plot of Training Error (Epoch v/s Error).

The algorithm can be decomposed in the following four steps: i) Feed-forward computation, ii) Backpropagation to the output layer, iii) Backpropagation to the hidden layer and iv) Weight updates [8].The algorithm should be stopped just before the start of over-fitting of training data. To achieve this we have to provide a suitable epoch value which we have set to 450 which resulted to a training error of 0.34659 which have been plotted in figure 10.

3) Optimization of ANFIS Classifier

The limiting factor is required for classifying the input as lesion pixel or other pixel. For this, we have to analyze the output value of ANFIS for sample data. After analyzing the output values for corresponding sample data values, we come up with following facts: average value of lesion pixel is 0.65 (greater than 0.5) and average value of skin and other pixel is 0.44 (less than 0.5). Our initial assumption was 1 for lesion pixel and 0 for skin pixel. We will take two values for limiting factor:

Value 1 = Mean of output values of input image processed by ANFIS (0.5 is mean value of 0 and 1).

Value 2 = [Mean + (0.5*Mean)] of output values of input image processed by ANFIS ([0.5+(0.5*0.5)] = [0.5+0.25] = 0.75 i.e. ¾ of output values of input image processed by ANFIS because average value of lesion pixel i.e. 0.65 is close to 0.75 than 0.5).

After applying both rules we achieved following results:

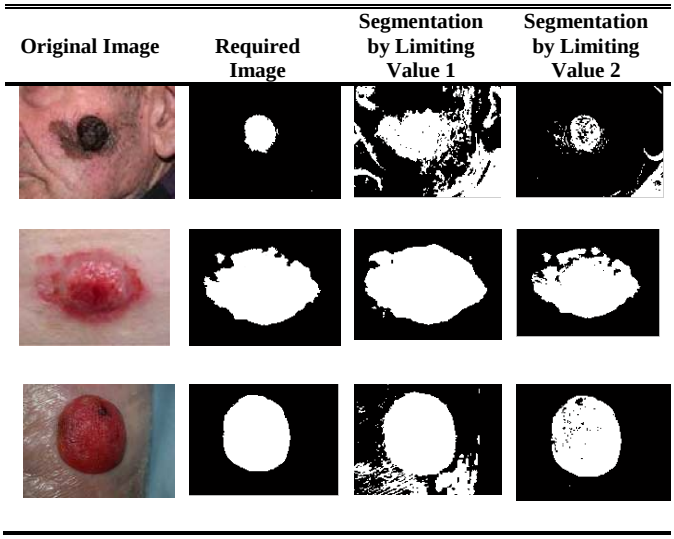

Fig. 11. Comparison of two values of limiting factor for different lesion images.

From figure 11, we find that limiting value 1 detects non lesion pixel as lesion pixels but limiting value two is more close to accurate lesion detection and segmentation. After analyzing the outputs, we come to conclusion that the second value (i.e. [Mean + (0.5*Mean)] of output values of input image processed by ANFIS) for limiting factor is appropriate for the segmentation of lesion images. Hence, we have applied this rule for doing segmentation of lesion image.

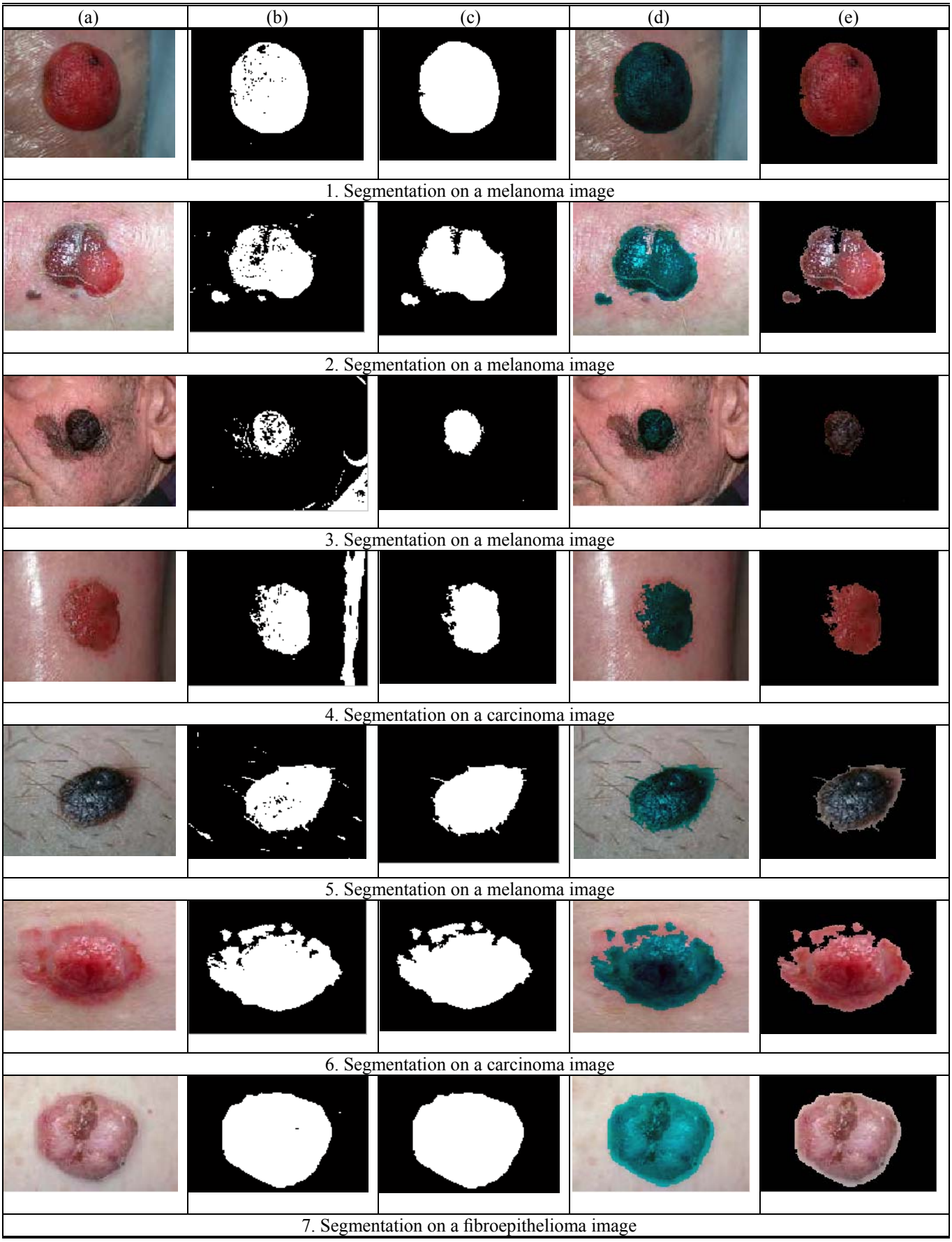

Fig. 12. Segmentation on different lesion images. Column (a) shows the original image. Column (b) shows the lesion pixels detected by ANFIS. Column (c) shows the enhancement of image in Column (b). Column (d) shows segmentation of the detected lesion from the original image. Column (e) shows the extracted lesion image.

III. RESULT

The above described methodology was applied on different skin lesion containing dermatology images which have been downloaded from DermAtlas [17], a website with open access to dermatological images. After segmentation by our proposed method we get the result shown in figure 12.

IV. CONCLUSIONS

This paper presents a novel approach for segmentation of colour images. The proposed method is applied on different pigmented skin lesion containing dermatological images to perform segmentation with the aim to detect lesion. After applying proposed segmentation technique, we find that the segmentation is achieved with good accuracy. This segmentation technique is able to isolate the lesion from rest of the image. For future work, this segmentation approach can be applied on other kind of colour images for target segmentation such as skin segmentation, etc. The colour space format can be changed to other formats depending on the usability and detecting ability of target in different kind of images.

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