ABCD Features Extraction for Malignant Melanoma Using Image Segmentation

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Abstract

Melanoma is the most malignant skin cancer. This is growing in melanocytes, the cells responsible for pigmentation. Using skin lesions features such as A: asymmetry, B: border irregularity, C: colour variation and D: diameter an attempt is made to determine if the skin tumour is a melanoma or a benign. Methodological approach to the features extraction of skin lesions in dermoscopic images is presented. Extracting specific attributes which can be used for computer-aided diagnosis of melanoma, especially among general practitioners. In the first step, eliminate surrounding in order to eliminate the residual noise by using morphological operations which are erosion and dilation. In the second step, an Otsu's segmentation is applied to the image of the skin tumour. This method reduces a colour image into an intensity image and approximately segments the image by intensity thresholding. Then, it refines the segmentation using the image edges, which are used to localize the boundary in that area of the skin. This step is essential to characterize the shape of the lesion and also to locate the tumour for analysis.

Keywords: image segmentation, morphological operations, Otsu's segmentation, clustering.

1. Introduction

Skin cancer as the most common cancer in human begins in the skin [1]. Some cancers also can start in other organs and spread on the skin, but these cancers are not considered as skin ones [2]. The different types of skin cancers commonly can be categorized as malignant melanoma and non-melanoma skin cancer (NMSC), the latter including Basal Cell Carcinoma and Squamous Cell Carcinoma as the major subtypes.

Melanoma, also known as **malignant melanoma**, is a type of cancer that develops from the pigment-containing cells known as melanocytes. Melanomas typically occur in the skin, but may rarely occur in the mouth, intestines, or eye. In women, they most commonly occur on the legs, while in men they are most common on the back. Sometimes they develop from a mole with changes such as an increase in size, irregular edges and change in colour, itchiness, or skin breakdown. The primary cause of melanoma is ultraviolet light (UV) exposure in those with low levels of skin pigment. The UV light may be from either the sun or from other sources, such as tanning devices. About 25% develop from moles. Those with many moles, a history of affected family members, and who have poor immune function are at greater risk. A number of rare genetic defects such as xeroderma pigmentosum also increase risk. Diagnosis is by biopsy and analysis of any skin lesion that has signs of being potentially cancerous. Using sunscreen and avoiding UV light may prevent melanoma. Treatment is typically removal by surgery. In those with slightly larger cancers, nearby lymph nodes may be tested for spread. Most people are cured if spread has not occurred.

For those in whom melanoma has spread, immunotherapy, biologic therapy, radiation therapy, or chemotherapy may improve survival. With treatment the five-year survival

rates in the United States is 98% among those with localized disease and 17% among those in whom spread has occurred. The likelihood that it will come back or spread depends how thick the melanoma is, how fast the cells are dividing, and whether or not the overlying skin has broken down. Melanoma is the most dangerous type of skin cancer. Globally, in 2012, it newly occurred in 232,000 people. In 2015 there were 3.1 million with active disease which resulted in 59,800 deaths. Australia and New Zealand have the highest rates of melanoma in the world. There are also high rates in Northern Europe and North America, while it is less common in Asia, Africa, and Latin America. Melanoma is more common in men than women. Melanoma has become more common since the 1960s in areas which are mostly populated with white people. This paper will be predicting melanoma skin cancer using image segmentation methods with extracts the features to better diagnosis.

2. Literature review

A Skin cancer is the most common form of cancer, globally accounting for at least 40% of cases. It is especially common among people with light skin. The most common type of non-melanoma skin cancer, which occurs in at least 2-3 million people per year, of non-melanoma skin cancers, about 80% are basal cell cancers and 20% squamous cell cancers. Basal cell and squamous cell cancers rarely result in death. In 2003, it was estimated that 105,000 people would receive a diagnosis of melanoma and a further 33,000 would die from the disease worldwide. In the United States, there was cause of less than 0.1% of all cancer deaths [3].

"Md.Amran Hossen Bhuiyan", "Ibrahim Azad" and "Md.Kamal Uddin" The segmentation is the most important stage for analyzing image properly since it affects the accuracy of the subsequent steps. However, proper segmentation is difficult because of the great verities of the lesion shapes, sizes, and colours along with different skin types and textures in "Image Processing for Skin Cancer Features Extraction" [4].

Skin cancer detection using Digital Image Processing by et al. Shivangi Jain, Vandana jagtap, Nitin Pise suggested a computer aided method used for the detection of melanoma skin cancer using image processing tools. The input to the system is the skin lesion image and then by applying novel image processing techniques, it analysis it to conclude about the presence of skin cancer. The image analysis tools check for the various melanoma parameters like asymmetry, border, colour, diameter (ABCD) by texture, size and shape analysis for image segmentation and feature stages. The extracted feature parameters are used to classify the image as normal skin and melanoma cancer lesion [5][6].

3. Methodology

First we can take a input as an image is acquired with a digital camera under consistent lighting. The proper interpretation of these dermoscopic images leads to increased clinical diagnostic accuracy. Most Automated Skin Lesion Diagnosis methods adopt the standard computer-aided diagnosis (CAD) pipeline which is illustrated in Fig. and it consists of five general stages. After the image is acquired, it contains many artefacts such as hair and oil bubbles which could bias downstream processes are identified. Next, the lesion is segmented from the surrounding healthy skin. After segmentation, discriminative features are extracted from the lesion. Features which are usually extracted are border, colour, entropy, compactness, radial variance of the mask, coarseness. Finally; by extracting these features the detection is done which finally shows the risk probability of the lesion which is present in the image. Mostly automatic skin cancer detection systems consist of following procedures:

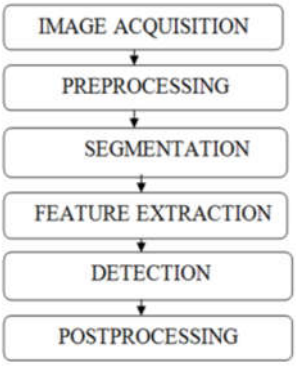


Fig: flow chart of skin cancer detection

Image acquisition: the input images take a digital dermotoscopic images from dermotoscope.

Image pre-processing: in this image pre-processing performing pre- processing operations like enhances the image and noise removing.

***Image segmentation*:** It is done to remove the healthy skin from the image and find the region of interest.

- ***Threshold Based Segmentation***: Histogram thresholding and slicing techniques are used to segment the image. They may be applied directly to an image, but can also be combined with pre- and post- processing techniques.

Otsu's method: This is optimal for thresholding objects from the background. This technique is based on a discriminate analysis which partitions the image into two classes. Given an image represented in L gray levels {0,1,2,……L},Otsu's thresholding method [10] partitions the image pixels into two classes C0={0,1,2……t} & C1={t+1,t+2……..L1}. Let the number of pixels in the gray level be , and n be the total number pixels in a given image. The probability of occurrence of gray level is defined as:

$$p_{i=}\frac{n_i}{n}$$

Co and C1 are normally corresponding to the object of intersect and the background, the probabilities of the classes are ω_0 and ω_1,

$$\omega_0 = \sum_{i=0}^{t-1} p_i \quad \text{and} \quad \omega_1 = \sum_{i=t+1}^{L-1} p_i$$

Thus, the mean of the two classes can be computed as:

$$\mu_0(t) = \sum_{i=0}^{t-1} \frac{ip_i}{w_{0(t).\mu_1(t)}} \quad \text{and} \quad \mu_1(t) = \sum_{i=t+1}^{L-1} \frac{ip_i}{W_1(t)}$$

An optimal threshold t* can be obtained by maximizing the class variance:

$$t^* = Arg \begin{cases} Max & \sigma_B^2 \\ 0 \le i \le L-1 & \sigma_T^2 \end{cases}$$

Where, Class Variance,

$$\sigma_B^2 = \omega_0(\mu_0(t) - \mu_1(t))^2 + \omega_1(\mu_1(t) - \mu_T(t))^2$$

Total Variance, $\sigma_T^2 = \sum_{i=0}^{L-1}(i - \mu_T)^2$

Total Mean, $\mu_T = \sum_{i=0}^{L-1} ip_i$

So, $t^* = Arg \begin{cases} Max \\ 0 \le i \le L-1 \end{cases} \omega_0(\mu_0(t) - \mu_1(t))^2 + \omega_1(\mu_1(t) - \mu_T(t))^2\}$

Otsu's method of thresholding gray level images is efficient for separating an image into two classes where two types of fairly distinct classes exists in the image.

Algorithm for Otsu's segmentation:

1. Compute histogram and probabilities of each intensity level
2. Set up initial $\omega_i(0)$ and $\mu_i(0)$
3. Step through all possible thresholds t=1,… maximum intensity

- Update ω_i and μ_i
- Compute $\sigma_B^2(t)$

4. Desired threshold corresponds to the maximum $\sigma_B^2(t)$

- ***Region-based segmentation:*** Splitting the image into smaller components then merging sub images which are adjacent and similar in some sense. It includes Statistical region merging, multi scale region growing, and morphological flooding [7-8]. It is based on the following techniques: 1) Split and merge 2) Statistical Region Merging 3) Multi-scale 4) Morphological flooding

Gradient Vector Flow (GVF): The GVF snack is well-known algorithm proposed in which has been successfully used in many medical imaging problems. The object boundary is approximated by an elastic contour X(s) =(X(s), Y(s)), S∈ [0,1] which is initialized in the image domain by the user or the heuristic criteria. The elastic contour is then modified according to the differential equation:

$$\frac{dx_{(s,t)}}{dt} = F_{int}\left(X_{(s,t)}\right) + V_{int}(X_{(s,t)})$$

Where, is an internal force, similar to the one used in traditional snakes tries to keep the shapes continuity and smoothness and V= (u(x, y), v(x, y)) is the GVF field. [12]The GVF field is a regularized version of the image or edge gradient which allows long range attraction of the contour toward the object boundary even if the contour is located in homogenous region where the gradient is zero. V can be obtained by minimizing the energy.

$$E = \iint \mu\left(u_x^2 + u_y^2 + v_x^2 + v_y^2\right) + |\nabla f|^2 |v - \nabla f|^2 \, dx \, dy$$

As it can be seen, this is an example of variation formulation of regularization. The parameter which adjusts the trade off between the first and second term of the integrand and set according to the level of noise present in the image. Also, where the value of the edge gradient is small, energy is dominated by the sum of the partial derivatives of the gradient is large, the second term dominates. In this case, setting v=∇ minimizes the energy. Using the calculus of variations, it can be shown that the GVF field can be found by showing the pair of Euler equation stated below:

$$\mu\nabla^2 u - (u - f_x)\left(f_x^2 + f_y^2\right) = 0$$
$$\mu\nabla^2 v - (v - f_x)\left(f_x^2 + f_y^2\right) = 0$$

Here, ∇^2 is the Laplacian operation. The initialization of the GVF snack is automated. A circle with a given radius is placed on the image.

- ***Colour Based Image Segmentation Using K-mean Clustering Technique:***

Although clustering is sometimes used as a synonym for segmentation techniques, we use it here to denote techniques that are primarily used in exploratory data analysis of high-dimensional measurement patterns. In this context, clustering methods attempt to group together patterns that are similar in some sense. This goal is very similar to what we are attempting to do when we segment an image, and indeed some clustering techniques can readily be applied for image segmentation.

Image segmentation techniques can be differentiated into the following basic concepts: pixel oriented, contour-oriented, region-oriented, model-oriented, and colour-oriented

and hybrid. Colour segmentation of image is a crucial operation in image analysis and in many computer vision, image interpolation, and pattern recognition system. The performance of colour segmentation may significantly affect the quality of an image understanding system [11].

This segmentation process is divided into two stages. First enhancing colour separation of medical image using de-correlation stretching is carried out and then the regions are grouped into set of three classes using k-mean clustering algorithm. Using this two step process, it is possible to reduce the computational cost avoiding feature calculation for every pixel in the image. Although the colour is not frequently used for image segmentation, it gives a high discrimination power regions present in the image.

Algorithm for k-means clustering: The k-means algorithm for partitioning, where each cluster's centre is represented by the mean value of the objects in the cluster.

Input: k: the number of clusters, D: a data set containing n objects.

Output: A set of k clusters. Method:

1) arbitrarily choose k objects from D as the initial cluster centres;
2) repeat
3) (re)assign each object to the cluster to which the object is the most similar, based on the mean value of the objects in the cluster;
4) update the cluster means, that is, calculate the mean value of the objects for each cluster;
5) until no change;

This segmentation process is divided into two stages. First enhancing colour separation of medical image using de-correlation stretching is carried out and then the regions are grouped into set of three classes using k-mean clustering algorithm. Using this two step process, it is possible to reduce the computational cost avoiding feature calculation for every pixel in the image. Although the colour is not frequently used for image segmentation, it gives a high discrimination power regions present in the image.

Feature extraction: The mole have features like Asymmetry, border irregularity, colour and diameter these are ABCD features of melanoma skin cancer lesions[10].

ABCD Rule:

STOLZ'S METHOD ABCD rule which is also called as STOLZ's method which is developed by Stolz et al is used for the Dermoscopic differentiation between benign melanocytic lesions and melanoma. Four features are extracted from lesion image. The features are Asymmetric(A), Border(B), Colour(C) and Diameter(D). The procedure of Stolz's method is to semi quantitatively assessing each of the four mentioned categories and assign them a numeric score [4]. Each score is scaled by a weight factor indicating empirically determined importance, and then the sum of these weighted scores yields the total dermotoscopic score, or TDS.

To calculate the ABCD score, the Asymmetry, Border, Colours, and Dermoscopic structures' criteria are assessed semi quantitatively. Each of the criteria is then multiplied by a given weight factor to yield a total dermoscopic score (TDS). TDS values less than 4.75 indicate a benign melanocytic lesion, values between 4.8 and 5.45 indicate a suspicious lesion, and values of 5.45 or greater are highly suggestive of melanoma.

***Asymmetry*:** To assess asymmetry, the melanocytic lesion is bisected by two 90º axes that were positioned to produce the lowest possible asymmetry score. If both axes dermocopically show asymmetric contours with regard to shape, colours and/or

dermoscopic structures, the asymmetry score is 2. If there is asymmetry on one axis only, the score is 1. If asymmetry is absent with regard to both axes the score is 0.

Border: The lesion is divided into eighths, and the pigment pattern is assessed. Within each
one-eighth segment, a sharp, abrupt cut-off of pigment pattern at the periphery receives a score 1. In contrast, a gradual, indistinct cut-off within the segment receives a score of 0. Thus, the maximum border score is 8, and the minimum score is 0.

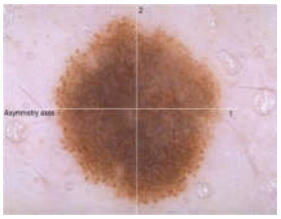
Colour: Six different colours are counted in determining the colour score: white, red, light brown, dark brown, blue-gray, and black. For each colour present, add +1 to the score. White should be counted only if the area is lighter than the adjacent skin. The maximum colour score is 6, and the minimum score is 1.

Dermoscopic structures: Evaluation of dermoscopic structures focuses on 5 structural features: network, structure less (or homogeneous) areas, branched streaks, dots, and globules. The presence of any feature results in a score +1 Structure less (or homogenous) areas must be larger than 10% of the lesion to be considered present. Branched streaks and dots are counted only when more than two are clearly visible. The presence of a single globule is sufficient for the lesion to be considered positive for globules.

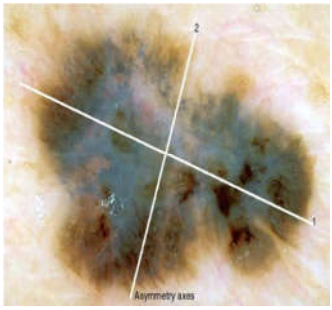
Criterion	Description	Score	Weight factor
Asymmetry	In 0, 1, or 2 axes; assess not only contour, but also colours and structures	0-2	X 1.3
Border	Abrupt ending of pigment pattern at the periphery in 0-8 segments	0-8	X 0.1
Colour	Presence of up to 6 colours (white, red, light brown, dark brown, blue-gray, black)	1-6	X 0.5
Dermoscopic structures	Presence of network, structure less or homogeneous areas, branched streaks, dots, and globules	1-5	X 0.5

Formula for TDS:[(A score x 1.3) + (B score x 0.1) + (C score x 0.5) + (D score x 0.5)]

Total Dermoscopic Score (TDS)	Interpretation
<4.75	Benign melanocytic lesion
>5.45	Lesion highly suggestive of melanoma



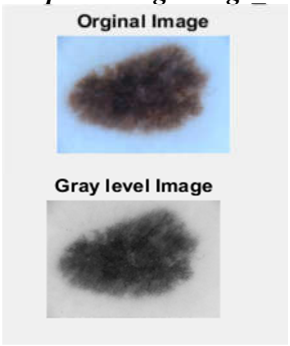
A = 0 (x 1.3);
B = 8 (x0.1);
C = 2
[light-brown, dark-brown]
(x 0.5);
D = 2
[network, globules]
(x 0.5)
--- TDS = 2.8 (benign) ---



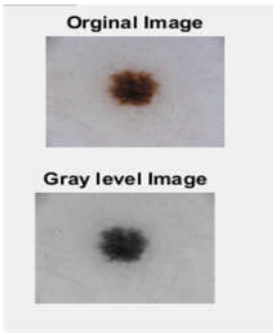
A = 2 (x 1.3);
B = 5 (x 0.1);
C = 5
[light-brown, dark-brown, blue-gray, black, white]
(x 0.5);
D = 4
[homogeneous areas, streaks, dots, globules]
(x 0.5)
--- TDS = 7.6 (malignant melanoma) ---

4. Experimental Results

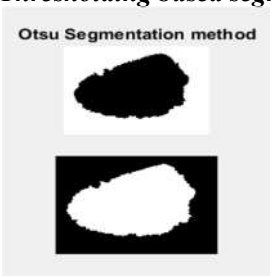
Pre-processing: image_isic_0000000:

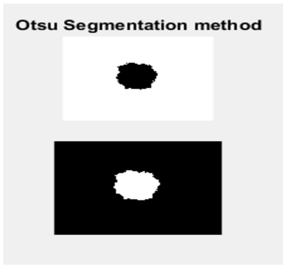


image_isic_0000001:

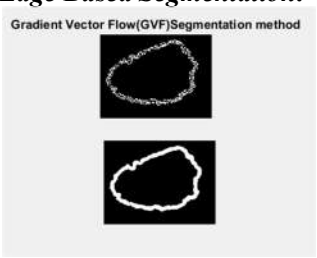


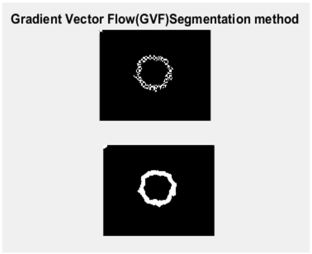
Thresholding based segmentation:



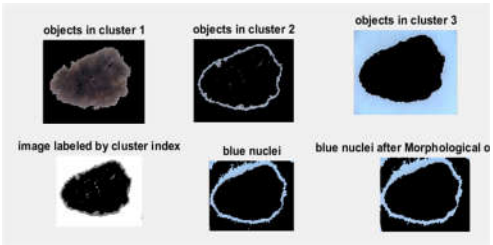


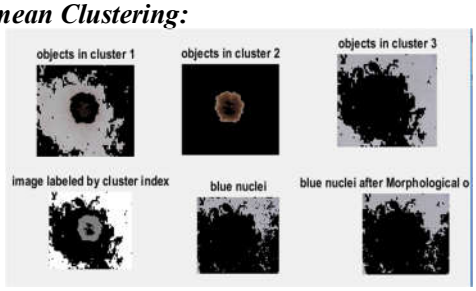
Edge Based Segmentation:





Colour Based Image Segmentation Using K-mean Clustering:





Tabular data:

Features	Img_isic_0000000	Img_isic_0000001
Asymmetry(0-2)*1.3	4.03	0.66
Border irregularity(0-8)*0.1	0.64	0.49
Colour variation(1-6)*0.5	0.94	1.06
Diameter(1-5)mm*0.5	1.25	1.25
TDS(total dermoscopic score) >5.45(melanoma)	6.85	3.46
Result	melanoma	benign

5. Conclusion

Image processing diagnosis system for melanoma skin cancer with features extraction. It can be concluded from the results that the proposed system can be effectively used by patients and physicians to diagnose. This tool is more useful for the rural areas where the experts in the medical field may not be available. Since the tool is made more users friendly and robust for images acquired in any conditions, it can serve purpose of automatic diagnostics of the Skin Cancer.

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