

A Methodological Approach for Early Melanoma Detection Using Smartphone Captured Images

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ABSTRACT

Researches on applications of mobile devices bring wide variety of uses in healthcare. One such work focus on detection of malignant melanoma using mobile image analysis. Dermoscopy is one of a current use, but need a special expertise for the detection of cancer melanoma. The image taken using smartphone is used for this purpose. It mainly focus on localization of the skin lesion by combining fast skin detection and fusion of two fast segmentation results. This also introduces some set of image features and to capture color variation and border irregularity which are useful for smartphone-captured images. It propose a new feature selection criterion to select a small set of good features used in the final lightweight system. The method introduces a new module for the detection of distorted images such as motion blur and alert users in such situations. The blurred image undergo deblurring to detect the correct result. The result of this application will identify whether the image is malignant melanoma or benign with their intensity value from smartphone captured images used.

Keywords: Malignant Melanoma, Otsu, Minimum Spanning Tree, Gray Level Co-occurrence Matrix, Local Binary Pattern

I. INTRODUCTION

Nowadays billions of people all around the world are using mobile devices including smartphones. There are different applications for mobile images. Among these healthcare applications have a major role [1]. Mobile image healthcare applications are practical and low cost. Anyone can access this method very efficiently.

The proposed work focus on detection of malignant melanoma using mobile image analysis. Melanoma is a kind of malignant growth that starts in the melanocytes. Most melanoma cells make melanin, so melanoma tumors are usually brown or black. The main cause of skin cancer melanoma is the excessive

exposure to sunlight. Scientists shown that Ultraviolet (UV) light from sun may cause melanoma on normal skin or may increase the risk of a mole on the skin turning into a melanoma [2]. UV rays can harm the DNA in skin cells. Some of the time this harm affects certain genes that control how skin cells grow and divide. If the working of genes is not proper, the affected cells may become cancer cells.

Melanoma are often noticed by self examining [3] the skin of unusual moles, sores, lumps, blemishes, markings, or changes in the way an area of the skin looks or feels could also be an indication of melanoma or another type of skin cancer, or a warning that it'd occur. Examining by a healthcare professional who specializes in skin problems called

Dermatologist. Dermatologist use a technique called dermatoscopy (also known as dermoscopy, epiluminescence microscopy [ELM], or surface microscopy) to look at spots on the skin more clearly. Then a photo of the spot may be taken to evaluate the skin. This technique distinguish suspect a melanoma from a normal mole or not. The method is cheap but required expertise and skill of a physician [4].

Following are the estimations of the American Cancer Society’s for melanoma in the United States for 2019 [5]:

- Approximately 96,480 new melanomas will be diagnosed (about 57,220 in men and 39,260 in women).
- Approximately 7,230 people are expected to die of melanoma (about 4,740 men and 2,490 women).

The melanoma rates have been increasing for the last 30 years. So need a method to assist melanoma early and diagnosis accurately which is low cost and accessible to anyone without help of clinicians.

II. METHODS AND MATERIAL

The proposed melanoma detection framework with some ongoing melanoma identification techniques: MED-NODE [6], on the openly accessible UMCG dataset from Department of Dermatology of University Medical Center Groningen (UMCG). UMCG is a difficult dataset. The dataset comprises of 70 melanoma and 100 considerate pictures.

The design introduces a complete mobile imaging system to detect malignant melanoma early. The research contributes different methods. The fast and lightweight segmentation process for identification of skin lesion. For smartphone captured images new computational features are introduced. It will improve the detection accuracy of the images taken.

It have classification tools to select good features and there is classification array to classify the melanoma and benign.

The images acquired by the mobile devices can be heavily affected by distortions such as motion blur [7]. These distortions can change the skin lesion appearance. This will smooth the border of the skin mole, confusing the segmentation and classification algorithms that the current system cannot compensate. So a novel module is proposed to deblur such distorted images. Fig. depicts the proposed model of melanoma detection.

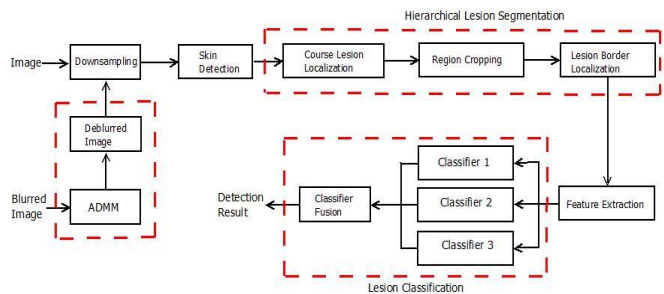


Figure 1. Flowchart of proposed method

The smartphone captured skin image is first undergo downsampling. Then the image is given to skin detection process. The skin detection module is used to discard pixels from non-skin regions to simplify the image for the subsequent processing step. This process will filter the unwanted artifacts.

A. Hierarchical lesion segmentation

A light weight segmentation method is necessary to develop a smartphone captured image system that achieve high precision under different conditions. The two segmentation results are the fused to get better result.

• Coarse Lesion Localization

For the segmentation module the downsampled image select two methods that is simple and easy to implement. Uses Otsu’s method [8] and Minimum Spanning Tree (MST) method [9] to get the initial segmentation result.

A simple and fast thresholding method that automatically calculates a threshold value from image histogram is the Otsu's method. This threshold value is then used to classify image pixels based on their intensities. But this method may not detect clear edges on the images such as lesion boundaries. The method is very simple and it take much less time compared to other segmentation methods.

A sensitive clear edges fast region based graph-cut method called Minimum Spanning Tree (MST) method is used. MST is not robust to detect smooth changes of color intensity but it can run at nearly linear time complexity in the number of pixels. After running two different segmentation methods and combination gives a good segmentation on lesion with clear border in a fast computation.

- **Border Localization**

Inorder to localize the border of the lesion correctly from the result obtained from segmentation methods uses the border localization process. First crop the lesion from the original high resolution image then the segmented lesion is obtained.

B. Feature Computation

From the lesion segmented from above methods compute features belonging to four categories. The four features extracted are color, border, asymmetry and texture to describe the lesion.

- **Color Feature**

Different color features are used for the skin lesion. The mean and variance of pixel values on several color features are extracted. The color channels used are red, green, blue from RGB image, gray scale from the gray image, and hue and value from the HSV image. Use the information from the histogram of pixel values to capture more color variation from the skin lesion [10][11]. Compute the histogram which have 16 bins of pixel values in lesion and the number of non-zero bins is used as feature. This can be also

applied on 6 channels mentioned above. Features such as num_red, num_green, num_blue, num_gray, num_hue and num_value are achieved from these channels.

A novel approach called Color Triangle is used for the skin lesion color feature. The lesion first divide the region into N partitions and these each partition is again divided into M subparts. After that, all these partitions are described by a M-component vector where each component is the average of pixel values of a subpart. To quantify the color variation of the skin lesion the maximum Euclidean distance between the vectors are used. The values of N can be taken as 4, 8, 12 and 16. Corresponding M can be taken as 2, 4 and 8. Fig shows the illustration of proposed method with N = 4 and M = 2.

- **Border and Asymmetry Feature**

The irregularity of border can be described by computing some shape features such as Solidity, Extent, Convexarea and Perimeter. Border feature can be used to detect melanoma with a mole of having higher probability of being melanoma. The border feature can be quantified using border irregularity. This can be done by approximating the lesion contour by multiple straight lines and use the angles between these lines to quantify the irregularity. Compared with the irregular ones, regular borders tend to have smooth and consistent changes between consecutive contour fitting lines.

- **Texture feature**

To quantify the lesion texture GLCM (gray level co-occurrence matrix) and LBP (local binary patterns) feature descriptors are used. The GLCM characterizes the texture of an image. This is done by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image. GLCM-based texture description is one of the most widely used and well known methods in many literatures. This work focuss on GLCM by considering each two adjacent pixels in horizontal direction. Four features extracted from GLCM to

describe lesion. They are contrast, energy, correlation and homogeneity. GLCM is a matrix which give a reasonable estimation of different features.

One of the most widely used texture descriptor for the skin lesion analysis is Local Binary Pattern (LBP) [12]. LBP combines shape and statistical information by a histogram of LBP codes which resemble microstructures in the image. The LBP is a 3×3 pixel block of local structure is a scale invariant measure. The LBP was then adapted to accommodate arbitrary block sizes. LBP uses two main parameters P and R. The number of pixel neighbors P on a circle of radius R of a given center pixel. P-1 bitwise shift operations of the circle are performed to generate rotation invariant LBPs and the smallest value is selected. This application adopt the LBP framework introduced in [12]. LBP shown better performance which is a complete mathematical formulation of the LBP operator and it has been extensively tested. The research extract the sign LBP (LBP_s) from the grayscale channel of the lesion image. The resulted LBP_s is a 36-dimensional vector.

As an enhancement to the current research the investigation uses the deblurring effect. If the user take images on mobile devices which is heavily affected by distortions like motion blur. Such distortions can change skin lesion appearance and will smooth the border of the mole on skin. This will confuse the segmentation and classification algorithms and get an incorrect output. To overcome this problem the research include a new module to detect such distorted images and the blurred image will undergo deblurring.

C. Blurring

First as a testing the convolution method is used to blur images or remove noise. For this purpose a kernel matrix or blurring filter is created. In image convolutions kernel is usually small matrix of numbers. Diversely sized kernels containing various

patterns of numbers produce various outcomes under convolution. The size of a kernel is random but 3×3 is often used. Then the kernel is overlaid onto a block of pixels in the image. The entries in these blocks is multiplied with corresponding pixel value. These products are then summed to find new value of the blocks center pixel. The kernel then shift one by one pixel and operation is repeated. Each pixels new values are the weighted average of neighbouring pixels original values. This reduce sharp contrasts between pixel intensities and blurring the edges in the image.

D. Deblurring

The blurred image can be deblurred by using the Alternating Direction Method of Multipliers (ADMM). It can be used to reduce blurring effect. ADMM is a method that is used to solve convex minimization problems. Deblurring can be done using minimization and smoothing.

$$\|Y - Hx\| + \lambda\phi(x)$$

Here Y is the blurred image and uses a blurring filter Hx. To this deblurred image smoothing is also adding for more accurate result. $\lambda\phi(x)$ is used for smoothing. After deblurring the image restore its maximum originality. This image is then undergo segmentation, feature extraction, feature classification and then the result is used to evaluate its malignancy of the skin mole.

E. Lesion Classification

Support Supervised learning models for classification and regression problems uses Vector Machines. They can solve linear and non-linear problems and they can also work well for many practical problems. The idea of Support Vector Machines is simple and it will show correct result. As an e.g. in a classification problem the algorithm creates a line which separates the classes. The intention of the line is to maximizing the margin between the points on either side called

decision line. The advantage of this procedure is, that after the partition, the model can easily estimate the target classes (labels) for new cases.

Support Vector Machines are really very effective in higher dimensional spaces. It is even very effective on data sets where number of dimensions is greater than the number of samples. In comparison to other classification methods like k-nearest neighbor or deep neural networks, Support Vector Machines have the advantages of high memory efficiency, speed and general accuracy.

The feature selection is performed for each feature by using the SVM classifier. Color, border, asymmetry, texture: GLCM features and edge density feature were identified for each category. For the given image the system computes the selected features for each category and then these features are passed into SVM classifiers [13]. For each feature subset in testing stage, the corresponding SVM is used to make a predict. The output of SVM classifier will be Malignant or Benign with their intensity score. Additionally, fusing the results from individual classifiers is very helpful as this combines valuable information gained in the training phase of each feature category. The intensity score indicates whether the given image is highly cancerous or not. Also evaluate the classification performance in terms of sensitivity, specificity and balanced accuracy.

F. Performance Evaluation

The performance evaluation in the experiment can be done using TP, FP, TN and FN as True Positive (the number of instances correctly predicted as required), False Positive (the number of instances incorrectly predicted as required), True Negative (the number of instances correctly predicted as not required) and False Negative (the number of instances incorrectly predicted as not required), respectively.

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

$$\text{Specificity} = \frac{TN}{TN+FP}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP}$$

III. RESULTS AND DISCUSSION

The target of the proposed method was to build up a framework that characterizes a picture to either melanoma or healthy one. The system was structured dependent on (1) efficient segmentation scheme by merging Otsu method and MST method. (2) it uses a set of features to extract the detectable information between malignant and benign melanoma and (3) a classifier scheme for selecting a set of particular features. Along with these methods a new module has been introduced for blurring and deblurring image.

Images of testing of Malignant Melanoma

First choose an image from the dataset created. The image will be malignant or benign. From the original image the system classify whether it is malignant or not.



Figure 2. Original image

On certain occasions, the pictures gained by the smartphones or chosen image can be intensely influenced by distortions, in specific motion blur. This blurring can be added by using the convolution method.

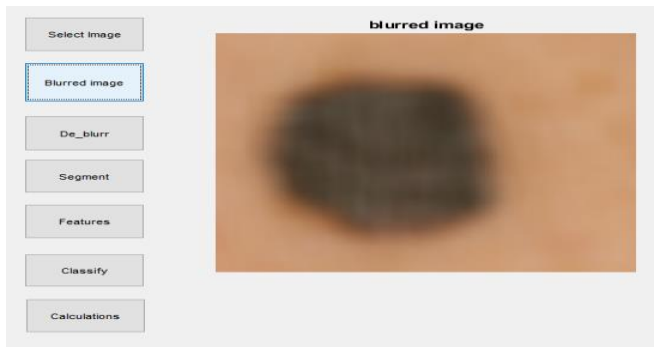


Figure 3. Blurred Image

But if this blurred image undergo segmentation it will show cannot segment message.

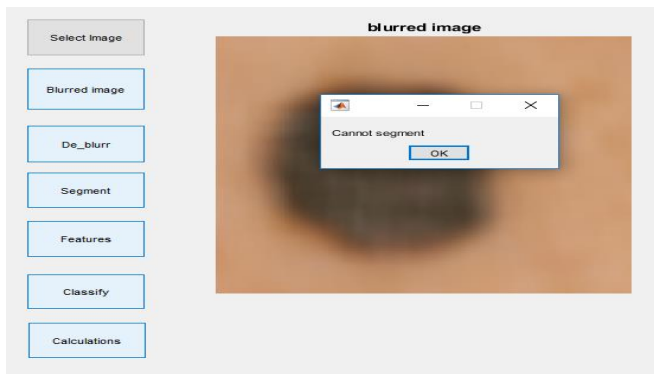


Figure 4. Message appears when blurred image undergo segmentation

For the segmentation purpose it must deblurr to get the correct output. The deblurring is done using ADMM method. ADMM is very simple and fast deblurring method.



Figure 5. Deblurred image

After deblurring the image, it will undergo segmentation. The results obtained by merging Otsu

and MST methods gives high accurate segmentation result than it is done separately.

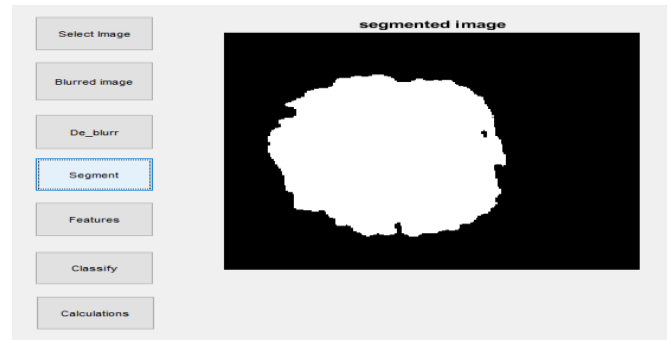


Figure 6. Segmented image

The features are extracted. Color Triangle image have four parts with color red, green, blue and magenta.

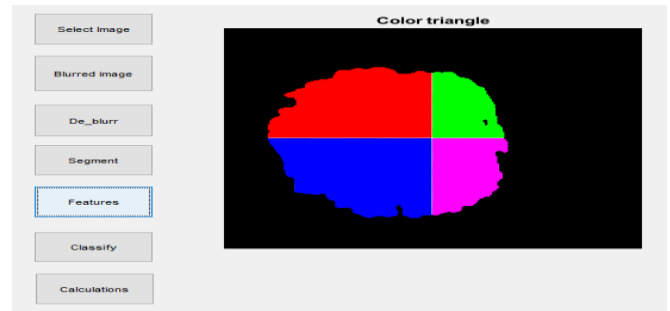


Figure 7. Imge of color triangle

The color feature graph have been plotted with total number of features on x-axis and intensity values on y-axis.

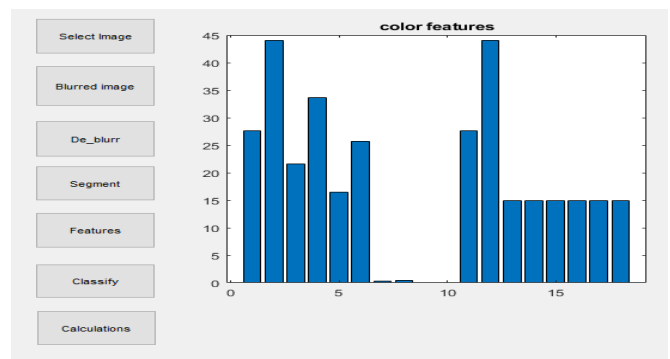


Figure 8. Color Feature

The boundary features can be plotted with total number of features on x-axis and intensity values on y-axis.

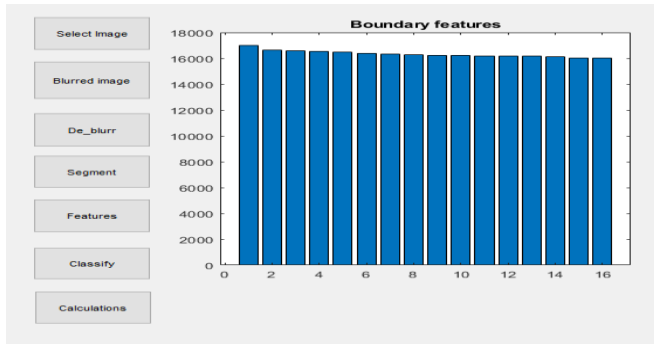


Figure 9. Boundary feature

The texture features are also plotted total number of features on x-axis and intensity values on y-axis.

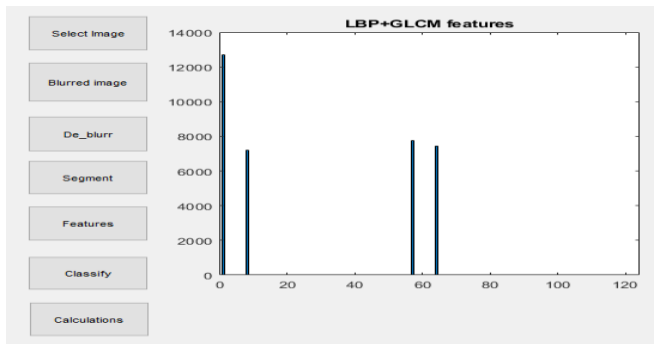


Figure 10. Texture feature

Then the classification will show the image given is malignant or benign.



Figure 11. Classification with intensity score

The measurements of sensitivity or recall, specificity or precision and accuracy measures are plotted. By analysing this measurements the accuracy of the research can be identified.

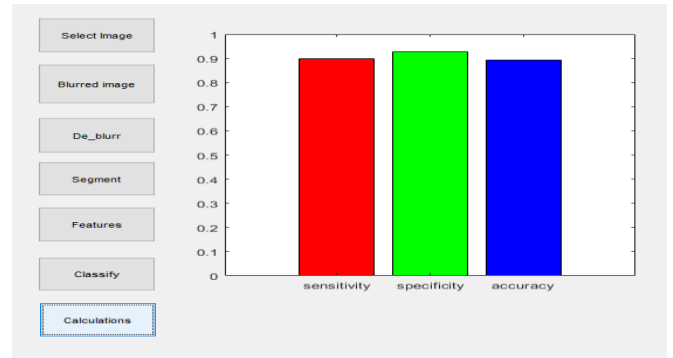


Figure 12. Measurements

IV. CONCLUSION

The research investigates melanoma detection using mobile image analysis. This is a fast and accessible method for mobile health care solution. It uses an efficient segmentation scheme by combining fast skin detection and fusion of two segmentation results. To capture color variation and border irregularity from smartphone captured images, a new set of features are introduced. Also it have efficient criterion for selecting good features. The output shows whether the selected image is malignant or benign with their risk score. The experimental results shown high accuracy taken from MED-NODE dataset which consist of 70 melanoma and 100 benign images. A new module is introduced for deblurring an image if the input is blurred which cannot be segmented. The method is very useful for the general public to access easily for early diagnosis of melanoma. The current prototype represents an initial step in the development of a more useful system and demonstrates that it is possible to do image segmentation, feature calculation, and lesion classification on a smartphone with good recognition accuracy.

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