

Early Melanoma Diagnosis with Mobile Imaging

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Abstract— We research a mobile imaging system for early diagnosis of melanoma. Different from previous work, we focus on smartphone-captured images, and propose a detection system that runs entirely on the smartphone. Smartphone-captured images taken under loosely-controlled conditions introduce new challenges for melanoma detection, while processing performed on the smartphone is subject to computation and memory constraints. To address these challenges, we propose to localize the skin lesion by combining fast skin detection and fusion of two fast segmentation results. We propose new features to capture color variation and border irregularity which are useful for smartphone-captured images. We also propose a new feature selection criterion to select a small set of good features used in the final lightweight system. Our evaluation confirms the effectiveness of proposed algorithms and features. In addition, we present our system prototype which computes selected visual features from a user-captured skin lesion image, and analyzes them to estimate the likelihood of malignance, all on an off-the-shelf smartphone.

I. INTRODUCTION

Melanoma is the most aggressive form of skin cancer. It is responsible for the majority of skin cancer related deaths. Most cases are curable if they are detected early. However, in some countries, there is a trend towards more advanced disease staging at presentation, due to lack of patients' awareness and delayed or missed diagnosis by primary care physicians [12]. There is a pressing need for an accessible and accurate pre-screening solution to improve the general awareness.

Increasingly, smartphones are equipped with multi-core CPUs and high resolution image sensors. All this creates the opportunity to use a smartphone to analyze a captured image for disease diagnosis and self-screening. Taking this opportunity, this work researches a novel mobile imaging system for early detection of melanoma.

Several automatic melanoma diagnosis systems have been proposed in the literature [14], [10], [2], [20]. However, they focus on dermoscopic images (including [22], which uses mobile phones for dermoscopic image analysis). Dermoscopic images are taken with the aid of liquid medium or non-polarised light source and magnifiers, under well-controlled clinical conditions. Dermoscopic images include features below the skin surface, which cannot be captured with normal cameras equipped in smartphones, as in our work. A few isolated work investigated smartphone-captured images. In [19], a mobile-system working for images taken from mobile camera is presented. However, to detect lesion, they used a very basic thresholding method. To describe lesion, only simple color feature (mean/variance of some

color channels, the difference of color through vertical axis) and border features (convexity, compactness) are extracted and subjected to a simple kNN classifier. [4] also focuses on images taken from mobile camera. The lesion detection and feature extraction are performed on mobile while the classification can be performed on mobile or cloud. However, in that work, the emphasis is on system integration, and the authors did not clearly mention what algorithms / features were used for diagnosis.

Generally, an automatic melanoma detection system can be divided into three main stages of segmentation, feature extraction, and classification.

The first stage aims to determine lesion region from image. There are several common methods to perform lesion segmentation [25], [2]: histogram thresholding, clustering, edge-based, region-based, and active contours. Among these methods, histogram thresholding and region-based are most often used. Histogram thresholding methods use image histogram to determine one or more intensity values for separating pixels into groups. The most popular thresholding method for lesion segmentation is Otsu's method [16]. Region-based methods form different regions by using region merge or region split methods.

The second stage aims to extract features described the lesion. There are many methods proposed such as pattern analysis, Menzies method, ELM 7-point checklist, ... [24]. However, most of these methods are usually applied to images taken from a dermatoscope. For melanoma, the most important warning sign is a new or changing skin growth. It could be a new growth or a change in the color, size or shape of a spot on the skin. To help people can self-examinations their skin, American Academy of Dermatology promoted a simple method called "ABCDE" [15] corresponding to **A**symmetry of lesion, **B**order irregularity, **C**olor variation, **D**iameter and **E**volving. There are many methods used in the literature to capture color variation, border irregularity, asymmetry¹. The reviews can be found in [14], [10], [2].

Although there are many features used in previous researches to describe color variation and border irregularity, most of these features are general features such as mean, variance of different color channels; compactness, convexity, solidity of shape.... They are not specifically designed to capture color and border information of lesion. Hence, in this work, we propose two new features which can efficiently describe the color variation and border irregularity of lesion.

¹Because computer-aided diagnosis systems usually diagnose a single image, evolving feature usually does not be used.

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As presented, there are many features can be extracted to describe color, border or texture of lesion. It likely has some noise features also redundancy between features which may reduce the classification rate. Hence, a feature selection that is done in offline mode to select only good features is necessary. Only selected features will be used to judge if a lesion is cancer/non-cancer. Furthermore, feature selection has a important role in mobile-based diagnosis system where there are strict computational and memory constraints. By using a small number of features, it will have some benefits such as reduce feature extraction time and storage requirements; reduce training and testing time; reduce the complexity of classifier.

Feature selection algorithms can be divided into two categories according to their evaluation criteria: wrapper and filter [13]. Wrapper approach uses the performance of a predetermined classifier to evaluate the goodness of features. On the other hand, filter approach does not rely on any classifiers. The goodness of features is evaluated based on how much the relevance between them and class labels. In this work, we follow filter approach because it is very fast which allows us to compare different methods. Furthermore, it is more general than wrapper approach because it does not involve to any specific classifier.

In filter approach, the relevance is usually characterized in terms of mutual information. However, the drawback of mutual information is that it only uses the probability of variables while ignoring the coordinate of variables which can help the classification. To overcome this drawback of mutual information, we propose a new feature selection criterion taking into account the coordinate of variables when evaluating the goodness of features.

The final stage of automatic melanoma detection is to classify extracted features of lesions into either cancer or non-cancer. Many classification models can be used at this stage such as Support Vector Machine (SVM), nearest neighbor, discriminant analysis [14], [10], [2].

Remaining sections of the paper are structured as follows. Section II presents the proposed segmentation procedure. Section III details features used to describe the lesion, our proposed color and border features, feature selection procedure, and our proposed feature selection criterion. Experiment results and mobile implementation are presented in section IV. Section V concludes the paper.

II. SEGMENTATION

It is challenging to achieve accurate segmentation of skin lesions from smartphone-captured images under loosely controlled lighting and focal conditions. Instead of using sophisticated segmentation algorithms, which can be computationally-expensive, we propose to localize the skin lesion with a combination of fast skin detection and fusion of fast segmentation results. Our segmentation process consists of two main steps. At first step, a mask of skin regions is generated using skin detection method. By doing skin detection, we discard pixels from non-skin regions to simplify the image for subsequent processing step. At second step,

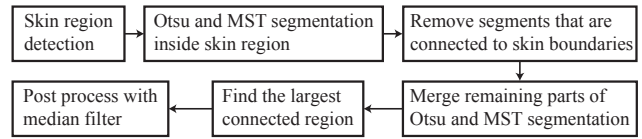


Fig. 1. Flowchart of segmentation procedure

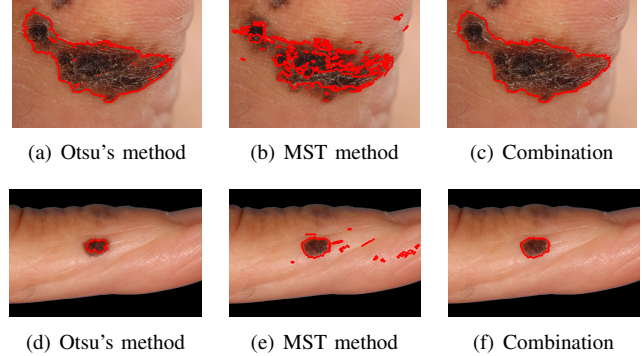


Fig. 2. Results of our proposed segmentation scheme. Images (a-c) are segmentation results by using Otsu's method, MST method, and combination of two methods for the first example. Images (d-f) are the segmentation results for the second example.

we extract the lesion by using a combination of different segmentation methods. Fig. 1 shows the flowchart of our proposed segmentation procedure.

A. Skin Detection

The reason of doing skin detection first is to simplify the image, so an exact classification of skin and non-skin region is not needed as long as we extract a simple foreground and keep the whole lesion region inside. Here we use an approach based on skin color model to detect skin pixels [5]. First we convert the image from RGB color space into YC_bC_r color space. We collect 100 skin images and 36 non-skin images from the internet to form our skin detection dataset. Skin images are selected with different skin colors and various lighting conditions. The skin color distribution is close to an elliptical distribution [11], so we detect skin pixels using an elliptical skin model on C_bC_r space [5], [11]. As the skin mole we want to detect may not have skin color, we fill all the holes inside the skin region.

B. Lesion Segmentation

Because of our object of developing a mobile-based diagnosis system, we need a segmentation method that can achieve high precision under the computation constraint. As different segmentation methods have distinct limitations, we want to apply several basic segmentation methods with low computation usage, and then use some criteria to merge the results.

After we get the skin region as the area to do our segmentation method, we perform two segmentation methods and use some rules to combine results from both methods. Here we select Otsu's method [16] and Minimum Spanning Tree (MST) method [8] to get initial segmentation results.

Otsu's method is a general histogram thresholding method that can classify image pixels based on color intensity, and it may not detect clear edges on image, for example, the lesion boundary. Otsu's method is simple and takes much less time compared to other lesion segmentation methods [10].

MST method is a fast region-based graph-cut method. It can run at nearly linear time complexity in the number of pixels. It is sensitive to clear edges but may not detect smooth changes of color intensity.

By combining the two different segmentation results, we expect to get a good segmentation on lesion with either clear border or blur border in a fast computation. Based on some rules to perform fusion of different segmentation in [10], we apply the following procedures to merge the two segmentation results. First, we remove all segments in either results that are connected to the boundary of skin region. Second, we take the union of the two results and then find the largest connected region in the union result. And last, we perform a post processing method of using median filter on the final segment to smooth the border. Fig. 2 shows results of single segmentation methods and their combination. Fig. 2(a-c) show an example where Otsu's method gives a better result than MST method. Because in this image, the lesion border is not clear, Otsu's method detects a more accurate border. Fig. 2(d-f) show an example where MST method gives a better result than Otsu's method. In this image, the lesion border is clear but the color is not uniform inside the lesion region, so MST method finds the exact border of the lesion. After we take the union from two different methods, we can get more accurate segmentation results.

III. FEATURE CALCULATION

A. Feature Extraction

Given the lesion image segmented from section II, we examine 80 features belonging to four categories (color, border, asymmetry and texture) to describe the lesion. These features are presented in follows.

1) *Color Feature*: Given a color lesion, we calculate color features widely used in the literature such as mean, variance of pixel values on several color channels. The used color channels are gray scale; red, green, blue (from RGB image); hue and value (from HSV image). To capture more color variation, we also use information from histogram of pixel values [14], [10], [2]. A histogram having 16 bins of pixel values in lesion is computed and number of non-zero bins is used as feature. This method is also applied on 6 channels mentioned above. Features achieved from these channel are called as *num_gray*, *num_red*, *num_green*, *num_blue*, *num_hue* and *num_value*.

For normal skin lesion, color varies uniformly from the center to the border. We propose a new feature to capture this characteristic. The lesion is first divided into N partitions and each partition is further divided into M subparts. After that, each partition is described by a M -component vector where each component is the average of pixel values of a subpart. Finally, maximum distance between the vectors quantifies the

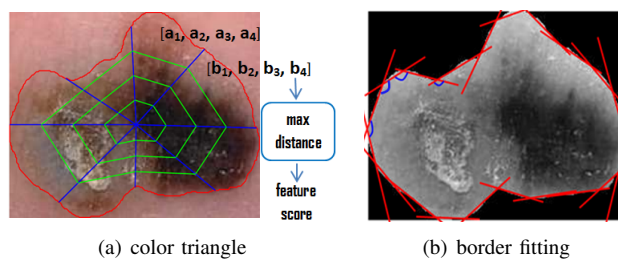


Fig. 3. Our proposed feature to quantify color variation (a) and border irregularity (b) of a skin lesion

color variation. This feature is called as color triangle feature. This proposed method is computed for gray scale, red and hue channel of lesion. Values of N are chosen as 4, 8, 12 and 16. For each value of N , values of M are chosen as 2, 4 and 8. An illustration for proposed method is presented in Fig. 6(a). Totally, we extract 54 color features to describe the color variation.

2) *Border Feature*: To describe the irregularity of border, we compute shape features such as compactness, solidity, convexity, variance of distances from border points to centroid of lesion [14].

We also propose a new method called as border fitting to quantify the irregularity of border. First, the lesion border is approximated by mean-square-error method with lines. After that, the angles between every two adjacent lines are computed. Average and variance of the angles are used to describe border irregularity. Number of lines L are chosen as 8, 12, 16, 20, 24 and 28. An illustration for proposed method is presented in Fig. 6(b). Totally, 16 features are extracted to describe the border irregularity.

3) *Asymmetry Feature*: To compute the asymmetry of lesion shape, we follow the method in [2]. The major and minor axes (first and second principal components) of lesion region are determined. The lesion is rotated such that the principal axes are coincided the image (x and y) axes. The object was hypothetically folded about the x -axis and the area difference (Ax) between the two parts was taken as the amount of asymmetry about the x -axis. The same procedure was performed for the y -axis (so, we get Ay). The asymmetric feature is computed as $\frac{Ax+Ay}{A}$ where A is lesion area.

4) *Texture Feature*: To quantify texture feature of lesion, a set of features from the Gray Level Co-occurrence Matrix (GLCM) of gray scale channel is employed. The GLCM characterizes the texture of an image 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 well-known and widely used methods in the literature [6]. In this work, GLCM is built by considering each two adjacent pixels in horizontal direction. Four features extracted from GLCM to describe lesion. They are contrast, energy, correlation and homogeneity. As shown in [6], to achieve a confidence estimation for features, GLCM should be dense. Hence, before GLCM calculation, the pixel values are quantized to 32 and 64 levels. It means that we

computed 8 texture features from two GLCM. To capture edge information in lesion, we also use Canny method to detect edges in lesion. Number of edge pixels are counted and normalized by lesion area. This number is used as feature. Totally, 9 features are extracted to describe the texture of lesion.

B. Feature Selection

Given set F of n features and class label C , the feature selection problem is to find a set S having k features ($k < n$) such that it maximizes the relevance between C and S . The relevance is usually characterized in terms of Mutual Information (MI) [17], [1], [7]. Because the consideration all possible subsets having k features requires C_n^k run, it is difficult for using exhausting search to find the best subset.

1) *Feature selection procedure*: Because of above trouble, in this work, we used the well-known feature selection procedure called Normalize Mutual Information Feature Selection (NMIFS) [7] to select features. In NMIFS, at beginning, the feature that maximizes relevance with target class C is selected as first feature. Given set of selected feature S_{m-1} , the next feature f_m is chosen such that it maximizes the relevance of f_m to target class C and minimizes the redundancy between it and previous selected features in S_{m-1} . In other words, f_m is selected such that it maximizes G function

$$G(f_m) = I(C, f_m) - \frac{1}{|S_{m-1}|} \sum_{f_s \in S_{m-1}} NI(f_m, f_s) \quad (1)$$

where I is mutual information function measuring the relevance between two variables and is defined as

$$I(X, Y) = \sum_y \sum_x p(x, y) \log \frac{p(x, y)}{p(x)p(y)} \quad (2)$$

NI is normalized mutual information function and is defined as

$$NI(X, Y) = \frac{I(X, Y)}{\min\{H(X), H(Y)\}} \quad (3)$$

where H is entropy function ².

2) *Disadvantage of MI-based criterion*: MI usually is widely used in feature selection problem to measure the relevance between variables. However, from (2), we observed that MI is a measure based on the probability functions. It is independent to coordinate of variable values which may be useful in classification context. For examples, in two categories classification, suppose that number of samples in each category are equal and there are two features f_1, f_2 which perfectly separate two categories. By Vapnik-Chervonenkis theory [21], the feature has larger margin between two categories will give a better generalization error. Hence, it should be better than another feature. However, by using MI, it is easy to show that these features will have same MI value with class label (C) which equals to 1. A well-known criterion considering the coordinate of

features is Fisher criterion (F-test). However, there are some disadvantages of Fisher criterion figured out in [9]. Fisher criterion may not be good incase (i) the distribution of the data in each class is not a Gaussian; (ii) mean values of classes are equal/approximate.

3) *New feature selection criterion*: To overcome drawback MI-based criterion, we propose a new criterion taking into account the feature coordinate when evaluating the goodness of features. Our new criterion is inspired from work of Wang et.al. [23] in face recognition problem. In that work, authors defined a new transformation called ‘‘Average Neighborhood Margin (ANM) maximization’’ which pulls the neighboring images of the same person towards it as near as possible, while simultaneously pushing the neighboring images of different people away from it as far as possible. We adapt ANM to feature selection problem by defining the goodness of feature f as

$$M(f) = \sum_{i=1}^N \left\| \sum_{k \in N_i^e} \frac{\|f(i) - f(k)\|_1}{N_i^e} - \sum_{j \in N_i^o} \frac{\|f(i) - f(j)\|_1}{N_i^o} \right\|_1 \quad (4)$$

where N is number of data points (samples); for each sample i , N_i^o is the set of the most similar samples which are in the same class with i ; N_i^e is the set of the most similar samples which are not the same class with i ; $f(i)$ is feature value of i^{th} sample. Eq. (4) means that a feature is good if each sample is far from samples belonging other classes while it is near to samples belonging same class. Because ANM criterion uses only local information and does not make any assumptions on the distributions of samples, ANM can overcome drawbacks of Fisher criterion.

Finally, to take advantages both MI and ANM, we define a new feature criterion which replaces G function in eq. (1) by following function

$$G(f_m) = \alpha * M(f_m) + (1 - \alpha) * I(C, f_m) - \frac{1}{|S_{m-1}|} \sum_{f_s \in S_{m-1}} NI(f_m, f_s) \quad (5)$$

where $\alpha \in [0, 1]$ is weight that regulates to the importance of ANM. Note that M is normalized to $[0, 1]$ before computing eq. (5).

IV. CLASSIFICATION EXPERIMENTS

A. Experiment Setting

The database includes 81 color images provided by National Skin Center, Singapore. Number of cancer and non-cancer images are 29 and 52, respectively.

The segmentation process in section II is applied on these images to extract lesion regions. After that, 80 features belonging four categories (54 color features, 16 border features, 1 asymmetric feature and 9 texture features) in section III-A are extracted to describe each lesion region. These features are normalized by z-score before subjecting to feature selection step. To compute mutual information between features, features should be first discretized. To discretize each feature, the interval $[\mu - 2\sigma, \mu + 2\sigma]$ is divided into k equal bins; where μ, σ are mean and standard deviation

²From information theory, $I(X, Y) \geq 0$; $I(X, Y) \leq 1$ if X or Y is binary variable; $0 \leq NI(X, Y) \leq 1$

	MI-based criterion	Our criterion
color	num_hue, color triangle (red channel, $N = 16, M = 8$), num_red, num_green	num_hue, color triangle (red channel, $N = 16, M = 8$), num_value
border	mean of border fitting ($L = 28$)	variances of border fitting ($L = 28, L = 8$)
asymmetry	$(Ax + Ay)/A$	
texture	correlation of GLCM (32 levels quantization), number of edge pixels, contrast of GLCM (64 levels quantization)	

TABLE I

SELECTED FEATURE FOR EACH CATEGORY WHEN MI-BASED CRITERION AND OUR CRITERION ARE USED IN FEATURE SELECTION

of feature. Points falling outside the interval were assigned to extreme left or right bin. From suggestion in [18], k should be $1 \leq k \leq 5$. We run feature selection with $k = 2, 3, 4, 5$. The best classification accuracy shown in next section is achieved at $k = 5$. Values of N_i^o and N_i^e in eq. (4) are set to 50% number of samples of class containing i^{th} sample. α in eq. (5) is set to 0.4.

Because all color, border, asymmetry and texture have important role in judging a lesion, we apply feature selection for each category of features. For each feature category, we select the subset of features giving highest classification accuracy³. After achieving the feature subsets for each category, a SVM classifier [3] is trained for each subset. In testing stage, for each feature subset, the corresponding SVM is used to make a predict. The output of SVM will be 1 (cancer) or 0 (non-cancer). Here, we use 5-folds cross validation for training and testing. To combine results of four classifiers, we sum their outputs (**sum-rule**). A lesion is judged as cancer if sum value is larger than 1.

B. Feature Selection Results

Table I shows selected features in each category when MI-based criterion and our criterion are used in feature selection. The classification accuracy is given in table II.

For texture features, feature selection using MI-based criterion and our criterion give same best feature subset. The highest accuracy is 80.61% when 3 features are selected.

Fig. 5(a) shows the classification accuracy with different number of selected color features. The MI-based criterion achieves highest accuracy 90% when number of selected features equals 4. The highest accuracy of proposed criterion is 92.09% when number of selected features is only 3.

From table I, we can see that color triangle features always appear in selected features for both MI-based criterion and our criterion. This confirms the efficiency of proposed color triangle features. We also see from this table that number of non-zero bins of histogram are a good feature to capture color variation.

Fig. 5(b) shows the classification accuracy with different number of selected border features. The MI-based criterion achieve highest accuracy 74.27% when only one feature is selected. By using MI-based criterion, we have no chance to get a higher accuracy even more features are added.

³Feature selection is not necessary to apply asymmetric category because only one asymmetric feature is extracted.

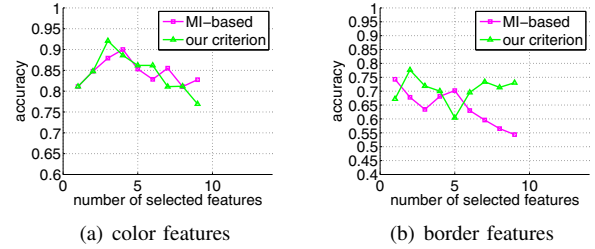


Fig. 4. classification accuracy for different number selected features when proposed criterion and MI-based criterion are used to select color features (a) and border features (b)

The highest accuracy of proposed criterion is 77.64% when 2 features are selected. From table I, we can see that border fitting features are selected features for both MI-based criterion and our criterion. This confirms the efficiency of proposed border fitting features.

Table II also shows the accuracy when four classifiers corresponding to 4 feature categories are combined by sum rule. When combined, our criterion outperforms MI-based criterion. The average accuracy of MI-based criterion and our criterion are 90.09% and 93.61%, respectively. Our criterion also achieves a high accuracy (96.67%) for cancer samples. It is important in practice where a high accuracy detection for cancer is required.

C. Mobile Implementation

Because the image taking from mobile may have a big size, the image will be resized to 512 pixels on their longer edge for reducing time processing and memory to store image. After lesion segmentation, 9 selected features (by our criterion, table I) including 3 color features, 2 border features, 1 asymmetric feature and 3 texture features will be extracted to describe that lesion. These features will be subjected to corresponding SVM classifiers. The results from 4 SVM classifiers will be combined by sum rule to give final score. The final score is in the interval $[0, 4]$. A high score means high cancer risk. The average processing time for each image on a Samsung Galaxy S4 Zoom (CPU: Dual-core 1.5GHz, RAM: 1.5GB, Camera: 16Mp) is less than 5 seconds. The screenshot mobile application is shown in Fig. 6.

V. CONCLUSIONS

In this paper, we proposed (i) an efficient segmentation scheme by combining fast skin detection and fusion of two fast segmentation results; (ii) new features which efficiently capture the color variation and border irregularity of segmented lesion and (iii) an efficient criterion for selecting features. From selected features by proposed criterion, an automatic melanoma diagnosis system using mobile is developed.

Features used in current system are hand-design features. By using automatic feature extraction methods e.g. sparse coding, it may help to find more efficient features.

	MI-based criterion					Our criterion				
	color	border	asymmetric	texture	combine	color	border	asymmetric	texture	combine
non-cancer	94.00	82.55	92.36	84.55	90.18	94.18	79.27	92.36	84.55	90.55
cancer	86.00	66.00	33.33	76.67	90.00	90.00	76.00	33.33	76.67	96.67
average	90.00	74.27	62.85	80.61	90.09	92.09	77.64	62.85	80.61	93.61

TABLE II

THE CLASSIFICATION ACCURACY (%) WHEN MI-BASED CRITERION AND OUR CRITERION ARE USED IN FEATURE SELECTION. THE ACCURACY ARE COMPUTED FOR EACH FEATURE CATEGORY ALSO THE COMBINATION OF FOUR CATEGORIES

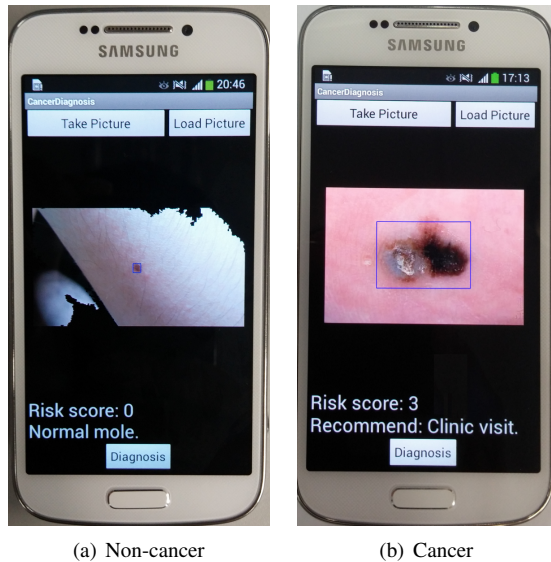


Fig. 5. Screenshot of application. (a) is a non-cancer sample. (b) is a cancer sample.

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