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# Automatic Segmentation of Vascular Patterns in Dermoscopy Images

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## INTRODUCTION

Melanoma is the most fatal type of skin cancer. The Canadian incidence rate of melanoma has doubled since 1973. Based on 2007 estimates about 1 in 63 Canadian men and 1 in 79 Canadian women are expected to develop melanoma during their lifetime [1]. However, if detected at an early stage, its chances of survival would be extremely high. Dermoscopy is a non-invasive diagnostic technique for the in vivo observation and evaluation of pigmented and non-pigmented skin lesions. It allows a better visualization and recognition of morphologic structures of the epidermis, the dermo-epidermal junction, and the papillary dermis, not visible by the naked eye [2]. In the last decade, dermoscopy has become a routine technique in dermatology practice and has done lots of contribution to the knowledge of the morphology of numerous cutaneous lesions. It has been stated that dermoscopy improves accuracy in diagnosing pigmented skin lesions (allowing 10-27% higher sensitivity) [2]. Dermoscope is a simplified microscope comprising of a high quality lens for 10 to 20-times magnification and a lighting system.

Various features may be found in dermoscopic images, each of which correlates with a histopathologic structure, suggesting a specific skin disorder [2]. Hence, pattern analysis is a critical task in dermoscopic diagnosis of skin lesions. In the dermoscopic criteria, several approaches or algorithms have been set in the last few years for examination. These assessments are mostly based on two basic sets of features; global and local, where the global features provide a preliminary categorization of a given lesion prior to more detailed assessment and the local features, if extracted precisely, provide a more detailed assessment of the lesion characteristics as well as diagnostic clues [2]. Among these local features, blood vessel morphology is an important one. The presence, shape and irregularity of vessels in skin lesions are suggestive clues for abnormalities and malignancies [3]. Blood vessels are the primary dominant diagnostic feature in non-melanocytic lesions [3]. Hence, the detection of blood vessels can provide more accurate diagnostic information.

In the past decade, there has been an increasing interest in the field of dermoscopic image analysis. There has been some recent work on detection and learning lesion features, mostly on non-vascular patterns using different pattern analysis and machine learning algorithms [4-8]. Eventually, these methods aim at making the analysis and interpretation of the dermoscopic images automated [9, 10].

In this paper, we are going to detect and segment vascular patterns in a set of dermoscopic images by means of pixel classification. The rest of the paper is organized as follows. Section 2 describes the dermoscopy data set and the preprocessing phase that we have performed to prepare the data for the analysis. In section 3 an overview of our approach and methodology is presented. Section 4 demonstrates the extraction of color and texture features from the images. In section 5 pixel classification is performed and the post processing as well as the results in terms of a mask image are presented. Finally section 6 provides the conclusion and remarks.

## DATA SET AND PRE-PROCESSING

### Image Set Description

The data consists of 200 dermoscopic images of skin lesions obtained by the use of a non-polarized contact dermoscope, from various lesions, ranging from malignant to benign, from small (less than 1mm by 1mm) to large (about 2cm by 2 cm), at different magnifications. These were true-color images with a typical resolution of 768×1024 pixels.

### Pre-Processing

Since vascular patterns in dermoscopy are narrow structures with presumably low edge contrast with their surrounding tissue, as the first step in preprocessing of the dermoscopic images, we have applied a contrast enhancement filter to the images. The filter is based on the negative of the Laplacian filter with a parameter $\alpha$ to control the shape of the Laplacian. Equation 1 shows the filter kernel.

$$f = \frac{1}{\alpha+1}\begin{bmatrix} -\alpha & \alpha-1 & -\alpha \\ \alpha-1 & \alpha+5 & \alpha-1 \\ -\alpha & \alpha-1 & -\alpha \end{bmatrix} \quad (1)$$

After applying this filter with $\alpha$=0.2, we obtained a sharpened image with a better contrast to visualize the edges. Figure 1 shows an original and sharpened version of a lesion in grayscale.

The second step of the preprocessing phase is to segment the lesion from the surrounding normal skin. This step has been done under the supervision of a dermatologist. The procedure is as follows. The lesion segmentation has been performed manually by the dermatologist and a set of points along the border of the lesion have been determined. These points have then been connected using a second order B-Spline function in order to achieve a mask image that segments the lesions from the surrounding area. Figure 2 demonstrates the same sample lesion as figure 1 and its corresponding mask image.

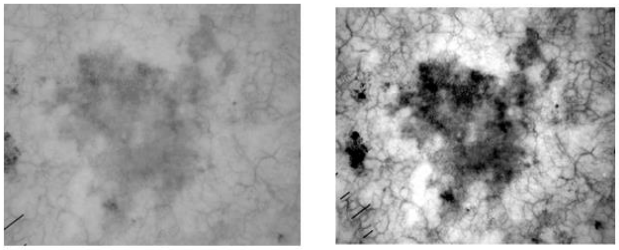

Figure 1: Left) A dermoscopic image. Right) Sharpened lesion using the filter *f*

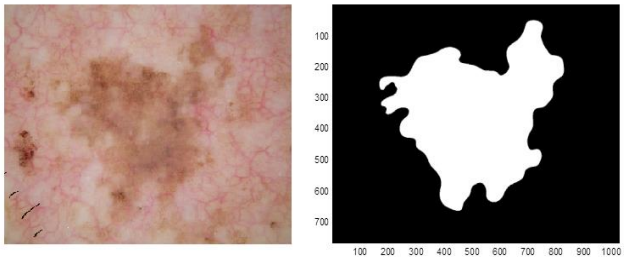


Figure 2: Left) Original lesion. Right) Mask image for lesion segmentation using 35 points

## TECHNIQUES AND METHODOLOGIES

In this project, in order to segment the blood vessels in dermoscopic images, we have used a machine learning framework. The main approach is as follows. After the preprocessing phase, the next step is to determine the color and texture features that are significant in blood vessel detection. We have done a number of experiments on the images in order to find which features are of importance in blood vessel segmentation. These variables form the input feature space for the classification framework. The next section, Color and texture feature extraction section, will list the variables used in the classification.

The third step is pixel selection. In this phase, under the supervision of a dermatologist, we have manually selected a number of pixels that are diagnosed by the dermatologist to be vessels and a number of pixels from regions that are diagnosed not to contain any vessels. After selecting pixels from both groups, the feature vectors for each pixel are calculated. This will form a data set for the

classification problem. The classification framework, aims to classify each pixel of the image as either vessel or non-vessel based on their features. Therefore, we are dealing with a binary problem. We have used a decision-tree classifier in order to perform pixel classification on the image. The result of the classification, is a model that when fed with a new unseen image, classifies each pixel of the image into either the vessel or the non-vessel group. Therefore, we can produce a mask image that segments the vessels in the image from the rest. Figure 3 below, demonstrates the schematic of the whole procedure described above.

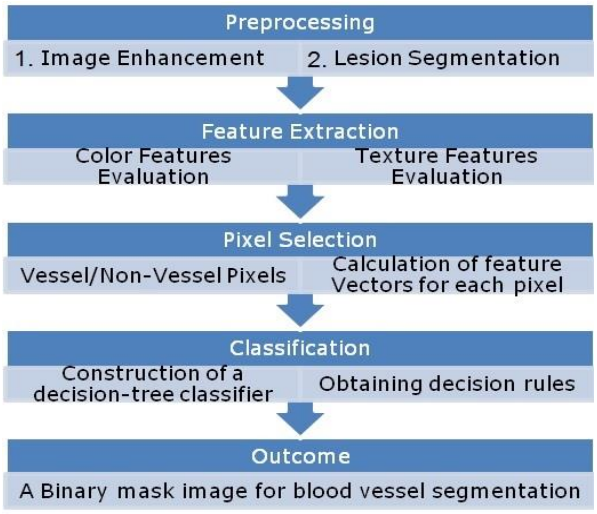


Figure 3: Overview of the approach

## COLOR AND TEXTURE FEATURE EXTRACTION

There are a variety of color and texture features in dermoscopic images. In order to better use the great deal of information hidden in these features, we need to first determine which features have significant effects in detecting blood vessels. In order to do so, we have selected a set of 50 dermoscopic images in which the vessels were the dominant local feature, i.e. blood vessels were the most visible property of the lesion. We have then visualized the image in each specific color channel and finally we have selected the following channels among all based on their power to differentiate the vessels from other parts of the lesion: The green channel, the green chromaticity, red chromacity, hue, luminosity and tristimulus values X and Y. For each channel, we have computed the pixel intensity values. Additionally, we have calculated the relative red/green position using the L*a*b color space and added it as a color feature. We also use five of the classical statistical texture measures: entropy, energy, contrast, correlation and homogeneity which are derived from a grey level co-occurrence matrix [11].

## PIXEL CLASSIFICATION

In this project we have used a decision-tree classifier in order to differentiate vascular patterns of dermoscopy images. We have constructed the tree using the decision tree function implemented by Matlab. As stated in the section Techniques and methodologies, under the supervision of a dermatologist, we have selected 40 pixels among vascular structures and 40 pixels among non-vascular structures for 180 images of the 200 image set and extracted their color and texture features. Since, the data set that is used for training is very large in size; it causes the classifier to generate complex rules and hence overfit the data. In order to avoid such a problem, we have used the optimal pruning method to reduce the size of the tree by replacing the branches of the tree which have less than 10 samples by a leaf. The resulting tree gives an accuracy of 0.92 on the training set. Figure 4 shows the final pruned tree. In this figure, X1 to X8 represent the aforementioned color features and X9 to X13 represent the mentioned texture features, respectively. Therefore, we have 13 features, each of which has a length of 14400 (180 images × 80 pixels in each).

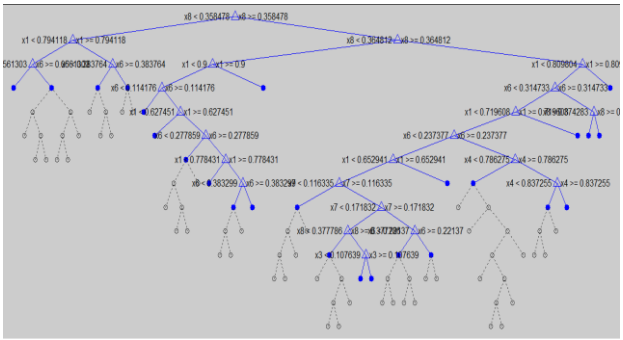

Figure 4: Final Pruned decision tree

The final pruned tree includes the features X1, X3, X4, X6, X8, X10 and X11 which are the pixel intensity values in green channel, red chromacity, hue, tristimulus value X, the relative red/green position using the L*a*b color space, energy and contrast, respectively. Using the binary classifier, each pixel of the image is labeled either 1 (as vessel) or 0 (as non-vessel). We have used this labeling to produce a mask image that segments the vascular structures from other areas. In order to evaluate the model obtained, we have tested the tree on 20 images of the set. We have obtained an accuracy of 78% on the test set. Figure 5 shows the mask image obtained by the pruned tree for detection of vascular structures to the lesion in figure 2.

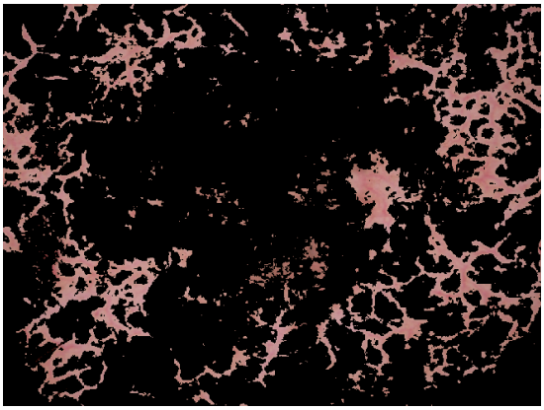

Figure 5: Vascular Mask Image of the Original Lesion

## CONCLUSION

In this project, a machine learning framework has been used to segment the vascular structures in dermoscopy images. The method consists of preprocessing, feature extraction, pixel selection, classification and post processing. The accuracy of the model has been tested on 20 images and an accuracy of 78% has been achieved. As our future work, we will work on developing a good validation test to better evaluate both the accuracy and sensitivity of our method.

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