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Automatic Skin Lesion Segmentation Using GrabCut in HSV Color Space

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Abstract: Skin lesion segmentation is one of the first steps towards automatic Computer-Aided Diagnosis of skin cancer. Vast variety in the appearance of the skin lesion makes this task very challenging. The contribution of this paper is to apply a power foreground extraction technique called GrabCut for automatic skin lesion segmentation in HSV color space with minimal human interaction. Preprocessing was performed for removing the outer black border. Jaccard Index was measured to evaluate the performance of the segmentation method. On average, 0.71 Jaccard Index was achieved on 1000 images from ISIC challenge 2017 Training Dataset.

Keywords: Skin lesion, segmentation, GrabCut, HSV, color space, Melanoma.

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1. Introduction

Skin Cancer is one of the most rapidly increasing cancer all over the world with one in every three cancer diagnosed is a skin cancer according to the World Health Organization [1]. Malignant Melanoma a type of skin cancer estimated to have 76,389 new cases and over 100,00 deaths in the United States in 2016 [2]. So, Early diagnosis is very critical, as study showed survival rate for Melanoma increased over 90% if detected in the early stage [1]. Since skin cancer occurs at the surface of skin, visual inspection by a dermatologist using Dermoscopy is the common way for diagnosis.

Inspection of the dermoscopic images for dermatologist usually a complex and time-consuming task. To assist the dermatologist and improve the accuracy of the diagnosis computer-aided diagnosis systems have been developed. Skin lesion segmentation is very important part of the CAD systems for diagnosis. However, automatic skin lesion segmentation of skin lesion is very challenging due to large variety of appearance in color, texture, and size for different patients. In addition to these hair, veins medical gauzes and light reflections makes it more difficult task. Figure 1 shown some example of the skin lesions.

In early years many literatures tried to solve this segmentation problem proposed methods based on mainly thresholding, Active contour, clustering and supervised learning. Authors in [3] used image enhancing using color and brightness saliency maps with Otsu thresholding. Garnavi et al. [4] used 25 different color channels for segmentation using thresholding. Region splitting and merging algorithm used in [5]. Authors in [6, 7] used the active contour methods for the segmentation. Melli et al. [8] used mean shift clustering. However, application of these methods was not very effective due to large difference in appearance of the skin lesion and requirement for proper preprocessing of the dermoscopic images.

Since last few years Convolutional Neural Networks (CNNs) become an obvious choice to the computer vision society [9,10]. Authors in [11,12,13,14,15] applied CNN for segmentation task and achieved high evaluations.

In this paper we demonstrate a simple yet powerful image segmentation technique GrabCut to segment the skin lesion using HSV color space and observed its impact on segmentation performance. The paper is organized as follows: Section 2 discuss about the data set used in experiments. Section 3 shows different steps to performed segmentation. Section 4 shown the segmentation outcomes. Section 5 and Section is dedicated to discussion on outcomes and conclusion respectively

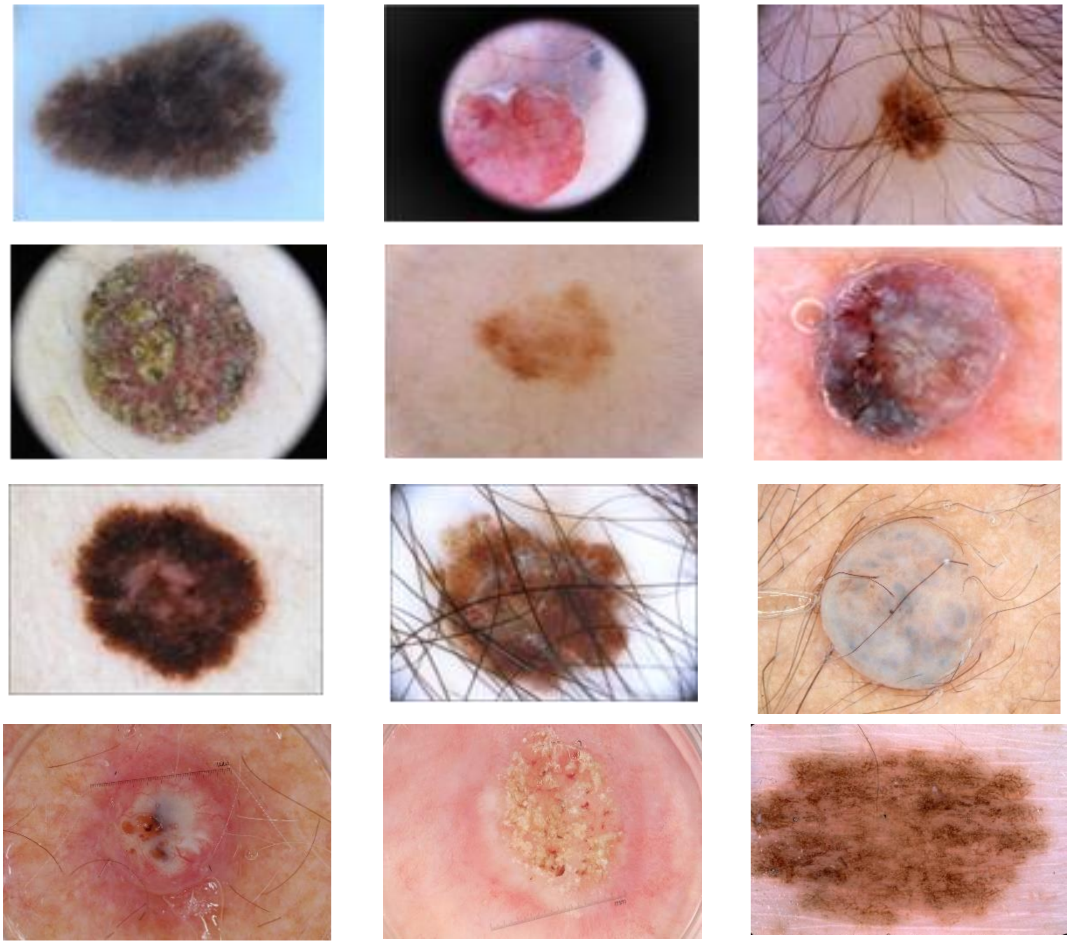


Figure 1. Sample Images from ISIC 2017 dataset.

2. Dataset

The dataset used for this paper was download from the International Skin Imaging Collaboration (ISIC) 2017 Challenge. ISIC 2017 dataset contains training set of 2000 images with corresponding ground truth images. We have used 1000 images from the ISIC 2017 dataset in this paper.

3. Method

GrabCut is one of the most powerful background and foreground extraction techniques that uses minimum graph cut for segmentation. Authors in [15] presented the algorithm. Using the edge and regional information of the given image an energy function was created and this function is being optimized depending on the binary label {0,1} provided by the minimum cut on the image graph.

In this paper an automatic modified version of GrabCut algorithm was used for skin lesion segmentation with minimal human interaction. Figure 2 represents the workflow of the pipeline used for segmentation. Preprocessed image (Section 3.1) was the input of the segmentation pipeline. Afterward k-means clustering was applied to cluster the pixels and BGR image is converted to HSV. Then the probable lesion mask was extracted from the image using adaptive thresholding. Following that thresholding strategy was applied whether to apply mask or not for applying GrabCut Segmentation.

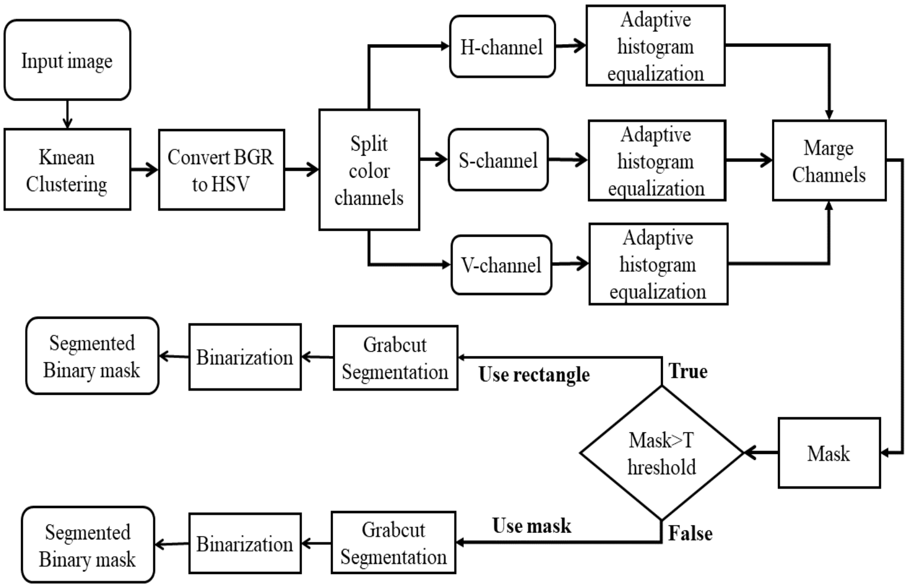


Figure 2. Overall pipeline of the segmentation.

3.1. Preprocessing

Preprocessing was performed to remove the outer dark border from the microscopic images. Figure 3 shown the preprocessing steps. Mask was created for each image depending on dark pixel values. Afterward the mask was used to fill the dark border pixel with the neighboring pixels using inpainting. Pre-processed image was the input to the segmentation pipeline.

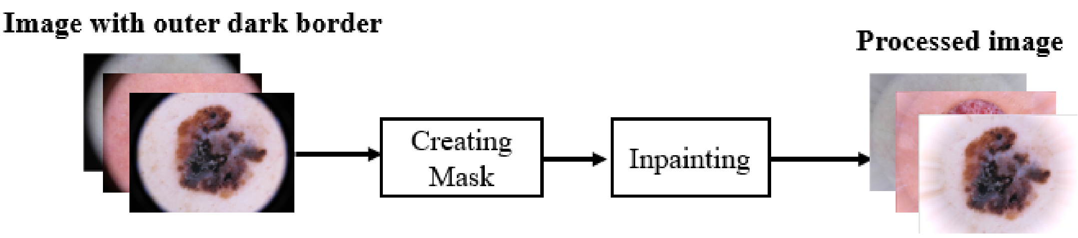


Figure 3. Dark outer boarder removal pipeline.

3.2. Color Quantification

Color quantization was performed applying k-means clustering. Then the BGR image was converted to HSV color space. All the channels were split, and Adaptive histogram equalization was performed on each channel separately. Afterward all the color channels were marge.

a)

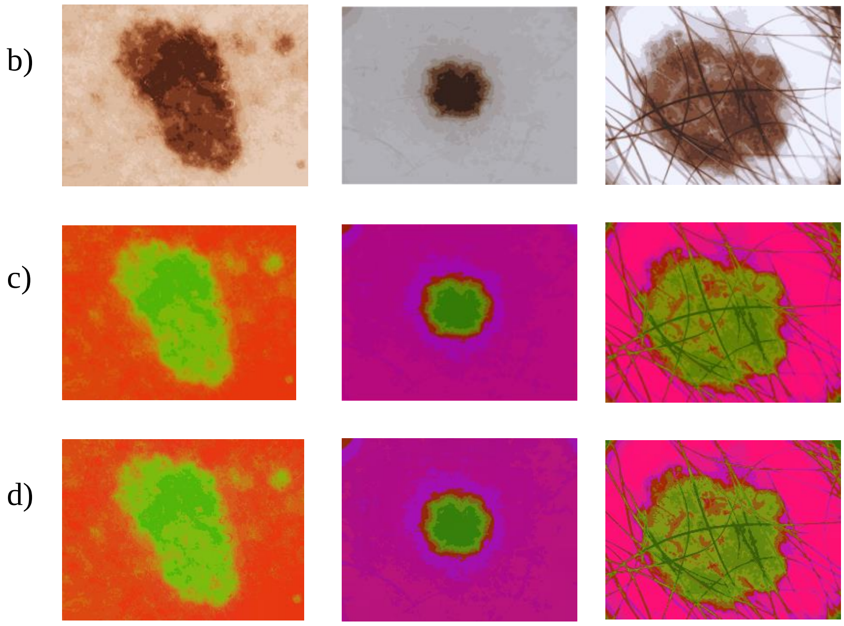


Figure 4. a) Original image. b) k-means clustering c) RGB to HSV and d) adaptive histogram equalization.

3.3. GrabCut Algorithm

Basically, the GrabCut algorithm is to simply apply a rectangle around the object, then the algorithm will define all pixels inside the rectangle as foreground and all pixels outside the rectangle as the initial background pixels. In other words, the opacity of the pixels inside the rectangle is α=1 and α=0 for outside pixels. Then two RGB three-channel Gaussian mixture models (GMMs) were generated corresponding the background and foreground, and clustering was performed for initial foreground and background pixels into k classes as k gaussian components of GMMs according to their RGB values by adopting k-means algorithm.

A graph was initiated depending on the GMMs distribution. Pixels were the nodes of the graph, and all the pixels belong to foreground connected to source node and all the pixels belong to background connected to sink node.

Next, initialization of each gaussian component of GMMs, and calculate the mean values and covariance values of parameters from the sample set of pixels, and each weight is the ratio of pixels' number of the gaussian component to total number of pixels. Afterward probabilities of each pixel inside the rectangle belongs to each gaussian component of the GMMs was estimated. The pixel belongs to the gaussian component has the largest probability. Then a mincut algorithm is used to segment the graph. It cuts the graph into source node and sink node with minimum cost function. The cost function is the sum of all weights of the edges that are cut. After the cut, all the pixels connected to source node become foreground and those connected to Sink node become background. The process is continued until the classification converges [15].

3.4. Proposed Automatic GrabCut

Proposed automatic GrabCur algorithm performed GrabCut by intrigrating two approaches utilizing one threshold parameter. First a mask was extracted as the probable lesion region which is used for GrabCut segmentation. But,if the extracted mask exced the threshold then the extracted mask was abundant and an ractangle was initiated for performing the Grabcut (Section 3.3).

In HSV color space most of the skin lesion appears to be green. Green color was extracted from the image and applying thresholding mask was obtained. Where ever the mask has value 1, image graph considered it as foreground and wherever was 0, considered as background shown in Figure 6. Then grabcut segmentation was performed using this mask.

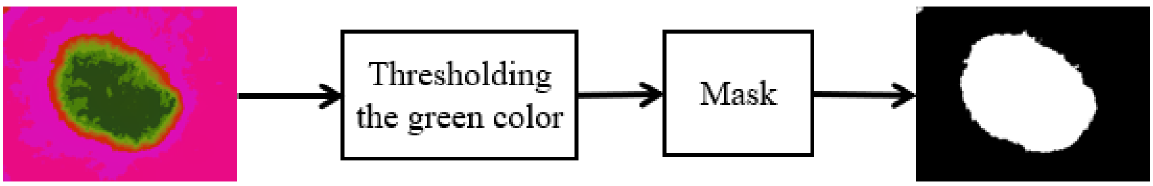
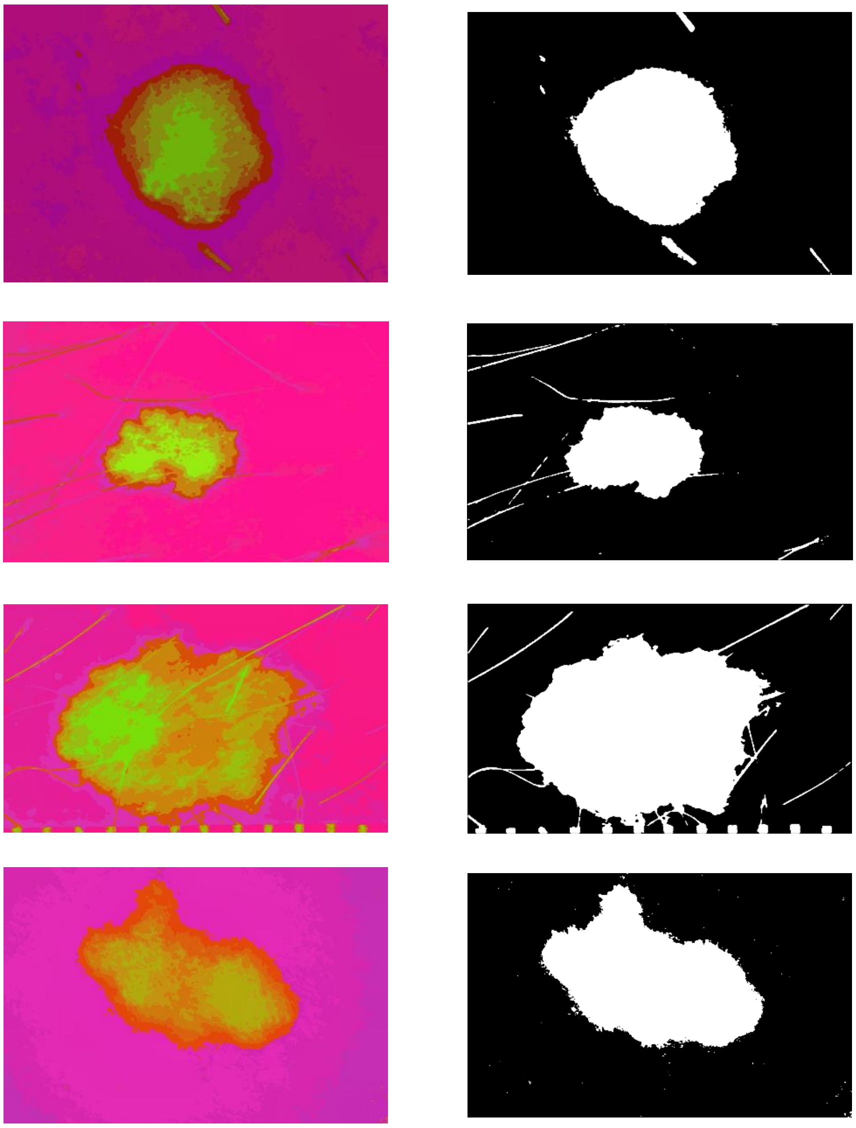


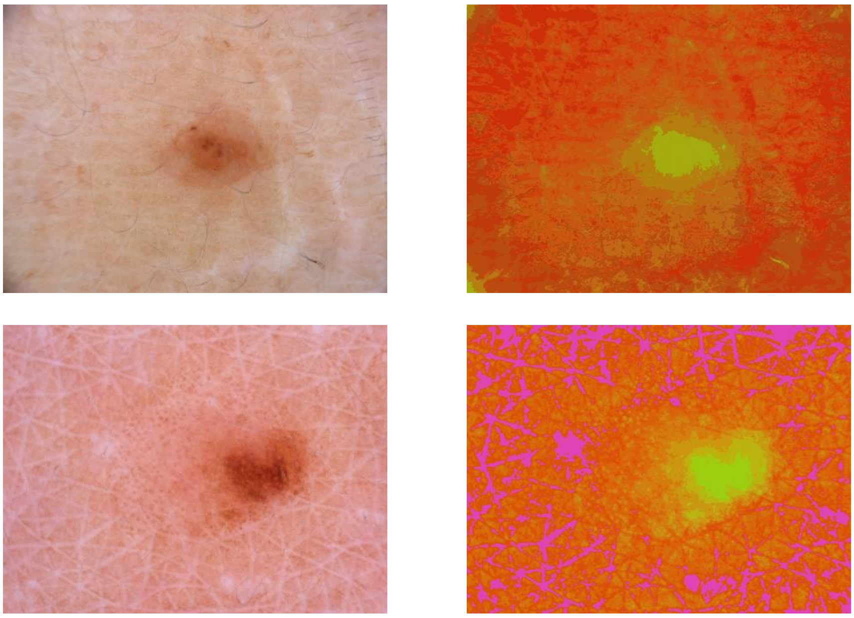
Figure 5. Mask creating workflow diagram.



a) b)

Figure 6. a) Enhance HSV image b) generated mask.

But in some cases, the idea of extracting mask depending on the green channel failed due to very little intensity different between the skin and lesion, and when the lesion is so big or small.



a) b)

Figure 7. Sample images where extraction of mask failed a)Original Image b) Enhance HSV image.

Image shown in Figure 7(a) sample of two original images, the mask extracted for these were completely white (all the pixels in the image consider as lesion pixels), as the enhance HSV image shown in Figure 7 (b), how the whole image has kind of distribution of green color.

To overcome this limitation, one thresholding approach was introduced. Threshold was calculated based on the mask dimension and intensity value. The threshold was calculated as the mask could be consist of maximum 70% pixels of the whole image. If the mask, consider more than 70% of the pixels of the image as lesion pixels then the mask was rejected. Estimation of this 70% pixels is assumed by the visual observation of the dataset. Very little amount of lesion belongs to more than 70% pixels of the image.

If the mask exceeds the threshold, a rectangle was generated, and rectangle was used for GrabCut segmentation. Equation (1) and Equation (2) shown the dimension of the rectangle.

$$\text{Height of rectangle} = \text{Height of image} - (0.03 \times \text{Height of image}) \tag{1}$$

$$\text{Weight of rectangle} = \text{Widht of image} - (0.03 \times \text{Width of image}) \tag{2}$$

Things outside the rectangle considered as background and GrabCut segmentation was performed.

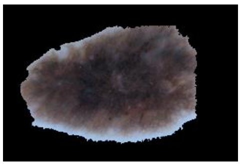
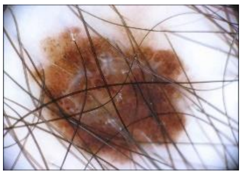
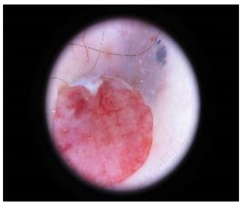
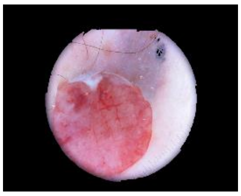
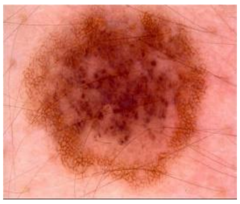
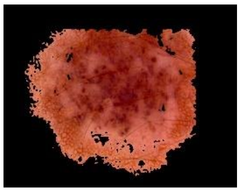
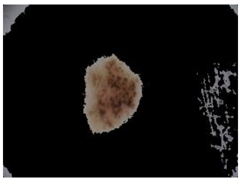
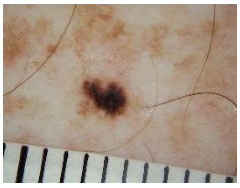
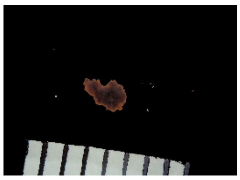
4. Result

To evaluate the performance of the proposed segmentation method we used the evaluation matrix called Jaccard Index (JC). Jaccard Index (also known as Jaccard coefficient index) gives the similarity and diversity of sample sets.

$$\text{Jaccard Index} = TP/(TP+FP+FN) \tag{3}$$

Here TP= lesion pixel segmented as lesion pixel, FP= non-lesion pixel segmented as lesion pixel, and FN= lesion pixel segmented as non-lesion pixel. We used ISIC challenge 2017 data applied proposed segmentation to 1000 images and achieved an average JC of 0.71. Some of the segmented performed by the proposed pipeline were shown in Table 1

Table 1. Qualitative and Quantitative results of segmentation.

Original Image	**Ground Truth**	**Segmented Image**	**JC**
			0.86
			0.83
			0.73
			0.75
			0.67
			0.17

5. Discussion

Proposed automatic segmentation technique required minimal human interaction as the mask and rectangle were generated automatically depending on the image which makes the proposed algorithm generic application capability. Segmentation is robust enough to segment the image without hair removal as shown in Table 1, row 2. Proposed pipeline performed comparable better if the contrast between the skin lesion and non-lesion pixels are very high shown in Table 1, row 1. As GrabCut is a foreground extraction technique, so other noise intensity different for the skin can be miss classified as lesion pixel by the algorithm as shown in Table 1, row 5 and 6. In Table 1, row 6 the algorithm was successfully segmented the lesion but also segmented the ruler which is false positive. The algorithm has been tested on 1000 images acquired from the ISBI 2017 challenge and achieved average Jaccard Index of 0.71. Compare to deep-learning approached its performance is low but it's a simple and time efficient approach compared to computationally expensive deep-learning approaches.

The performance can be improved by exploring more precise mask creating strategies, applying different color spaces, improving the foreground probability estimation functionality to the proposed modified GrabCut approach.

5. Conclusions

In this work, a framework was proposed for skin lesion segmentation based on automatic GrabCut segmentation. Auto Extracting mask and rectangle initialization strategies was shown for making the segmentation algorithm automatic and generic. The algorithm achieved over 0.71 average Jaccard index for 1000 test images. Future work will be focused on exploring different color channels to improve the performance.

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