Effect of Color Enhancement on Early Detection of Skin Cancer using Convolutional Neural Network

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***Abstract*—The prevalence of skin cancer is significantly increasing each year due to the damage of the ozone layer in the atmosphere that makes more ultraviolet radiation passing through. Knowing this situation, it is important to develop a simple image processing technique that can be used in the early detection of skin cancer. The skin cancer detection becomes highly active research since 2016 due to the ISIC has released a large skin cancer image dataset. Several types of research propose hand-crafted image processing with machine learning, but the technique is a little bit complicated. The aim of this study is to investigate the effect of simple image processing technique, contrast enhancement using CLAHE and MSRCR as contrast enhancements with CNN. The results show that compares to MSRCR, CLAHE is more suitable to be used in color image enhancement for early detection of skin cancer using CNN. But, the original and CLAHE-enhanced dataset give the same accuracy in the training and validation. The main contribution of this study is that the image contrast enhancement is not required for the skin cancer screening purpose.**

***Index Terms*—benign, CLAHE, CNN, early detection, entropy, malignant, skin cancer, screening**

I. Introduction

According to the World Health Organization (WHO), globally, skin cancer is diagnosed in every three cancers and every year increases due to more solar ultraviolet radiation passing through the atmosphere. The gold standard to diagnose skin cancer is skin biopsy with histopathology. However, this procedure is painful due to invasive technique to get the skin tissue sample. One of the common methods is using medical imaging tools, such as dermoscopy, cross-polarized light and fluorescence photography, high-frequency ultrasound, optical coherence tomography (OCT), and confocal microscopy [1], [2]. The main advantages of digital dermoscopy are cost-effective diagnosis tool and can be used in long-term surveillance [3]. Since 2016, dermoscopy image analysis become one of the very active research field due to the International Skin Imaging Collaboration (ISIC) release a large public dataset, inexpensive computational unit and development of open source software in machine learning [4].

In 2011-2016, there are 133 articles that are related to skin cancer diagnosis apps using smartphones [5] and in July 2014, there are 39 apps for iPhone and/or Android [6]. Mobile skin cancer apps that are equipped with machine learning can revolutionize the diagnosis system in the near future [7], [8] due to can provide low-cost diagnostic care [9] and the general practitioners or dermatologists need to be trained to use the digital dermoscopy analysis system [3].

The main problem with skin image acquisition using a smartphone is the image quality that depends on the environmental conditions, such as lighting and skin color. The example of these skin color images is shown in Figure 1. It can be addressed using image enhancement techniques, i.e. multi-scale retinex with color restoration [10] or histogram equalization due to it simplicity. Another image enhancement technique that is commonly used Several studies propose Contrast-Limited Adaptive Histogram Equalization (CLAHE) to eliminate non-uniform illumination in RGB skin image [11], [12], [13], [14].

Recent researches that fused hand-crafted and deep learning techniques to diagnose skin cancer have shown successful result in term of accuracy [15], [16], [17], [18], [19]. This study explores a new possibility of lightweight image processing and deep learning techniques in the early detection of skin cancer. Common image enhancement techniques, CLAHE and Multiscale Retinex Color Restoration (MSRCR), is used in this study. The main purpose of this research is to compare the effect of contrast enhancement using CLAHE and MSRCR in the early detection of skin cancer using deep learning techniques. The main limitation of the study is only two class of classification that is addressed, i.e. benign and malignant, due to the focus is in the early detection of skin cancer.

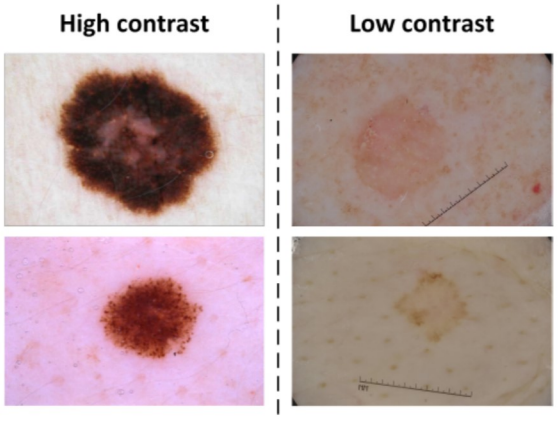

Fig. 1. High and low contrast skin images.

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TABLE I
SKIN CANCER DATASET DETAILS

Dataset	Class	Number of images
Train	Benign	13,629
	Malignant	1,145
Validation	Benign	4,373
	Malignant	785

II. METHODS

This study used images from an international repository of dermoscopic images, ISIC archive 2019, that is developed by ISIC [20], [21], [22]. In total, there are 19,932 images that are used as training (14,774 images) and validation (5,158 images) processes. The number of images in this dataset is based on the ISIC archive 2019. Table I shows the detail of the dataset that is used in this study.

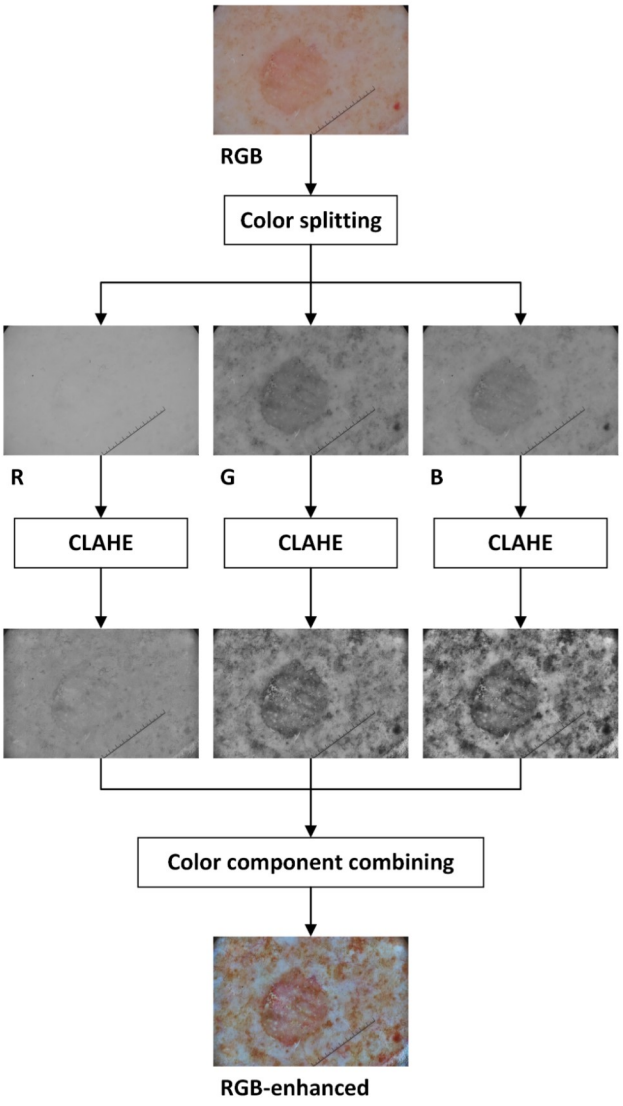

Fig. 2. Block diagram of color skin image enhancement using CLAHE.

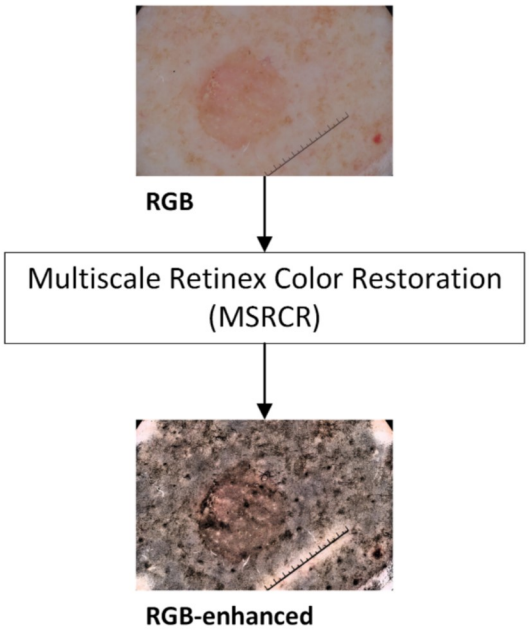

Fig. 3. Block diagram of color skin image enhancement using MSRCR.

In this study, there is no hand-crafted of image processing technique except color image enhancement using CLAHE and MSRCR. The block diagram of skin image enhancement is shown in Figure 2. The input of the block diagram is the RGB color image. The first process is color splitting to get three image channels due to CLAHE can only process one image channel. Therefore, there are three image enhancement processes for each channel to get three enhanced images. The next process is color merging to get the RGB color-enhanced image. Visually, the skin lesion more clearly detected in the enhanced image than the original image. Block Diagram of the color image enhancement using MSRCR is shown in Figure 3.

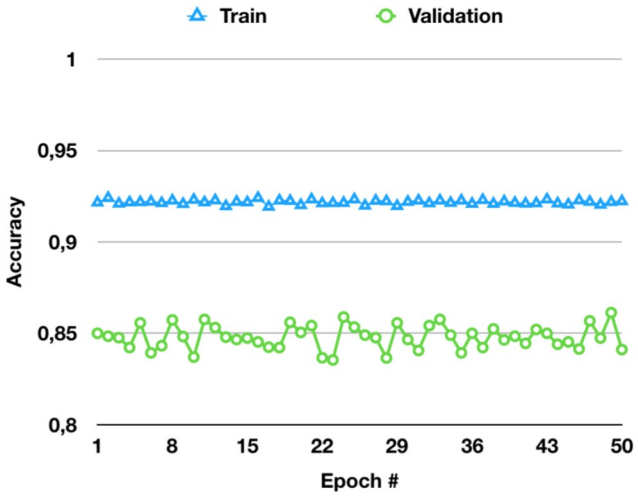

Fig. 4. Train and validation accuracy of the original image dataset.

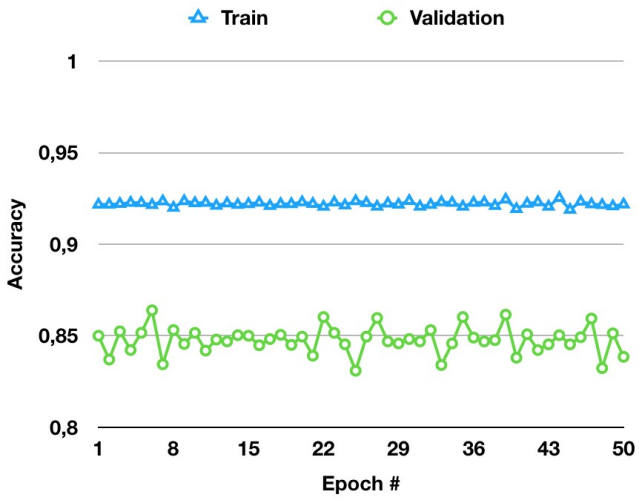

Fig. 5. Train and validation accuracy of the CLAHE-enhanced image dataset.

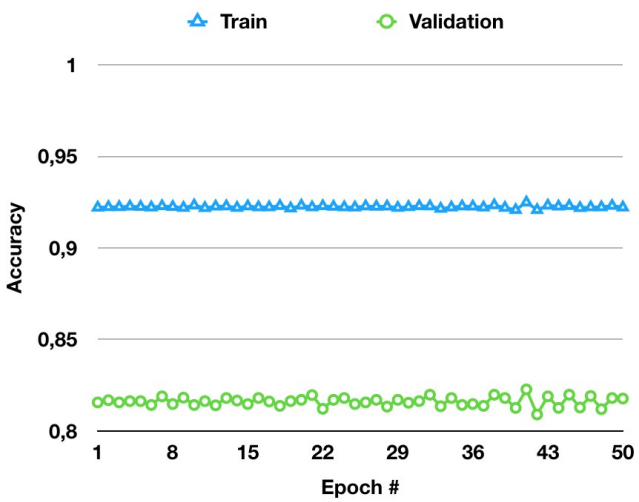

Fig. 6. Train and validation accuracy of the MSCRC-enhanced image dataset.

Convolutional Neural Network (CNN) is used as classifier in this study due to this is the common method in Dermoscopy Image Analysis (DIA) since 2015 [23], provide higher classification accuracy [24] than the dermatologist efficacy [15], [25]. VGG16 is used in this study as CNN architecture [26]. There are two types of images that are used in this study, the first dataset consists of the original images (without image enhancement) or the original dataset. The second dataset consists of the enhanced image from the first dataset or enhanced dataset. The study is implemented using Tensorflow as an end-to-end open-source machine learning platform that is run in a common Personal Computer (PC) equipped with a 2.7 GHz processor and 8 GB of RAM. In the ISIC archive 2019 dataset, there are several image dimensions, i.e. 1024 $\times$ 768; 1504 $\times$ 1129; 962 $\times$ 722; 2592 $\times$ 1944; 2018 $\times$ 1536; 722 $\times$ 1043; and 3024 $\times$ 2016; 4288 $\times$ 2848; and downsized to 600 $\times$ 450 pixels. To increase the computation speed, the dimension of all input images is reduced to the smallest image size of the ISIC 2019 dataset, i.e. 600 $\times$ 450 pixels. The assumption is that the image information still remains during the downsizing process. In this study, the number of epochs is set to 50. All the processes in this study are quite simple. There are no other image processing techniques that are used other than CLAHE and MSRCR. Using these approaches, it is expected that the results of this study can examine the role of image enhancement using CLAHE and MSRCR in the early detection of skin cancer using CNN.

III. Results

The training and validation accuracy of the original image dataset is shown in Figure 4. This first epoch gives training accuracy of 0.9216 and the last one is 0.9223. The best training accuracy, 0.9241, is achieved in epoch #2. From the graph, the training accuracy is steady at around 0.92. The value of validation accuracy is a little bit different from the training. In Figure 4, the validation accuracy of the original image dataset is steady in around 0.85. The best validation accuracy is 0.8613 that achieved in epoch #49. The last epoch gives validation accuracy of 0.8411. The standard deviation of training data 0.0011 and 0.0065 for validation data.

Figure 5 shows the training and validation accuracy of the enhanced image dataset using CLAHE. The training accuracy in the CLAHE-enhanced dataset is steady at around 0.92, approximately close to the original dataset. The best accuracy value is 0.9253 in epoch #44 and the lowest value is 0.9189 in epoch #45. While the validation accuracy of the CLAHE-enhanced dataset is steady in around 0.85. The best validation accuracy value is 0.8639 in epoch #6 and the lowest is 0.8309 in epochs #25. In the final epoch, the training accuracy value is 0.9218 and 0.8385 for validation accuracy. The standard deviation of accuracy for the training is 0.0012 and 0.0073 for validation data.

The accuracy of training and validation of the enhanced image dataset using MSRCR is shown in Figure 6. Compare to the original and CLAHE-enhanced dataset, the validation accuracy is relatively steady at around 0.815. The final accuracy values of training and validation of the MSRCR-enhanced dataset in epoch #50 are 0.9222 and 0.8177. The standard deviation of accuracy for the training is 0.0006 and 0.0026 for validation data.

IV. Conclusions and Future Works

The validation accuracy of original and enhanced datasets shows a similar result, the value is around 0.85 with mean 0.8479 for the original dataset, 0.8476 for the CLAHE-enhanced dataset, and 0.8161 for the MSRCR-enhanced dataset. In general, there is no significant difference between the original and CLAHE-enhanced datasets, in terms of training and validation accuracy. While there is a significant difference in the validation accuracy of the MSRCR dataset. Even though the mathematical formulation of MSRCR is more complex than CLAHE and MSRCR needs more computation load than CLAHE, the accuracy of the MSRCR-enhanced dataset

is around 0.81 which is lower than the original and CLAHE-enhanced dataset. Visually, several skin cancer images only have low contrast that could be addressed using histogram-based enhancement, including CLAHE. Whereas, MSRCR algorithm has good performance to enhance the image with poor visibility conditions, e.g. low-light image.

This study has presented a simple image processing technique as a hand-crafted enhancement to investigate the contribution of CLAHE and MSCRC in machine learning to detect skin cancer. The result of the study has revealed that compare to MSRCR, CLAHE is more suitable to be used in color image enhancement for early detection of skin cancer using CNN. But, the original and CLAHE-enhanced datasets give the same accuracy in the training and validation. The main contribution of this study is that the image contrast enhancement is not required for skin cancer screening purposes. Moreover, it can reduce the computation load. This result is essential for the development of the mobile app for early detection of skin cancer using machine learning in a smartphone which has limited computation resource.

Future works will focus on increasing the number of class that is used in classification to investigate the further effect of contrast image enhancement in more class of skin cancer. Another research opportunity is to investigate the effect of the significance of each RGB color channels in the skin cancer detection. Work in progress of this study is investigating other ABCD (Asymmetry, Border irregularity, Color, and Diameter) components as a common method in skin cancer detection, i.e. Asymmetry, Border irregularity, and Diameter.

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