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Preprocessing of Fundus Images for Detection of Diabetic Retinopathy

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Abstract— **In recent years, the lesions detection in fundus image become popular area of research in machine learning. The detection of symptoms in fundus image is typically used in diseases that related to eyes such as diabetic retinopathy where the main symptom is exudates. Symptom detection in fundus image depends on many factor. The common factors are varying contrast condition and the large size of the fundus image that will affect the training process for object detection. Furthermore, color similarity of the features in fundus image and the symptoms also one of the factor, for example the similarity between optics disc and exudates. In this paper, we discuss the different preprocessing stage in order to improve the quality of fundus image to mark the optic disc location for detection of optic disc in future work. We have used several datasets namely Kaggle, DIARETDB1 and DRIMDB datasets in this study. The results that we have achieved in SSIM value, clearly shows that the preprocessing was able to increase the image quality.**

***Index Terms*— Contrast Variation, Diabetic Retinopathy, Fundus Image, Optic Disc, Preprocessing.**

I. Introduction

DIABETES is a one of metabolic diseases which caused by hyperglycemia resulting from defects in insulin secretion, insulin action, or both [1]. In general, there are three main types of diabetes which are type 1 diabetes, type 2 diabetes and gestational diabetes which occurs during pregnancy [2]. From previous studies, the number of diabetes worldwide is expected to increase from 2.8% to 4.4% from 2000 to 2030 [3].

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The complication of diabetes is associated with long-term damage, dysfunction, and failure of different organs, especially the eyes, kidneys, nerves, heart, and blood vessels [1].Furthermore, based on the survey, 50% of the diabetes patients will have problem of diabetic retinopathy (DR) [4], a retinal eye disease that caused by diabetes [5]. DR affects the fine vessels in the eye and the vision of the patient which can lead to the blindness if there is no early detection of this disease [6].

The fundus is the region located at the back of eyeball from the front of the eye. This region predominately consists of the retina. Figure 1 depicts the normal color fundus image which consists of the main features of retina [7]. Fundus images are examined this region in order to diagnose the diseases that related to the eyes by observing the image of the region. In general, retina is a part of the body where the blood vessels directly can be observed [8]. From the observation, the abnormalities of blood vessels in retina as well as the abnormalities of the eye can be detected.

Retinal fundus images can be captured by using a fundus camera [9]. A fundus camera is a useful tool to present a detailed view of the back of eye [10]. In order to evaluate the captured fundus images, it requires a highly skilled and qualified ophthalmologist [11].

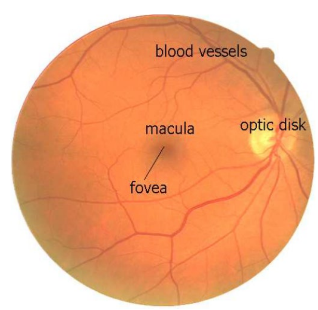


Fig. 1. Normal color fundus image with the main features of retina

The fundus diagnosis is required for early detection of disease where the symptoms are related in the body's blood vessels. In fundus diagnosis, there are two groups of main abnormalities that visible in fundus image. The first group of abnormality usually related to the diseases of the eye such as glaucoma and cataracts whereas the other part of abnormality is lifestyle-related illnesses like hypertension, arteriosclerosis and diabetes [8].

In addition, for lifestyle-related illnesses can be defined by the condition of the blood vessels in the fundus image. Figure 2 shows the signs of common abnormalities that effect the condition of blood vessels like micro aneurysm, exudates and hemorrhage that can observed from a fundus image [12].

By observing the fundus images, an ophthalmologist is able to decide the stages of DR for diabetic patients [13]. In general, the visible characteristics of normal fundus images will include optic disc (OD), fovea and blood vessels. Whereas, for abnormal structures of fundus images specifically for DR patients, the presence of exudates and hemorrhages can be seen [14].

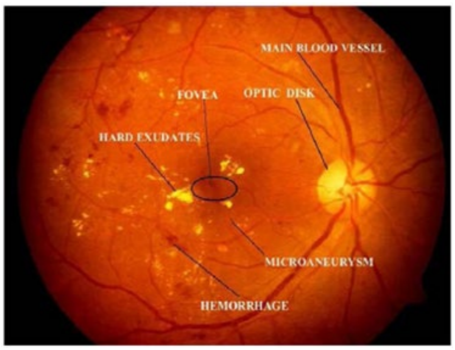


Fig. 2.Fundus image with the presence signs of abnormalities.

According to [15], in the past two years, many researchers in the medical image have been attracted to the automated detection of normal and abnormal features in retinal images. The detection of features in the fundus images utilize various methods depends on the variety of variables including contrast enhancement [16], and background images [17]. Preprocessing techniques were compulsory in order to increase the quality of fundus images [17].

In previous works, the most common techniques applied in preprocessing are filtering and contrast enhancing [17]. Local contrast enhancement method that is commonly used in literature is based on histogram domains [18]. For example, [19][3] proposed contrast-limited adaptive histogram equalization (CLAHE) to improve the contrast and correct non uniform background. The drawbacks with this method is the complete range of histograms are not fully employed for image enhancement as well as some fine details are suppress with this method [20]. Preprocessing techniques require raw fundus images to enhance the process by machine learning algorithms [14].

In this paper, we present the preprocessing of the fundus images that consists a few steps i.e. color normalization, background removal or resize images and generate more training datasets by flipping and rotating the original fundus images. The purpose of this paper is not only to prepare the dataset for DR detection, but to generate as much as variability as possible to the data in order to train a more robust deep learning (DL) classifier.

This paper is organized in four sections. Section 2 present the step by step on the methodology of preprocessing techniques required for raw fundus images. Results are discussed in Section 3 and followed by conclusion in Section 4.

II. Methodolgy

The overall process of preprocessing techniques that are presented in this paper is summarized in Figure 3. As shown in the diagram, there were three steps involved in the preprocessing techniques. The first step was normalization on the color of fundus images using Reinhardt-Stine method [21]. It was followed by ground truth labelling of OD, resizing the images and generating more images using rotation and flip techniques.

In this study, all the datasets are accessible by the public and all the fundus images have been collected from diabetic patients. Based on literature review, a few public datasets for fundus images have been chosen as described below:

(i) Kaggle datasets [14] – 600 fundus images,
(ii) DIARETDB1 datasets [22]– 230 fundus images and
(iii) DRIMDB datasets [23] – 200 fundus images.

All the datasets had different qualities in terms of color brightness and sizes.

A. Image Cropping

In order to reduce the process in preprocessing, it is essential to crop the images to remove non-essential areas. In addition, the position of the fundus images was not uniform and they need to be standardized.

At this stage, the black background in the images had been cropped out from the images so that, the images would only consist of fundus images solely. This may avoid the Reinhardt-Stine method to focus too much on the majority black area when normalizing the image colors.

B. Color Normalization: Reinhardt-Stine method

In this stage, the color of fundus images had normalized so that the appearance of the fundus images follows the standard or normal color of fundus images. The color of fundus images might be different due to lighting and the position of the camera when capturing the images.

The linear transform that had used is 'lαβ' color space by Ruderman et al [21]. This approach maps the color distribution of an over or under stained image to that of a well stained target image. By using Reinhard's method, the color distribution of an image will be matched to the target image based on a linear transform in a perceptual color space as well as to match the means and standard deviations of each color channel in the two images in that color space [24].

This method provides an advantage in remaining the structure of source image as well as the contrast of the processed image which similar to the contrast of target image [25]. Figure 4 depicts the flow of algorithm of color normalization using Reinhardt-Stine method.

C. Ground truth labelling of OD

For this research, The MATLAB Ground Truth Labeler (GTL) application was used in order to label the ground truth data for the network to extract during the training phase. This application provides an easy solution to mark various shapes region of interest (ROI) labels and scene labels in a video or

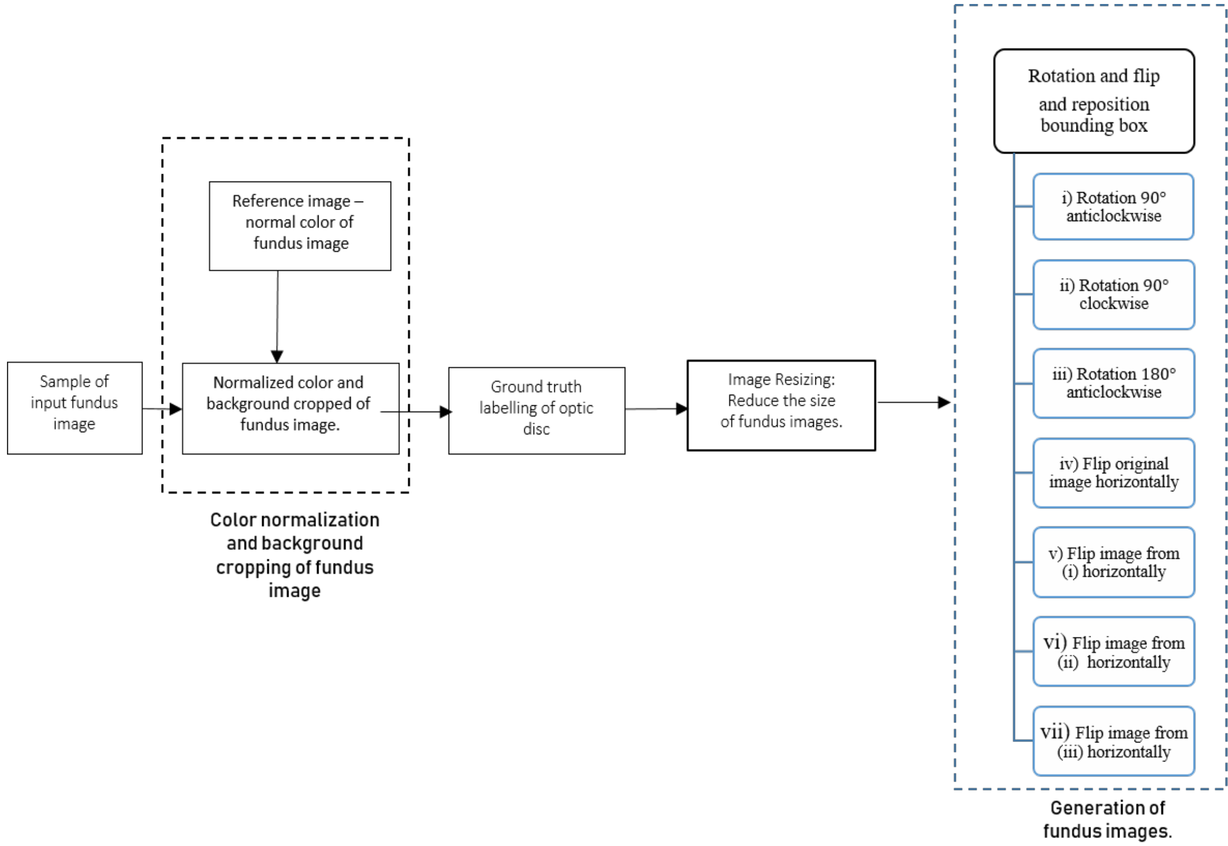


Fig. 3. Flow Diagram of Fundus Images Preprocessing.

image sequence. It can be done by manually label on frame from an image collection.

For this preprocessing stage, the area of interest that had been marked is OD which one of main features in fundus images. This sign was labeled with rectangle bounding box shapes as shown in Figure 5. As the appearance of OD is very similar to exudates, the first step before exudate detection is the removal of optic disc. Before proceeding with the detection of exudates, it is necessary to train the network with the OD.

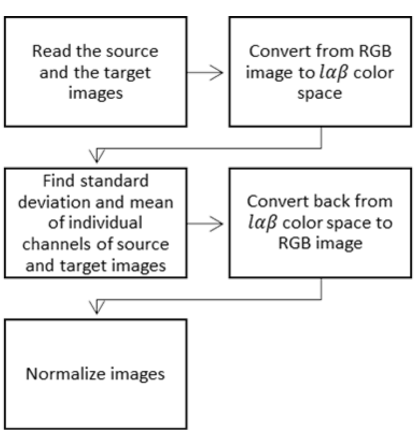


Fig. 4. Steps for color normalization using Reinhardt-Stine method

It is compulsory in order to distinguish the exudates and optic disc due to appearance of both features where there are similar in intensity, color and contrast [14].

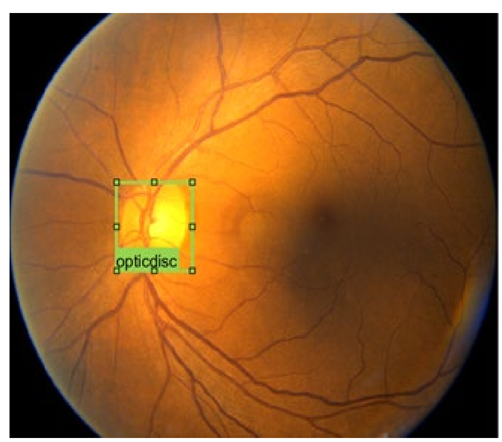


Fig. 5. Rectangle bounding box of optic disc

D. *Image Resizing*

Here, all the fundus images were resized by downscale or reduce the original size images by 0.25. The purpose is to minimize the running time and required memory of convolution layer to load the images and train the convolutional neural network (CNN) [26]. Downscaling will present important features whole scale sacrificing detail. It also helps the training speed of the DL network.

E. Image generation: Rotating and Flipping

An important consideration when training DL networks is the number of data. More data helps DL generalization. However, it is difficult to obtain a lot of data for DR cases. Therefore, variabilities must be added to the existing data to generate more data to help DL to learn better.

In this stage, the fundus images together with the ground truth rectangle bounding box were rotated and flipped to generate more fundus images. In order to train the functions of deep learning, the large datasets of images are required [27].

The fundus images had been rotated and flipped into seven different directions as stated in Figure 3. Then, on those generated fundus images, the position of optic disc is marked. along this process which is based on the ground truth of optics disc labeled in original fundus image as mentioned in step C).

At the end of this stage, the positions or coordinates of the ground truth of optic disc for all generated fundus images will be saved for later use in the subsequent stage. Figure 6 shows the labels on how the position of optic disc have been programmed in this research.

As shown in the Figure 6, x_0 and y_0 have been measured from AB (upper side of fundus image) and AD (left side of fundus image) respectively whereas w_0 and h_0 presented the width and height of OD in fundus image.

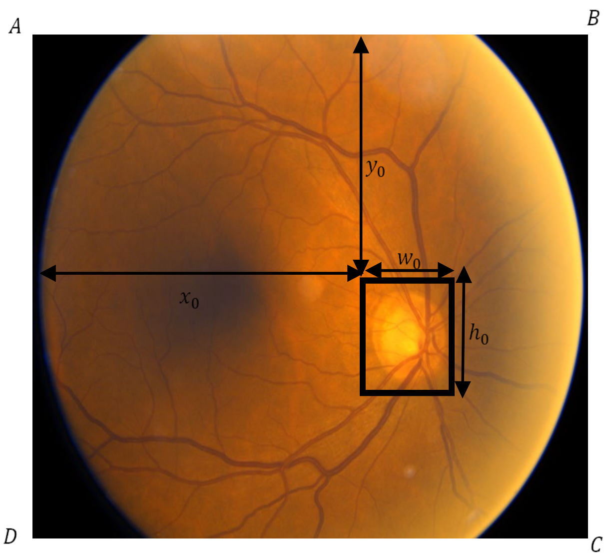


Fig. 6. Details measurement on location of OD in fundus image.

Next, Table I depicts the formulas for the positions of OD that have been measured in fundus image from various conditions of fundus image where fundus image was rotated and flipped into multiple directions. For each condition of the fundus image, the x and y length has been measured from the upper side and left side of the fundus image as presented in Figure 6. The measurement of the position of OD in the original image always been as a reference for the position of OD for each condition or direction of the fundus image.

TABLE I
EQUATION OF POSITION OD FOR DIFFERENCE CONDITIONS OF FUNDUS IMAGE

Position of OD	x	y	w	h
i) Original image	x_0	y_0	w_0	h_0
ii) Rotate (i) 90° anticlockwise	y_0	$AB - w_0 - x_0$	h_0	w_0
iii) Rotate (i) 90° clockwise	$BC - h_0 - y_0$	x_0	h_0	w_0
iv)Rotate (i) 180° anticlockwise	$AB - w_0 - x_0$	$BC - h_0 - y_0$	w_0	h_0
v) Flip (i) horizontally	$AB - w_0 - x_0$	y_0	w_0	h_0
vi) Flip (ii) horizontally	$BC - h_0 - y_0$	$AB - w_0 - x_0$	h_0	w_0
vii) Flip (iii) horizontally	y_0	x_0	h_0	w_0
viii)Flip (iv) horizontally	x_0	$BC - h_0 - y_0$	w_0	h_0

III. RESULTS AND DISCUSSIONS

A. Performance measures

The performance evaluation on normalized images can be evaluated using image quality metrics such as Structural Similarity Index Metric (SSIM) [25]. SSIM had been introduced by [28] for image measurement. By using SSIM method, the similarity between the images are able to measure. The value that calculated using this method can be referred to as a quality measure of an image where that image must be compared with the perfect quality image [25].

By referring to [28], SSIM index is based on the computation of three terms, namely the luminance term, the contrast term and the structural term. The overall index is a multiplicative combination of the three terms which,

$$SSIM(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma}$$

where

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu^2{}_x + \mu^2{}_y + C_1},$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma^2{}_x + \sigma^2{}_y + C_2},$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}$$

where $\mu_x, \mu_y, \sigma_x, \sigma_y$ and σ_{xy} are the local means, standard deviations, and cross-covariance for images x, y.

The typical range of SSIM value is 0 to 1. The highest quality when an image equivalent to the reference image represented by 1 and 0 indicates the poor quality.

B. Result analyses

A sample visualization that produced from the normalization process is shown in Figure 7. As shown, Figure 7 (a) shows the sample input test color fundus images which experience effective image color normalization and image crop. Figure 7 (b) shows the reference image where the original test image referred to normalize the color of fundus image. Lastly, Figure 7 (c) visualizes the fundus image after the color is successfully normalized and the majority background of the image cropped out and only the background at the edge of the image remained. The area of the images had been successfully minimized. By removing the most area of the background, the object detection can be focused only on the fundus area.

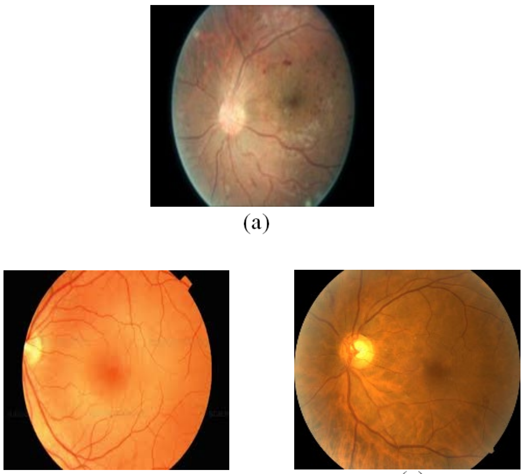


Fig. 7. (a) Original image; (b) reference image (perfect color of fundus image; (c) Normalized and cropped image

Fundus images of different direction are shown in Figure 8. Figure 8 (a) shows the original image of fundus image which successfully rotated and flipped into 7 different directions as visualizes in Figure 8 (b), (c), (d), (e), (f) and (g). The ground truth of optic disc has been successfully marked and saved. It is required in order to train the optic disc detector

Figure 9 depicts the plots of SSIM index of the fundus images after normalization and resize. Figure 9 (a), (b) and (c) indicates a detailed SSIM values of different datasets.

In this study, the SSIM index of the fundus images calculated after all the processing stage completed in order to check the quality of the images. It attains by comparing the processed image with the perfect quality reference image.

As shown in Figure 9 (a) the Kaggle datasets are effectively attains a high SSIM value with the maximum value is 1 and minimal value is only 0.9511. Likewise, the fundus images from DIARETDB1 datasets are successfully normalized by attaining high SSIM where the maximum value is 1 and minimal value is 0.9534 as shown in Figure 9 (b). Lastly, by referring to Figure 9 (c), the datasets of fundus image by DRIMDB are also effectively gains high SSIM value with the maximum value is 1 and minimal value is only 0.9523. All these values of SSIM values clearly showed the effective normalization outcome of the fundus image using Reinhardt Method.

Table II separately shows the average SSIM value that obtains from three different datasets that have been plotted. From Table II, it can be clearly seen that. after the preprocessing the best quality of fundus image from the three datasets is achieved with the SSIM values in average were approximately equal to 1.

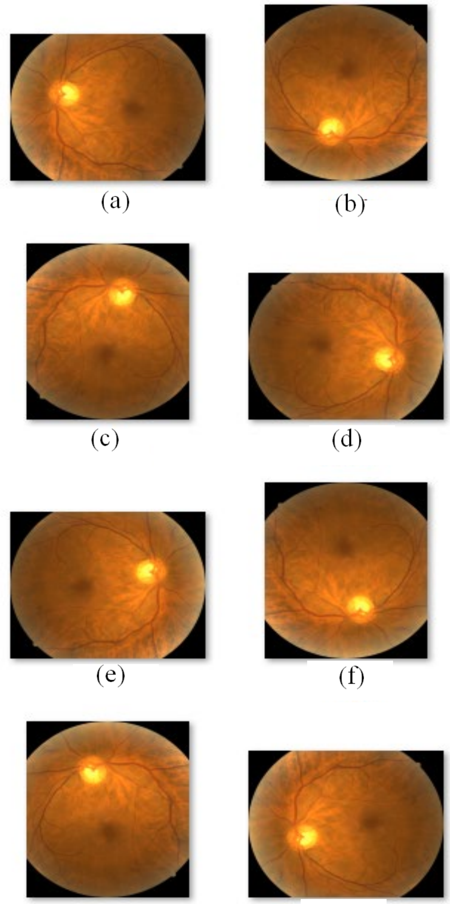
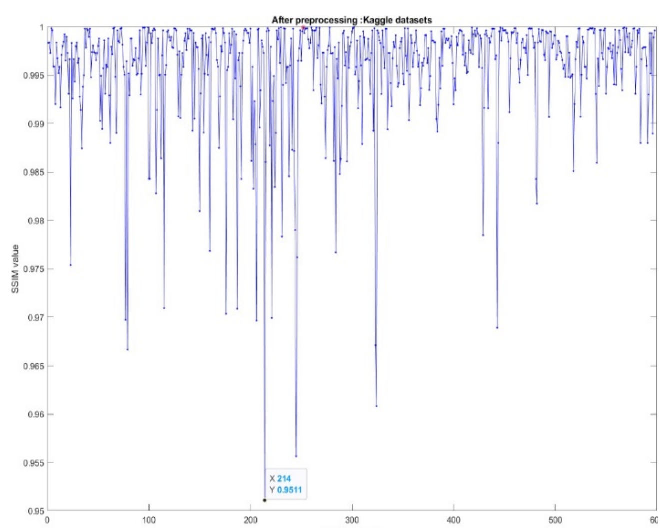
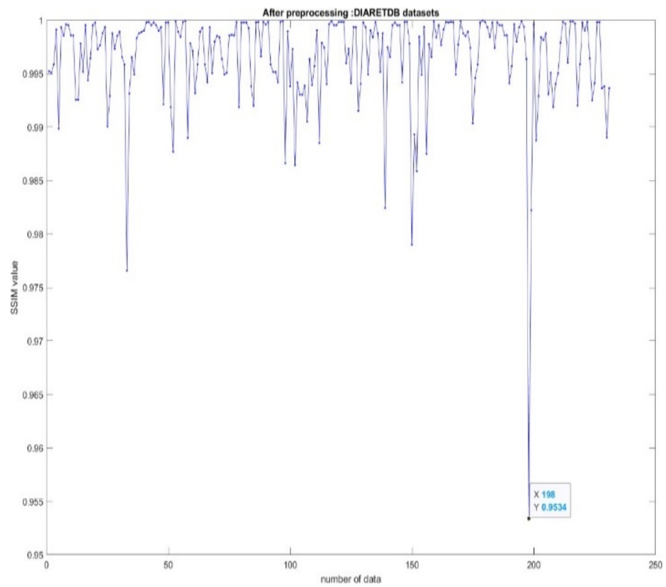


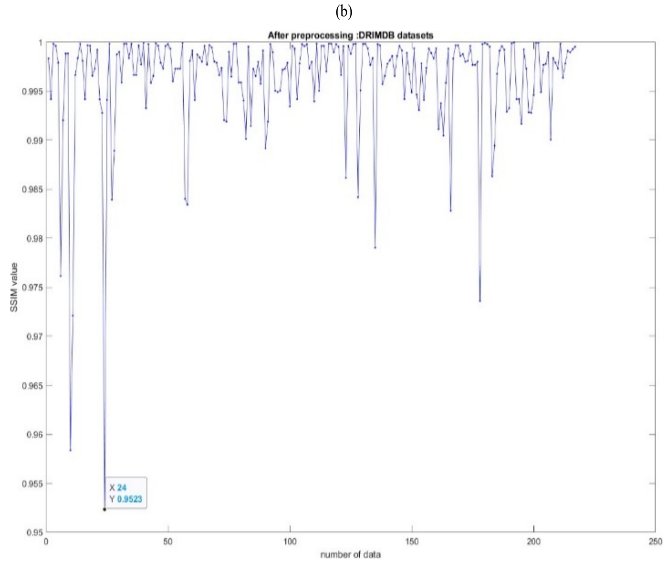
Fig. 8.Results of rotated and flipped fundus image accordingly as stated in Fig.3.



(a)



(b)



(c)

Fig. 9. (a) SSIM values for Kaggle datasets (b) SSIM values for DIARETDB datasets (c) SSIM values for DRIMDB datasets

TABLE II
AVERAGE SSIM VALUES AFTER PROCESSING

Datasets	Average SSIM value
Kaggle	0.9959
DIARETDB1	0.9965
DRIMDB	0.9962

IV. CONCLUSION AND FUTURE WORK

The multi stage of preprocessing of the fundus image successfully improve the quality of the images. By observing the results, the quality of all the images including the image generated, especially in contrast variation achieved the high SSIM values in average.

In the future, we will continue our research on deep learning area for the detection of optic disc and exudates in fundus image where all the preprocessed fundus image in this study will be used.

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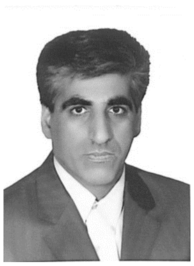

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