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Retinal Image Quality Assessment Using Morphological Operations

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Abstract: Retinopathy of Prematurity (ROP) disease affects newborn babies born preterm. The disease has five stages, with stage IV and V being critical where if the disease is not diagnosed at stage III when the vessels begin to grow abnormally, the reversing it is not possible. Diagnosis and treatment are possible between stage I-III. Hospitals without eye specialists, a doctor can be instructed on how to capture retina image which is transmitted online to an ophthalmologist for disease diagnosis. Different devices produce images of varying qualities and during transmission, some image features could be lost. Some images are captured under poor lighting conditions resulting to poor quality images being generated. This study proposes an algorithm which performs quality assessment of retina images before being used to diagnose ROP Stage II or III disease. The algorithm was developed and tested using Retinopathy of prematurity disease data of 91 images available at the Kaggle database and the objective was to separate images of quality from non-quality ones. The algorithm was able to separate quality from non-quality retina images with 92.82% sensitivity, 96.98% specificity and 97.31% accuracy. Performance evaluation was conducted by means of estimating the similarity measure of DSC and Jaccard index (JI), producing agreeable indices of 94.81% DSC and 88.42% JI.

Keywords: Algorithm, Retina image, Blood vessels, Retina vascular structure

1. INTRODUCTION

Retinopathy of Prematurity (ROP) is an eye disease affecting newborns born before term. Retina vessels do not grow normally and stop growing at some point causing the illness [1]. The symptom of the disease is very different for each stage. The first stage has the formation of a thin white line showing the beginning of the stopping of the growth of the vessels [2-3]. The second stage the white line grows in width and depth and its color turns from white to pink II [1-3]. For stage three the abnormal vessels growth is more visible during diagnosis and should be diagnosed at this stage because treatment is possible at this stage [3]. Stage four is a severe stage where the retina begins to detach and causes blindness at stage five [1-3].

ROP disease diagnosis requires an ophthalmologist capturing fundus images for examination. For hospitals without an ophthalmologist, or for cases where a hospital has many babies requiring examination and only one ophthalmologist is available, an image of the eye is taken using fundus camera, printouts of the image generated and sent to an ophthalmologist for diagnosis. The transmission of images causes image quality reduction and in some cases distortion. Retinal image quality evaluation is a vital process done before ROP disease diagnosis to ensure that the image being used is clear and the diagnostic features required are visible. Image features which determine the quality of the image can be altered depending on the type of device used to capture the image, background lighting during image capturing, and the experience of the person capturing the image [4-5]. There are two dimensions used to classify a retina image as of good quality: content and clarity [6]. Clarity is the degree of image visibility in the dimensions of image structures, sharpness, homogeneity, and illumination [6], and is required by diagnostic systems for Retinopathy of Prematurity disease classification. Content is assessed by ensuring that all image features are

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present, and none is missing, confirming image corners, blood vessels, retina zones, macula which must be present for accurate disease diagnosis [7].

An image can be clear, but its features are distorted or unavailable which makes it impossible to diagnose the disease, for example as shown in Figure 1, image 'a)' is clear and all image contents are available, image 'b)' is not clear, image 'c)' is clear, but the valuable contents for analysis are not available. While diagnosing ROP disease, if the image captured is of poor quality, that image is discarded and another one is captured, in some hospitals the department that does image capturing is different from the ophthalmologist department, so an ophthalmologist must request the patient to go back and have a clear image captured which is a tedious and costly process [8]. Using unclear images for the disease diagnosis can lead to wrong medication and treatment causing severe problems including blindness. To eliminate these challenges, this study developed an algorithm for use by specialists capturing the images and an ophthalmologist performed an assessment of the image quality for ROP stage II and III disease diagnosis. The algorithm can be used to perform an assessment of retina images for any retina disease diagnosis. The data used to develop and test the algorithm are retina images captured for ROP disease diagnosis and available at the Kaggle online database [9].

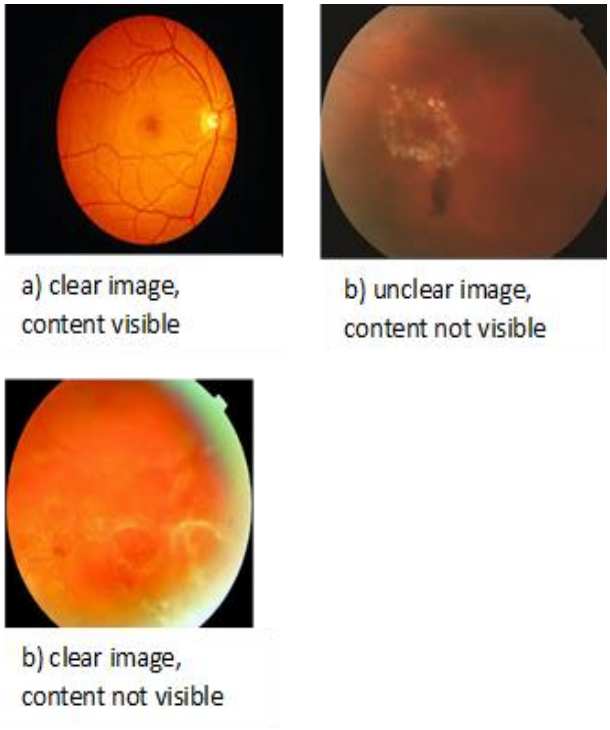

Figure 1. Image clarity versus visibility

2. LITERATURE REVIEW

Retina quality assessment approaches are of two types: Objective methods which are performed to investigate the presence of some specific features which must be present for compliance to some standards while subjective methods in which the quality of an image is done subjectively by an expert thus classifying the image as either of poor quality or of quality [10]. For subjective method, judgement on quality is done as per the point of view by that expert without an explanation on why an image has been classified as of quality or not, meaning it can be classified as of quality by another expert, so quality takes different meanings for different experts [10]. Objective methods are used for retina image quality assessment and are of three classifications: No-reference, reduced reference, and full reference [10-11]. No-reference approach investigates image clarity and not content, reduced reference which is also called partial reference investigates image quality to confirm if at least some features are available without the presence or absence of all image features [11]. Full reference investigates quality of an image and the presence of all image contents. Image distortion as a result of the medium of image transfer, storage can be assessed using full reference method [11-12].

Two studies [13-14] used colored channels for extraction and confirmation of any available feature outliers, their absence would mean that the image does not have sufficient quality. Yang et al. [15] developed an algorithm to check image outliers and sort retina images from non-retina images. A similarity index value was assigned to all retina images. Shao et al. [16] developed an algorithm to check the presence of image contents by examining the position and length of the vessels. Distances between the contents were measured to separate normal from abnormal images. Kumar and Samal [17] developed an algorithm for image content analysis and vessel extraction combining the use of CLAHE technique together with a two-dimensional Gabor wavelet filtering with Top-hat transformations. Their work is able to classify images of quality by examining the presence of retina vessels and extracting the vessels.

Soomro et al. [18] came up with vessel enlargement technique for quality assessment which managed to segment and extract the vessels. They applied the PCA approach for converting colored images into grayscale images. Anisotropic approach was used to normalize arrays for the vessels achieving an accuracy of 95%. Raza et al. [19] developed an algorithm to check image content and reduce image noise for vessel visibility. This method was effective in detecting image edges through a developed image frame. Deledalle et al. [20] engineered an innovative approach for assessing quality of an image and vessel detection through noise reduction. Their approach was only able to detect the presence of huge vessels and not small ones. Rocha and Douglas [21] developed a technique to enhance image contrast by first separating quality from

non-quality images. The work came up with a model for image preprocessing to determine quality. Wang et al. [22] proposed a technique to create a clear visibility of image contents using morphological operations. Image backgrounds were enhanced, and vessel contrast checked then segmentation of the background performed.

The work by Zago et al. [23] preprocessed images using morphological operations and separated an image from its background. Image enlargement was done to provide a better view of the vessels however they could not lesion on the images. Abdel et al. [24] used images of different color shades and illumination where their preprocessing activities involved morphological operations to filter non quality images. Sazak et al. [25] developed an algorithm to measure the length of each blood vessel which was used as a classification for quality or not.

Gardner et al. [26] came up with a classification model using support vector machine technique to diagnose the presence of diabetic retinopathy by extracting the disease diagnosis features from the images. Their work achieved unsatisfactory results as critiqued by Acharya et al. [27] because the algorithm could not extract all image features for effective disease diagnosis. [27-28] proposes naïve bayes classifier to extract features to be used for training their model which provided better results. The model losses were huge and incorrectly classifying images to the wrong classes. The errors were attributed to the size of data sets, and they propose the use of huge dataset to training machine learning models to over the challenges of datasets imbalance. The work by Roychowdhury et al. [29], combined two approaches for feature extraction: support vector machine and K-nearest neighbor and used gaussian mixed modelling to building the model for disease diagnosis. The model was complex with huge dimensions of weight and took very long to complete running the epochs.

[30] developed a mobile application deep retina which utilized fractional pooling layers for feature analysis and classifications. The support vector machine approach was used to ensure that extracted features were mapped as input vectors to the model and output vectors as the classifiers. A mathematical morphology algorithm was developed by Luiz and Marengoni[31] for retina image segmentation and vessels extraction. Image vessels were used to create binary vascular tree like vessels for extraction which was successful. Buket et al. [32] conducted a review of performance evaluation for three machine learning techniques for retina image segmentation for retina disease diagnosis, namely fuzzy logic, artificial neural network and support vector machine, Artificial neural network had the best feature extraction and disease diagnosis. Feng et al. [33] developed an architecture to map foreground and background image features to ensure that during feature extraction, no features as lost. Image contrast was also reduced to enhance features visibility.

Zhou et al. [34] came up with a hidden Markov model to distinguish between small from huge image vessels, a binary line was used to connect features and generate vessel structure. This work was enhanced by Mondal et al. [35] who incorporated an algorithm to filter noise and effects of image distortion. Morphological operations were applied to reduce image contrast with both top and bottom hats applied. Fuzzy logic model was built with the extracted features to distinguish vessels from non-vessels. Images with no adequate vessels were classified as low quality. Tchinda et al. [36] separated images of quality from non-quality ones by developing a retina image edge detection algorithm. Images whose edges could not be detected were classified as non-quality and vice versa. Villalobos et al. [37], used diabetic retinopathy images from DRIVE database to build an adaptive algorithm using matched filters to extract the retina vascular structure and image features.

The work by Zhu and Schaefer [38] used piecewise retina vessel extraction approach using gaussian scaling method. A boundary was created around the image and its vessels for accurate extraction. To separate quality images for diabetic retinopathy disease diagnosis, [39] first preprocessed the images by converting all images to grayscale and extracting the vessels. Images with missing or distorted vessels were classified as non-quality. To examine image features, Chanwimaluang and Fan [40] used the optic disc as the point of referencing to tracing all image features. Images were filtered and pixel localization applied to join all structures for extraction, however their model took longer to execute. Kaur and Sinha [45] applied Gabor filtering approach for retina image segmentation. Diabetic retinopathy images from DRIVE database were used, twelve Gabor filters were initiated at a range of zero to one hundred and seventy. The authors did a comparative analysis of the performance of their model with the work done by [37], where their model outperformed the model by [37] which had been developed using gaussian filtering method.

To extract all image vessels, Zhang et al. [42] developed a model which divided a retina image into vessels and non-vessels. Their model was able to extract all features as well as spots, short and long veins, blobs, optical disk. Images without all the features were classified as non-quality. The work by Kumar et al. [43] applied a two-dimensional kernel model with a module for image preparation which filtered quality from non-quality images before vessel extraction. The authors used diabetic retinopathy images from the STARE database which were few hence model errors of over fitting. A study by Khan et al. [44] constructed a hybrid model applying the hessian matrix for vessels segmentation. Big vessels were separated from small vessels and images whose small vessels could not be identified were classified as not of quality.

3. METHODOLOGY

Kaggle database [9] is a repository of many different types of images and we were only able to extract images of ROP disease, a total of 91 images: 39 images without the disease, 19 images for the first stage, 22 images containing the disease second stage, 11 images of the disease third stage. Images are all collected from Different hospitals by different ophthalmologists and labelled as per the disease stage. As shown in Table 1, data was augmented to achieve 1900 images for ROP stage II and 2100 images for ROP stage III. Additionally, as illustrated in Figure 2, the proposed algorithm was trained to identify presence or absence of the image vessels and use those features to classify the image as of quality or non-quality. Region of Interest (ROI) was the Macula and presence of the blood vessels. A circular frame of size 224*224 pixels was set, and blood vessels extracted from the images. In addition, separation from the background was also done.

TABLE I. DATA SUMMARY

Dataset	ROP Stage II	ROP Stage III
Kaggle	22	11
Augmented dataset	1,900	2,100
Total	1,922	2,111

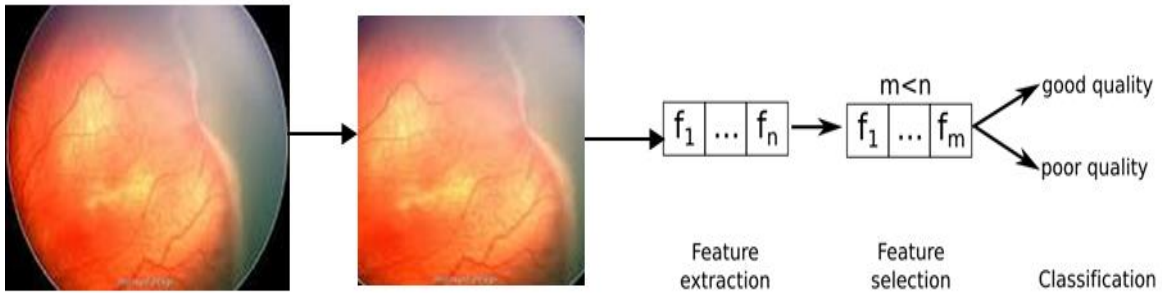

Figure 2. Retina quality assesment steps

A. Image Conversion to Grayscale

As shown in Figure 3, all images were converted to grayscale for uniformity. The algorithm follows the structure: ap=read('image.jpg');bq=rgb2gray(a);print(bq);

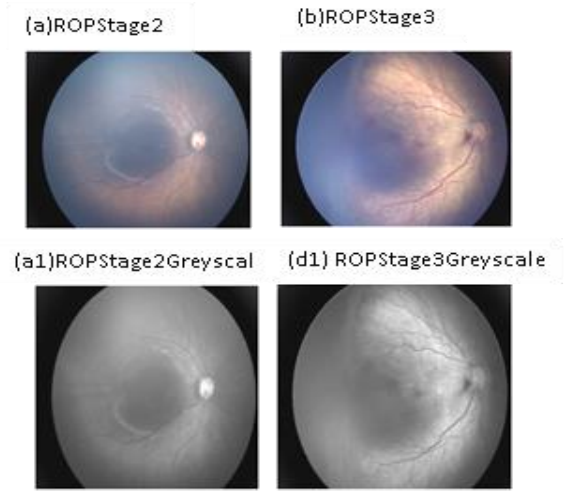

Figure 3. Grayscale conversion output

B. Image Enhancement

As shown in Figure 4, this stage helped to reduce image contrast, enlarge the image for a better view of the blood vessels. The algorithm structure can be summarized as:

C. Image Feature Extraction

The algorithm for vessel extraction begins by first reading the image which is already enhanced and applies a spatial filtering technique to filter non vessels from vessels before extraction as shown by the below algorithm and Figure 5.

ap = read('input'); dimension = Xdimesion(ap); for (dimension =5) %change image color

Intializethreshold = 11; Vessel = (threshold, extract,ap);

%Print resulting output; figure=print (125); print(ap); header ('original Image');

map (125); print (Vessel); header ('Vessel resulting output');

InitializeVesselfunction = Extract(ap).

IK=read('image.jpg'); sub-plot (2*2*1), Print (IK);

Header ('NoROP Nonaugmented'); Channel-G=IK (:3); Print (1*1*1);

print (Channel-G); Header ('NoROP Channel-G'); Enhanced = (Channel-G);

Print (1*1*1), print (CLAHE_Output);

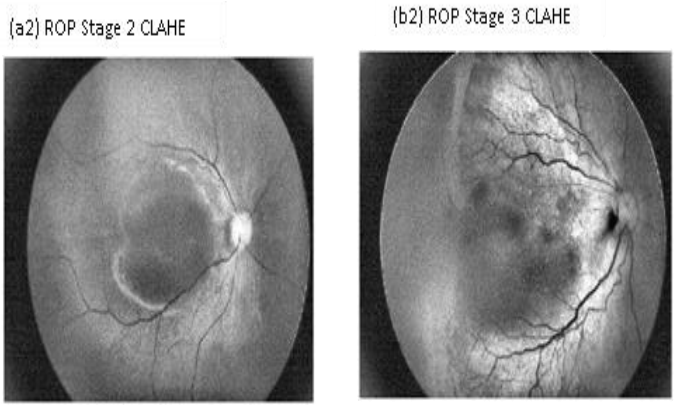

Figure 4. Image enhancement output

k1=[6 -2 -2; 6 0 -2; 6 -2 -2]/12;

k2=[-2 -2 6; -2 0 6; -2 -2 6]/12;

k3=[-2 -2 -2; 6 0 -2; 6 6 -2]/12;

k4=[-2 6 6; -2 0 6; -2 -2 -2]/12;

k5=[-2 -2 -2; -2 0 -2; 6 6 6]/12;

k6=[6 6 6; -2 0 -2; -2 -2 -2]/12;

k7=[-2 -2 -2; -2 0 6; -2 6 6]/12;

k8=[6 6 -2; 6 0 -2; -2 -2 -2]/12;

firstoriginalimage=filtering(k1,ap); secondoriginalimage=filtering(k2, ap); thirdoriginalimage =filtering (k3, ap);fourthoriginalimage=filtering (k4, ap); fifthoriginalimage=filtering(k5,ap); sixthoriginalimage=filtering (k6, ap);

sevenoriginalimage=filtering(k7,ap); eightoriginalimage=filtering (k8, ap); print=(size);

Vessel=print(size); end.

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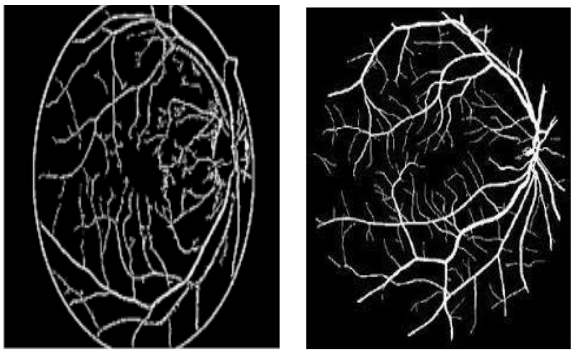

a) Dilated image b) Eroded image

Figure 5. Image dilation and erosion output

D. Image Quality Classification

This was the final step of the algorithm which classified images as either quality or non-quality as shown in Figure 6 and Figure 7.

```
function []=main();path='..\dataset\';
out_path='..\results';ImgType='png';
Imgs = dir([path '/' ['*.',ImgType]]);s=512;
name=[];for i=1 : length(Imgs);
image=imread([path,Imgs(i).name]);
[mask,image]=Cropping(image,3);
image=image(:,:,2);
image=double(imresize(image,[s,s])); tic
feature(i,:,:)=QualityAssessment(image);

end
name{i}=Imgs(i).name;

save([out_path,'curvelet_method1_khatam'],'feature','name');
disp(i)
end
end
%% ----------------------------------------------------
function [feature]=QualityAssessment(image)
CC = fdct_wrapping(image,1,2,4);
for j=1 : length(CC)
coef=CC{2};
C=[];
for i=1 : length(coef)
temp=coef{i};
cc=temp(:);
C=[C;cc]; Print (“quality image”);Else
Print (“non quality image”)
end
[a,b]=hist(C,-25:1:25);
a=a./sum(a); a([1,end])=[];

feature(j,:)=[var(a),var(C),skewness(C),kurtosis(C)];
end
```

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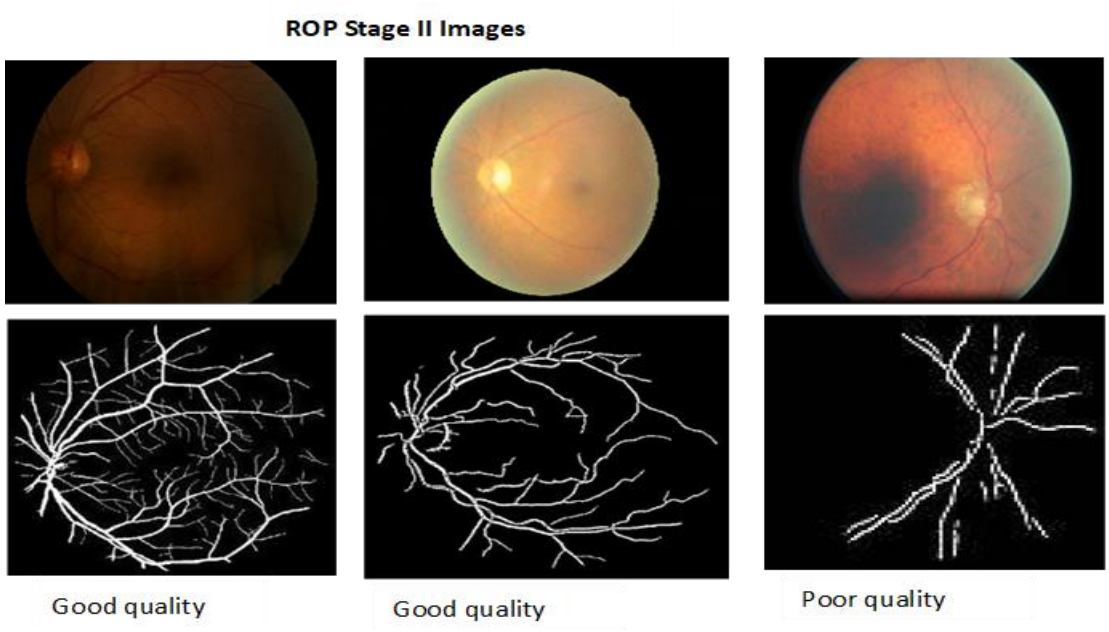

Figure 6. ROP stage II image quality assessment output

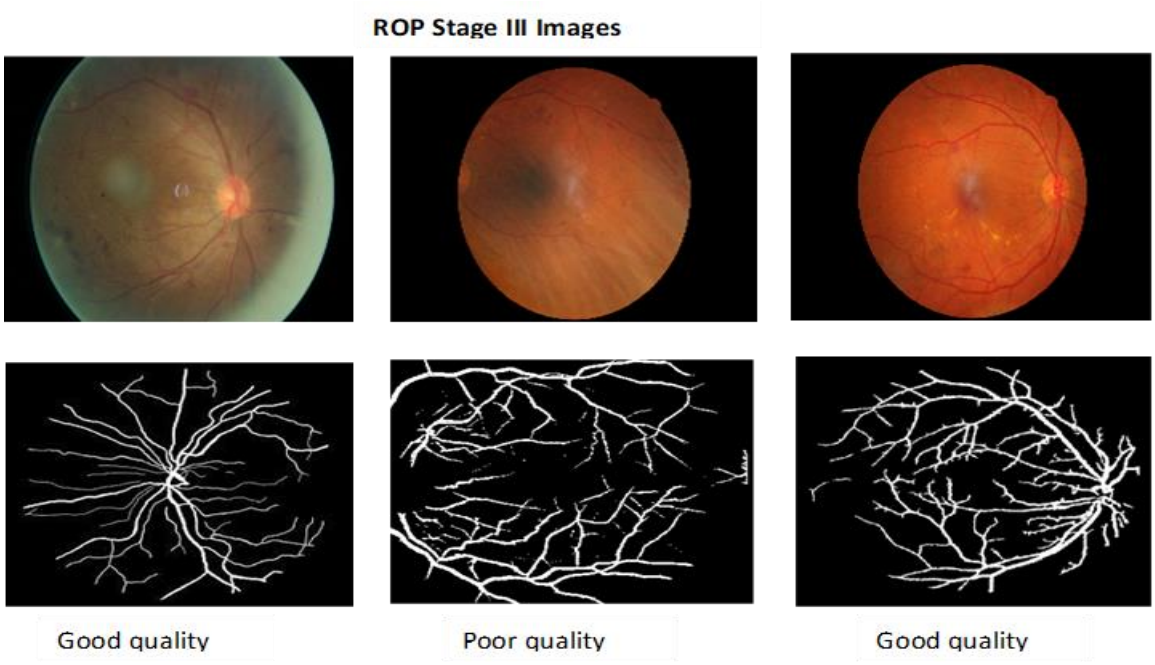

Figure 7. ROP stage III images quality assesment output

E-mail:author's email

4. RESULTS AND DISCUSSION

Retina image features such as spots, lesions, vessels can be extracted by first having the images preprocessed to create a clear view of the features before extraction. Mathematical morphology technique [45] can effectively be used to preprocess images and display these features as the image content for quality evaluation. To maximize feature extraction, an image can be divided into zones using a morphological image structuring element. In this work we set two elements with values, one representing an acting element and zero for non-acting elements [46]. We highlighted regions where these two values were outside the vascular structure matrix. The procedure was repeated while changing the position of the elements which produced three outcomes: Missing to mean the element was not found on the image foreground, and Hint to denote that the element was near the image foreground covering some parts of the foreground and fit to mean that the element covered every section of the foreground.

Accuracy, sensitivity, and specificity was evaluated through the inter-rater reliability Kappa method [47]. An ophthalmologist manually provided a labeling of the images whether as of quality or not and that was our first rating then the results of the algorithm were considered as the second rater. Equations 1-3 is to compute the outputs where: Where True Positive "TP" represent that quality images were labeled as quality ones, True Negative "TN" represent images which are of quality classified not to belong to that class, False Positive "FP" represent an image of poor quality classified not to belong to that class, False Negative "FN" represent an image of poor quality classified to its right class.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

TABLE II. CONFUSION MATRIX FOR ROP STAGE II AND III IMAGE QUALITY CLASSIFICATION

Kaggle dataset		0	1
	0	30	2
	1	20	1
Hospital Dataset		0	1
	0	400	3
	1	300	2

As shown in Table 2, we had two raters, the ophthalmologist, and the algorithm. From the Kaggle dataset, 30 images of ROP stage II were correctly classified by both the ophthalmologist and the algorithm to be of poor quality, while two (2) images of ROP stage II were classified by the ophthalmologist to be of quality, but the algorithm classified them as of non-quality. 20 images of ROP stage III were correctly classified by both the ophthalmologist and the algorithm to be of poor quality, while one (1) image of ROP stage III was classified by the ophthalmologist to be of quality, but the algorithm classified it as of non-quality. From the hospital dataset, 400 images of ROP stage II were correctly classified by both the ophthalmologist and the algorithm to be of poor quality, while 3 images of ROP stage II were classified by the ophthalmologist to be of quality, but the algorithm classified them as of non-quality. 300 images of ROP stage III were correctly classified by both the ophthalmologist and the algorithm to be of poor quality, while 2 images of ROP stage III were classified by the ophthalmologist to be of quality, but the algorithm classified them as of non-quality.

5. CONCLUSION

Retinal image quality assessment is vital to support ROP disease diagnosis. It is usually a difficult task for eye specialists to manually look through image printouts to diagnose the disease or stage. With the current technological advancement, many applications have been developed for assistive eye disease diagnosis and most of these applications require training and tested with images of quality. This work developed a mathematical morphology algorithm to determine whether a retina image is of quality or not. As explained in the introduction section, an image is of quality if the image structures, sharpness, homogeneity and illumination are visible and that all image features are present, and none is missing, confirming image corners, blood vessels, retina zones, macula which must be present for accurate ROP stage II and III disease diagnosis. Each image was preprocessed, features extracted and selected for quality classification. The algorithm was able to separate quality from non-quality retina images with 92.82% sensitivity, 96.98% specificity and 97.31% accuracy. Performance evaluation was done through the estimation of the similarity measure of Dice Similarity Index (DSC) and Jaccard index (JI), producing agreeable indices of 94.81% DSC and 88.42% JI.

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None

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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