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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, 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 babies born before term. Their retina vessels do not grow normally and stop growing at some point causing abnormality [1]. The disease symptoms differ at every Stage. The first Stage has the formation of a thin white line which forms when retina vessels stop growing [2], [3]. In Stage II, the white line grows in width and depth and its color turns from white to pink [1], [2], [3]. For Stage III, the abnormal vessels growth is more visible during diagnosis and should be diagnosed at this stage because treatment is possible [3]. Stage four is a severe stage where the retina begins to detach and causes blindness at Stage V [1], [2], [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 are generated and sent to a hospital with many ophthalmologists for diagnosis. The transmission of images can cause image quality reduction and in some cases distortion. Retinal image quality evaluation is a vital process which should be done before ROP disease diagnosis to ensure that the image contents are visible for accurate diagnosis. Image features is a key parameter for determining image quality and can be affected by many factors including: the type of device used to capture the image, room lighting during image capturing, and the experience of the person capturing the image [4], [5]. There are two dimensions used to examine the quality of an image: content and clarity [6]. Clarity refers to 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 refers to the components that constitute an image and is assessed by ensuring that all image features are present, and none is missing, such as 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 for accurate disease diagnosis 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 examining the presence of ROP disease, if the image captured is of poor quality, the image is discarded, and another one is captured. In some hospitals, the department that does image capturing is different from

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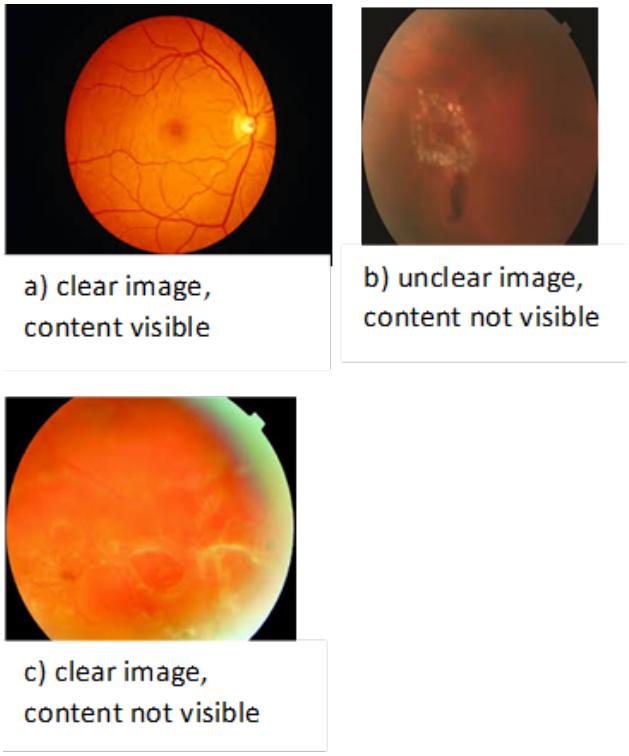

Figure 1. Image clarity versus visibility

the ophthalmologist's 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 recommendation for medication and treatment causing severe problems including blindness. To eliminate these challenges, this study developed an algorithm for retina image quality assessment using ROP Stage II and III images to assist ophthalmologists in sorting images of quality from non-quality ones. The algorithm can be used to perform quality 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].

2. LITERATURE REVIEW

Retina quality assessment approaches are of two types: Objective methods whose aim is to investigate the presence of some specific features which must be present for compliance to some standards and subjective methods where 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 of an expert without an explanation on why an image has been classified as of quality or not, meaning it can be classified as of non-quality by another expert, so quality takes different meanings for different experts. Objective methods are used for retina image quality assessment and are of three classifications: No-reference, reduced reference, and full reference [11]. The no-reference approach investigates image clarity and not content. Reduced reference classification, 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. Full reference investigates the quality of an image in reference to 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 [12]. The algorithms for examining retina images quality for both objective and subjective methods are classified into two: Morphological operations methods and Machine Learning approaches.

A. *Morphological operations for retina image quality assessment*

Mathematical morphology approaches apply set theory notation to guide on the extraction of image features, enabling the tracing of important image features such as image boundaries, structure, veins, blobs [13]. The application of morphological operations in retina image quality assessment provides many capabilities of image examination which involves image rotation, shrinking, enhancement, and this helps to provide a better view of image contents [14]. As shown in Table I, two studies [14], [15] 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. [16] 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. Images were first pre-processed to obtain image structure and available features were represented into values, a Weibull model was also developed to fit the values and extract features of the dimensions: shape, coefficient of variation, frequency sub-band and direction sub band features. A learning method was applied to match the features with quality scores.

Shao et al. [17] 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. Their work was innovative though image quality cannot only be examined by only the available contents but also other measures such as clarity. Soomro et al. [18] came up with vessel enlargement technique for quality assessment which managed to segment and extract the vessels. They applied the Principal Component Analysis (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 and Hu [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 detect lesions 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.

B. Machine Learning methods for retina image quality assessment

Binju and Rajesh [25] developed an algorithm (hybrid NIQE-PIQE) using images from DRIMDB and DRIVE databases to evaluate the quality of the images. The algorithm first assigns a score on the images based on their quality then a Deep Neural Network model is trained to categorize the images into three classes: low, medium and high quality. High quality images were pre-processed to eliminate noise achieving an accuracy of 97.7%, sensitivity of 95.6% and specificity of 99%. Shi et al. [26] developed an algorithm (RMHAS) containing three modules, the first module for assessing image quality, the second for image segmentation to extract vessels and the third module for measuring the length of extracted vessels. Their work utilized 220 images from a privately owned database achieving an Area under curve (AUC) of 0.91. Wan et al. [27] developed a model to first sort retina images into two classes, low quality and high quality. The model was trained and tested using images from EyePACS database, proprietary dataset, STARE, DRIVE, CHASEDB databases. Their work did not present important parameters of the model accuracy, Sensity and specificity.

Guo et al. [28] developed a Deep Neural Network model using 55,931 color fundus images to examine three retina image features: Location of image features, clarity and artifact achieving an accuracy of 89.7%. Huang et al. [29] developed an application named RIQA using images from three databases: EyeQ (28,792 images), EyePACS (2000 images) and OIA-ODIR (1000 images). Data was augmented and batch normalization applied plus image resizing to achieve uniformity. Their system achieved a highest ROC value of 0.96. A study by Bouris et al. [30] developed a Convolutional Neural Network (CNN) model for retina image quality assessment using the optic disc as a feature of reference. Their work used 2377 images where 1002 images were classified as of good quality, 609 acceptable quality and 766 poor qualities, achieving an accuracy of 91% and AUC of 0.98.

Peter et al. [31] applied ensemble technique to preprocess images and classify them as quality or non-quality before diagnosing Diabetic Retinopathy disease. Their work used images from public databases: APTOS, DDR and EyePACS. The notable limitation of their work was not precisely stating their model accuracy and AUC. Qi et al. [32] developed a model for retinal image quality assessment for images collected from children with myopic cases undergoing treatment. The study conducted retina image quality assessment even though the focus was more on the disease treatment and not showing the results of the output on quality assessment. Yue et al. [33] developed an algorithm to improve the quality of retinal images. The work first collected 250 images from a low light camera setting background which were augmented to achieve 2000 images. Their work managed to separate images of quality from non-quality but did not publish information of their model AUC.

A study by Li et al. [34] 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. Feng et al. [35] 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. [36] 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. [37] 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. The work by Kumar and Suraj [38] 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. As shown in Table II, König et al. [39] developed a neural network model for retina image quality assessment in real time. Two neural network models were trained and tested separately using 2272 color fundus images and 2494 fluorescein angiography images respectively to present an image contrast, focus, shadow, noise and reflection. The model achieved an accuracy of 93% for training and testing using fundus images and 89.5% using fluorescein angiography images.

Kaur and Sinha [40] 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. [41] 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 Zhu and Schaefer [42] used piecewise retina vessel extraction approach using gaussian scaling method. A boundary was created around the image and its vessels for accurate extraction. Tchinda et al. [43] 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. Lenskiy and Lee [44], Villalobos-Castaldi et al. [45] developed a convolutional Neural Network model for extracting image content features, their work did not provide details of the model accuracy, specificity and sensitivity. To examine image features, Chanwimaluang and Fan [46] 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.

3. METHODOLOGY

As shown in Figure 2, the process of developing the algorithm begins by inputting colored ROP Stage II and III images. The images were obtained from Kaggle database [9] which is a repository of many different types of images. There was a total of 91 images: 39 images without the disease, 19 images of Stage I ROP, 22 images of Stage II ROP, and 11 images of Stage III ROP. Images from this database are collected from different hospitals by different ophthalmologists and labelled as per the disease stage. As shown in Table III, data was augmented to achieve 1900 images for ROP Stage II and 2100 images for ROP Stage III. The second step involved converting the images to grayscale to achieve uniformity of color. Contrast Limited AHE (CLAHE) was applied to enhance the images in size to achieve a better size of view. Feature extraction was the third step where features such as blobs, lesions, vessels were extracted. As shown in Figure 3, the algorithm was trained using extracted features to classify the images into two classes: Good quality and Poor quality.

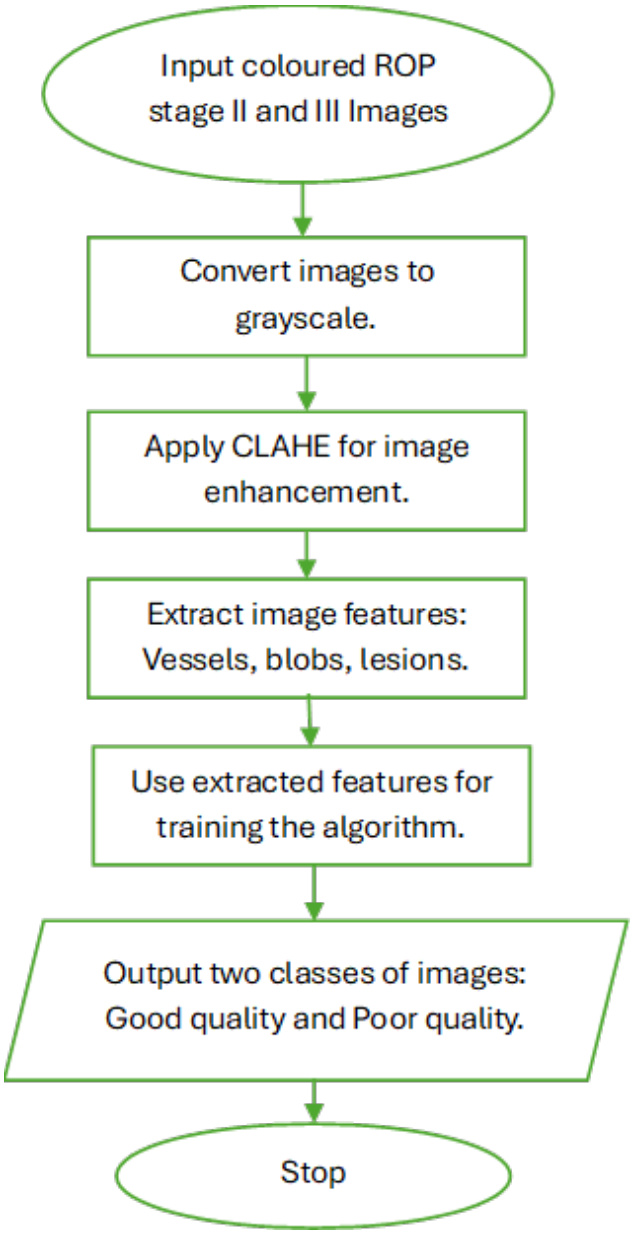

Figure 2. A Flowchart for the algorithm development

TABLE I. SUMMARY OF MORPHOLOGICAL STUDIES FOR RETINA IMAGE QUALITY ASSESMENT

Citation	Year	Classification	Technique	Accuracy
Abdushkour [14]	2017	Feature extraction	None	-
Koh et al. [15]	2017	Feature extraction	None	-
Yang et al. [16]	2018	Quality assessment	None	-
Shao et al. [17]	2018	Image contents	None	-
Abdel et al. [24]	2018	Image contents	None	-
Kumar and Suraj [38]	2019	Quality assessment	CLAHE	-
Soomro et al. [18]	2018	Image content	PCA	95%
Raza et al. [19]	2021	Image content	None	-
Deledalle et al. [20]	2019	Vessel extraction	None	-
Rocha and Douglas [21]	2020	Quality assessment	None	-
Wang et al. [22]	2019	Quality assessment	None	-
Zago et al. [23]	2018	Quality assessment	None	-

TABLE II. SUMMARY OF MACHINE LEARNING STUDIES FOR RETINA IMAGE QUALITY ASSESMENT

Citation	Year	Classification	No.of Images	Accuracy	Sensitivity	Specificity	AUC
König et al. [39]	2023	CNN	2272	93%%	-	-	0.91
Binju and Rajesh. [25]	2023	NIQE-PIQE	-	97.7 %	95.6%	99%	-
Shi et al. [26]	2022	RMHAS	220	-	-	-	0.91
Wan et al. [27]	2022	CNN	-	96%	-	-	-
Sinha [40]	2022	CNN	-	96%	-	-	-
Guo et al. [28]	2024	DNN	55931	89.7%	-	-	-
Huang et al. [29]	2024	RIQA	3000	-%	-	-	0.96
Bouris et al. [30]	2023	CNN	32377	91%	-	-	0.98
Peter et al. [31]	2024	CNN	36133	82.66%	-	-	-
Qi et al. [32]	2023	CNN	-	-	-	-	-
Yue et al. [33]	2023	CNN	2000	-	-	-	-
Li et al. [34]	2019	SVM	-	-	-	-	-
Feng et al. [35]	2020	CNN	-	-	-	-	-
Zhou et al. [36]	2020	CNN	-	-	-	-	-
Mondal et al. [37]	2020	CNN	-	-	-	-	-
Zhang et al. [41]	2020	CNN	-	-	-	-	-
Zhu and Schaefer, [42]	2020	CNN	-	-	-	-	-
Tchinda et al.[43]	2021	CNN	-	-	-	-	-
Lenskiy et al.[44]	2021	CNN	-	-	-	-	-
Villalobos et al.[45]	2019	CNN	-	-	-	-	-
Chanwimaluang and Fan [46]	2019	CNN	-	-	-	-	-
Kumar et al.[38]	2019	CNN	-	-	-	-	-

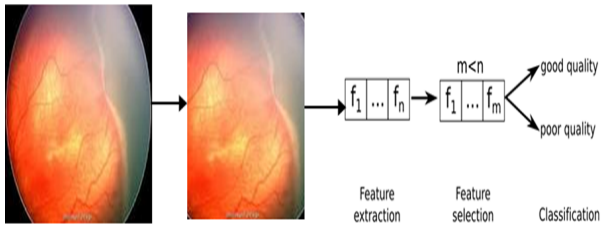

Figure 3. Retina quality assessment steps

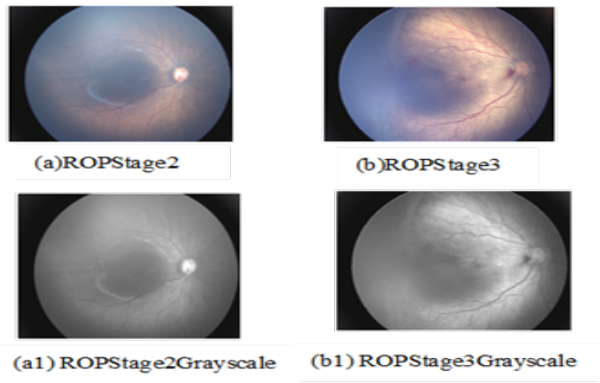

Figure 4. Grayscale conversion output, original ROP Stage II (a), original ROP Stage III (b), image a converted to grayscale (a1), image b converted to grayscale (b1)

TABLE III. DATA SUMMARY

Dataset	ROP stage II	ROP stage III
Kaggle	22	11
Augmented dataset	1900	2100
Total	1922	2111

A. *Algorithm Development Platform*

Image preprocessing was done on a MATLAB (R2022B) environment and for the image quality assessment, OpenCV library was applied. The algorithm was built on a Windows Operating System, Intel CORE i7 Gen 8 with a 2.7 GHz and a RAM of 1 TB on NVIDIA GEFORCE RTX 40 Series, powered by a new ultra-efficient NVIDIA Ada Lovelace, 3rd Gen RTX.

B. *Image Conversion to grayscale*

As shown in Figure 4 and 'Algorithm Section 1, all images were converted to grayscale for uniformity. Algorithm Section 1: Grayscale image conversion
ap=read('image.jpg');bq=rgb2gray(a);print(bq);

C. *Image Enhancement*

As shown in Figure 5, this stage helped to reduce image contrast, enlarge the image for a better view of the blood vessels. 'Algorithm Section 2' shows the steps for image enhancement. Algorithm Section 2: Image enhancement
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);

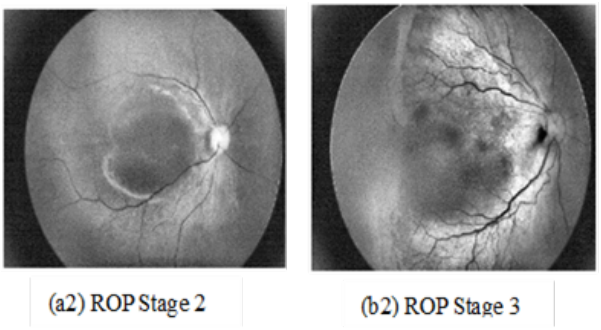

Figure 5. Image enhancement output, image a in figure 4 enhanced (a2), image b in figure 4 enhanced (b2).

D. *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 'Algorithm Section 3' and the output in Figure 6. Algorithm Section 3: Image feature extraction
ap = read('input');ap = read('input');
dimension = Xdimesion(ap); for (dimension =5)
Intializethreshold = 11;
Vessel = (threshold, extract,ap);figure=print (125); print(ap);
header ('original Image');map (125); print (Vessel);
header ('Vessel resulting output');InitializeVesselfunction = Extract(ap).
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.

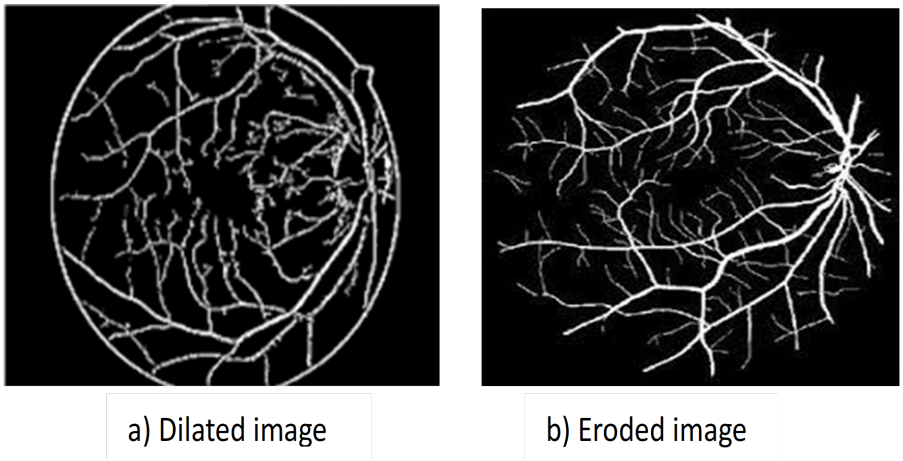

Figure 6. Extracted image features, output of dilation (a), output of image erosion (b).

E. Image Quality Classification

This was the final section 4 of the algorithm was used to classify images as either quality or non-quality and the output is as shown in Figure 7 and Figure 8. Figure 7 shows a sample output for ROP Stage II images for quality assessment while Figure 8 shows the output for ROP Stage III images. Algorithm Section 4: Image quality classification

```
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);
namei=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=CC2;
C=();
for i=1 : length(coef)
temp=coefi;
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;
end
```

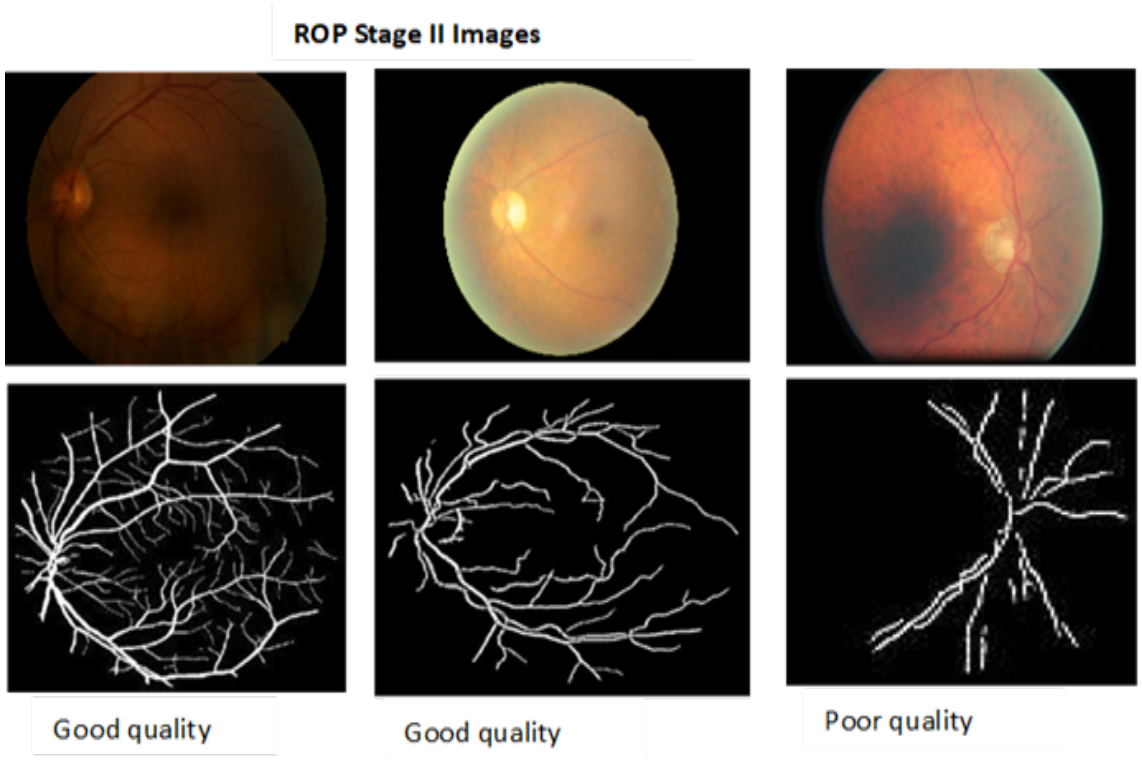

Figure 7. ROP Stage II image quality assessment output

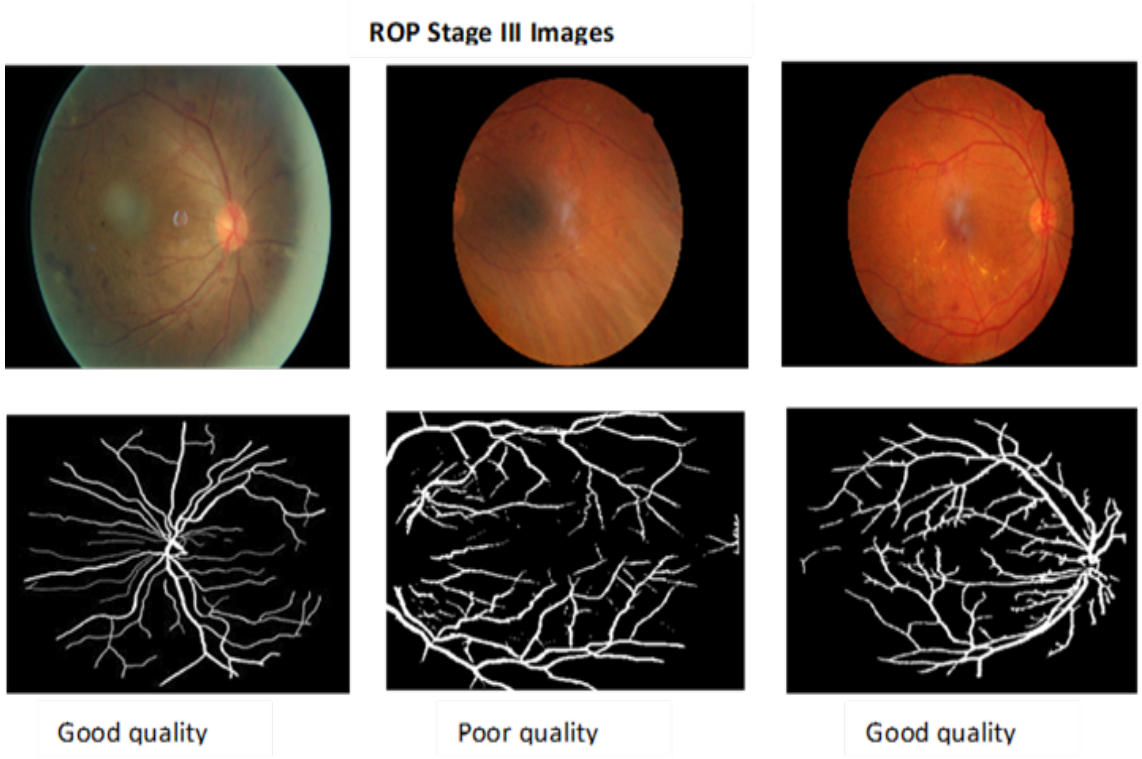

Figure 8. ROP Stage III images quality assesment output

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 [47] 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 [48]. 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, '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 [49] . An ophthalmologist manually provided a labeling of the images whether as of quality or not and that was the first rating then the results of the algorithm were considered as the second rating. Equations 1-3 were used to compute the outputs 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.

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

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

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

As shown in Table IV, 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. A total of 300 images of ROP Stage III were correctly classified by both the ophthalmologist and the algorithm to be of poor quality, while two (2) images of ROP Stage III were classified by the ophthalmologist to be of quality, but the algorithm classified them as of non-quality.

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

		Human Rating(0)	Human Rating(1)
Kaggle dataset	Algorithm rating for ROP Stage II images (0)	30	2
	Algorithm rating for ROP Stage III images (1)	20	1
		Human Rating (0)	Human Rating (1)
Hospital dataset	Algorithm rating for ROP Stage II images (0)	400	3
	Algorithm rating for ROP Stage III images (1)	300	2

Studies applying morphological operations for retina image quality assessment were divided into three categories: Image vessel extraction and feature extraction to determine available features [14], [15], [21], quality assessment studies based on assigned values [16,18,19,22,24] and image contents with edge detection [17], [20], [25]. It is observable that all studies evaluated image quality based on some parameters of image contents which constituted the available features without paying more focus on image clarity which our algorithm was able to do. Studies utilizing Deep Learning applications for retina image quality assessment showed an increased rate of accuracy however most of them did not publish important information such as sensitivity, accuracy and specificity of their models, the case for [28], [30], [31], [32], [33]. Other studies [29], [36], [37], [38], [39], [41], [42], [43], [44], [45], [46] did not publish information on the number of images used to train and test their models or the design of their models which was a limitation.

5. STUDY LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

This work was limited to achieving its objectives of developing an algorithm for retina image quality assessment

which was successfully achieved. Kaggle database is the only publicly accessible database with ROP Stage II and III images and had 91 images which were not adequate. To overcome these limitations, data was augmented to increase the volume of images and to generate a variety. Having succeeded in developing an algorithm with the capability to accurately separate retina image of quality from non-quality ones, and with the advancement of the development of Machine Learning algorithms for retina diseases diagnosis, we recommend the extension of this work to utilizing the output of the algorithm to train a model for diagnosing Retinopathy of Prematurity (ROP) Stage II and III disease.

ROP Stage I and II are initial stages of the disease and can develop and heal without any medical intervention but when the disease progresses to Stage III, diagnosis and remedial action is needed so as to avoid reaching Stage IV and Stage V which are associated with blindness. The disease diagnosis has been a burden to many nations because of the lack of enough eye specialists together with the economic burden for the diagnosis. Hospitals without eye specialists use clinicians to capture eye images and transmit them to hospitals with ophthalmologists to assist in the disease diagnosis. Image transmission through different mediums can affect image quality hence the need for computer aided systems to separate images of quality from non-quality ones before disease diagnosis. Having achieved the objectives of this work, further work is needed towards expanding the developed algorithm to be able to detect the presence or absence of ROP disease as well as the disease Stage II and III. We also recommend that existing privately-owned databases for ROP images be made public for research purposes so as to promote the development of better systems for diagnosis of the disease.

6. 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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8. COMPETING INTEREST

All Authors declare no Competing Interests

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