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Feature Extraction for Retina Image Based on Difference Approaches

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ABSTRACT

Automatic disease diagnosis using biometric images is a difficult job due to image distortion, such as the presence of artifacts, less or excessive light, narrow vessel visibility and differences in inter-camera variability that affect the performance of an approaches. Almost all extraction methods in the blood vessels in the retina produce the main part of the vessel with no patalogical environment. However, an important problem for this method is that extraction errors occur if they are too focused on the thin vessels, the wide vessels will be more detectable and also artificial vessels that may appear a lot. In addition, when focusing on a wide vessel, the extraction of thin vessels tends to disappear and is low. Based on our research, different treatments are needed to extract thin vessels and wide vessels both visually and in contrast. This study aims to adopt feature extraction strategies with different techniques. The proposed method in segmentation and extraction with three different approaches, namely the pattern of shape, color, and texture. Testing segmentation and feature extraction using STARE datasets with five classes of diseases namely Choroidal Neovascularization, Branch Retinal Vein Occlusion, Histoplasmosis, Myelinated Nerve Fibers, and Coats. Image enhancement on Myelinated Nerve Disease Fiber is the best result from the image of other diseases with the highest value of PSNR of 35.4933 dB and the lowest MSE of 0.0003 means that the technique is able to repair objects well. The main significance of this work is to increase the quality of segmentation results by applying the Otsu method. Testing of segmentation results shows improvements with the proposed method compared to other methods. Furthermore, the application of different feature extraction methods will get information on disease classification features based on patterns of suitable shapes, colors, and textures.

Keywords: Color Pattern, Feature Extraction, Segmentation, Shape Pattern, Texture Pattern.

1. INTRODUCTION

Biometrics is a popular technology using biological characteristics to identify individuals [1] among others, with the face, iris of the eyes, ears, tongue, fingers, and retina. The retina is a thin membrane located at the back of the eyeball that functions to convert light into nerve signals. There are many disorders, diseases or abnormalities in the retina of the human eye caused by certain factors. Some retinal disorders that will be discussed are *Choroidal Neovascularization, Branch Retinal*

Vein Occlusion, Histoplasmosis, Myelinated Nerve Fibers, and Coats. The use of retinal images for the diagnosis of Diabetic retinopathy is done [2] with the Lattice Neural Network with Dendritic Processing (LNNDP) method compared to Support Vector Machines (SVM) and Multi-Layer Perceptrons (MLP). This method has a weakness in the image that has a similarity will cause the accuracy decreased.

In general, automatic disease diagnosis through biometric imagery is a complicated job, usually, there are five steps taken: preprocessing, segmentation, extraction, classification, and recognition. This study focused on preprocessing for enhancement, segmentation, and extraction of retinal blood vessel features. Threshold method is one of the many methods used in segmenting the image [3]. Thresholding is an effective and simple method to separate objects and backgrounds [4]. A segmented image into two classes, called bilevel thresholding, whereas, in the segmentation of more than two classes, it is called multilevel thresholding. Otsu and Kapur are two classic methods in multilevel thresholding.

Prior to the segmentation process, the image of the acquisition still has poor lighting, blur, and low contrast level. Therefore the poses enhancement is required [5]. By using the image formation model of scattering method to the improve a color retinal image. The results showed that the proposed method could work well on lighting problems, increased contrast, and color. Despite successfully handling lighting and color issues, but improvements in blurry images with very low contrast. In [6] is conducted such research on enhancement processes to eliminate noise in image, grayscale and contrast reduction, enhances retinal vessels in the image. The research aims to reduce the difference in intensity between vessels, to produce good retinal vessel segmentation. The extraction process calculates the thickness of blood vessels and the area of the object to extract the foreground pixels. In [2] using the LNNDP method, however the problem is the method removes important detail information from the blood vessels.

In recent years, research on vessel extraction in retinal imagery has grown widely with the resulting algorithm. Gray-level co-occurrence matrices [7], neural networks [8], matched filters [9], and region growing [10] are some of the best techniques. Almost all extraction methods in the blood vessels in the retina produce the main part of the vessel with no patalogical environment. However, an important problem for this method is that extraction errors occur if they are too focused on the thin vessels, the wide vessels will be more detectable and also artificial vessels that may appear a lot. On the contrary, while we were focusing on a wide vessel, the extraction of thin vessels tends to disappear and is low. Based on our research, different treatments are needed to extract thin vessels and wide vessels both visually and in contrast. We, therefore, proposed the strategic for extraction of vessel features with 3 different techniques or approaches. They motivate us more to develop feature extraction techniques in blood vessel segmentation.

The proposed method for feature extraction by applying different approaches are shape, texture, and color. The expected contribution in this research is to improve the quality of segmentation by applying the Otsu method with connectivity, area, and length parameters. Furthermore, better segmentation results will produce accurate feature extraction. By taking different approaches, the shape, color, and texture are expected to increase the classification of diseases based on the retinal image.

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2. RELATED WORK

Research conducted in [2] utilize DRIVE and STARE datasets to detect chronic retinal diseases by using LNNDP. The proposed methodology requires four steps: (1) Pre-processing, (2) Computing features, (3) Classification and (4) Post processing. The results obtained show the advantages of simple algorithms, do not require parameters and automatically build the structure to solve certain problems. The F Score is better for the LNNDP method compared to SVM and MLP.

Automatic vessel feature extraction in non-fluorescein retinal images is performed by [11] which does heavy tasks are performed in applications such as diabetic retinopathy screening. Nonetheless, there are complex variations in vessel shape and also the modelling accuracy of retinal vascular structures is challenging. Therefore, a new approach is proposed to extracts blood vessels in the non-fluorescein retinal fundus image using orientation aware detector (OAD). The OAD is designed in accordance with a local-oriented vessel feature and has a linear elongated structure. Vessel orientation is modeled efficiently by Fourier transform distributions. Thus, either wide or thin vessels can be extracted with two-scale segmentation. Where the edge operators are applied on a large scale while Gabor filters are applied on a small scale. The experimental results show that the OAD approach outperformed the existing segmentation method by achieving a competitive CAL measurement of 80.82% for the DRIVE database and 68.94% for STARE.

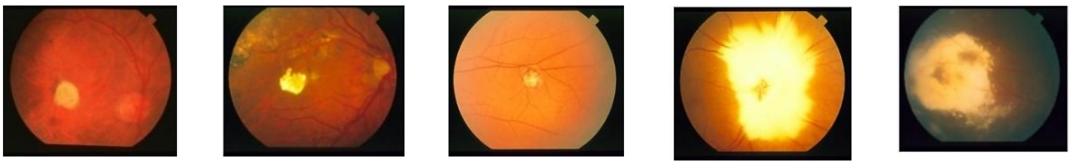
A Research by [7] presents a method for extracting blood vessels from retinal images that swift, more efficient and automatically. It is based on the second local entropy and on the gray-level co-occurrence matrix (GLCM) matrix. The blood vessel contours have an algorithm which was design to have the flexibility of definition. With the information from GLCM, statistical features are calculated as threshold values. The performance of the proposed approach is assed in terms of accuracy, sensitivity, and specificity. With each result obtained were 0.9648, 0.9480 and 0.9759. The other aspect which was evaluated in this method is the required time for the segment. Its average by the proposed method is 3 seconds for the image size 565 × 584 pixels.

Segmentation using multilevel thresholding is time-consuming and involves a large calculation. To solve this problem, several optimization methods are applied. There are several optimization methods that have been successfully implemented in multilevel thresholding, including Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). One interesting example of multilevel thresholding with GA is shown on [12],[13]. Next, [14] in his research using multilevel thresholding to the segment with the Improved Differential Search Algorithm (IDSA) algorithm. Image segmentation with multilevel thresholding based on PSO ever done [15], [16], [17]. Here the Lime method which is a function of the threshold value is optimized by the PSO optimization method.

Furthermore, retinal vascular segmentation with Particle Swarm Optimization (PSO) algorithm has been investigated [18] by utilizing a multiscale filter that is superior to a single scale due to better noise reduction. The main problem in applying this method is determining the exact parameter value of the filter. Multiscale filters that use two suitable filters provide high sensitivity, specificity, and accuracy but performance improvements are still needed. Detection of vessel vessels for ophthalmology and cardiovascular disease by [19] incorporating Gaussian smoothing, top-hat operator morphology, contrast enhancement, and noise reduction and the results outperform the latest methods with balanced sensitivity and accuracy. In this case, the preprocessing procedure does not increase the contrast between the vessel and the background which reduces the overall detection performance. Even, [20] and [11] emphasizes the difficulty of manually selecting segmentation by the expert as a reference, highlighting the difference in outcomes between the truth labels on the image dataset. Retinal vessel segmentation is automatically an alternative to manual detection [21]. The Otsu technique seeks the threshold value of optimization by minimizing intra-class and maximizing variation between classes [22]. This step includes estimation and background reduction. Estimates of the background are carried out using a morphological approach. It aims to reduce the illumination and noise present in vascular images during pixel classification [23].

3. STARE DATASET

Retina image data used obtained from the website Structured Analysis of the Retina, California. Retinal image data provided in the form of a sample database of retinal imagery. There are 400 samples of retinal imagery given by the Structured Analysis of the Retina website. However, only 5 samples of retinal images were used in this study. The given retinal image sample features the retina of the eye with abnormal vascular shape conditions and retinal image of the eye that has patches presented in Figure 1.



(a) (b) (c) (d) (e)

FIGURE 1. Retinal images based on diseases are obtained from the Stare dataset, the classification of images diagnosed has a disease in the patient by the ophthalmologist, Determination of the type of disease adjusted to the scope of the study, namely images that have characteristics based on shape patterns, color patterns, and texture patterns. (a) Choroidal Neovascularization, (b) Branch Retinal Vein Occlusion, (c) Histoplasmosis, (d) Myelinated Nerve Fibers and (e) Coats

4. METHODS

Feature extraction used in the image to be identified using three different feature extractions, namely shape and size feature extraction, color feature extraction, texture feature extraction. Extraction of feature shapes is used to differentiate the shape of an object with other objects and the size is used to distinguish the size of an object from another object using a wide or circumference parameter. Color feature

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extraction is used to distinguish an object with a certain color that can use hue values or represent a representation of visible light such as red, orange, green, blue, and purple. Texture feature extraction is used to distinguish the texture of objects from other objects. The complete feature extraction process for three approaches is based on shape patterns, color patterns and texture patterns are presented in the flowchart in Figure 2.

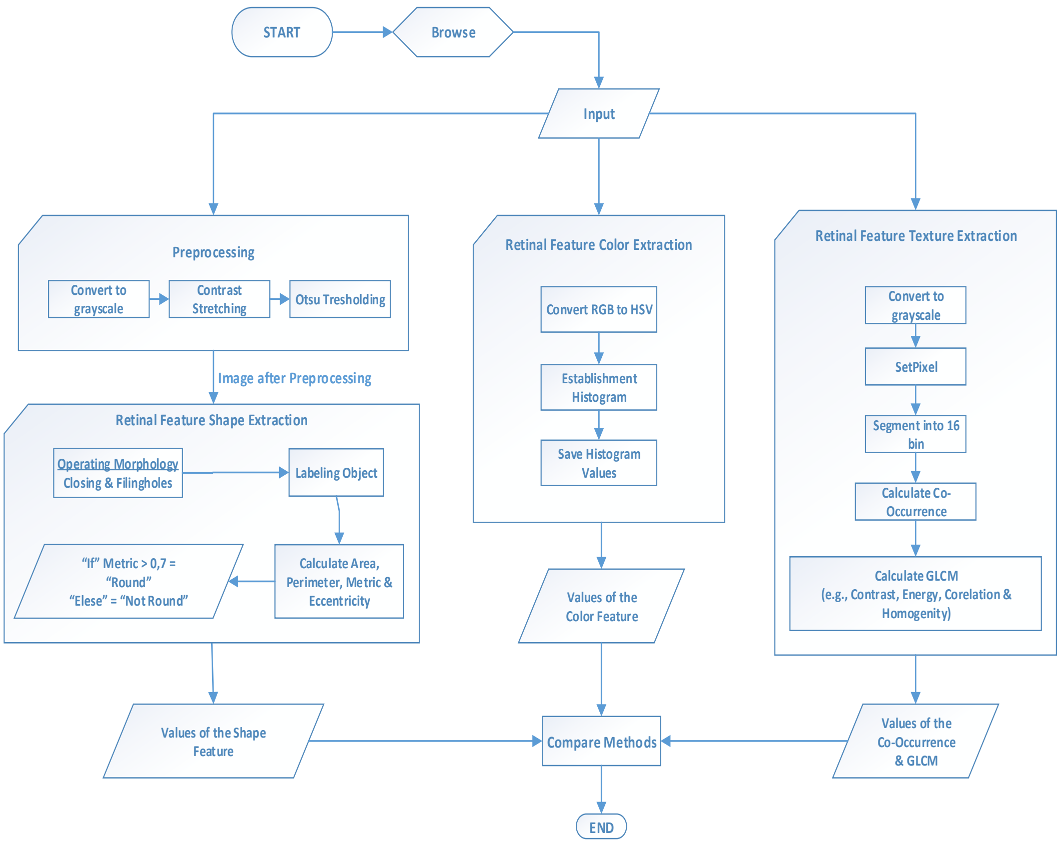

FIGURE 2. Flowchart of feature extraction process for 3 (three) techniques, based on shape patterns, color patterns, and texture patterns

The following steps, present how to extract the features of an object's shape in a digital image based on parameters of the area, perimeter, metric, and eccentricity. The area is the number of pixels that make up an object. While the perimeter is the number of pixels in the object boundary. Eccentricity is the value of comparison between the distances of the foci ellipses minor with the foci ellipse major of an object. The RGB image will be converted to the grayscale image, then Otsu thresholding method is used for segmentation. The algorithm used in retrieving the shape features of an image can be shown in Figure 3.

Color extraction is one method that separates between objects with the background based on certain color features of the object. The color extraction process begins with converting the original color space of RGB (Red, Green, and Blue) into the color space of HSV (Hue, Saturation, Value). Algorithm for extracting retinal images based on the following color patterns as follow,

```
Algorithm:  Shape Extraction
Type color : record <Red, Green, Blue : integer >
Procedure RBG_to_grayscale (input RGB  : array [1..255, 1...255] of color, output grayscale :
array[1..255,1...255] of real )
For i <~ 0 to 255 do
        For j <~ 0 to 255 do
        Read(RGB [i,j].R)
        Read(RGB [i,j].G)
        Read(RGB [i,j].B)
        Grayscale [i,j] <-  (0.2989 * RGB[i,j].R) + (0.5870 * RGB[i,j].G) + (0.1140 * RG B[i,j].B)
        End for
End for
Procedure OtsuThreshold(input grayscale :  array[1..255,1...255] of real ,  output binaryImage : array
[1..255,1..255] of integer)
i , j , weightB, weightF, sumB , sumA         : Integer
MeanB , MeanF, ClassVariance , TempVar  : Real
for i <~ 0 to 255 do
for j <~ 0 to 255 do
                histogram [ grayscale[ i , j ] ] <~ histogram [ grayscale[ i , j ] ] + 1
                end for
end for
for t <~ 0 to 255 do
  weightB <~ weightB + histogram[t]
  weightF <~ (255*255) – weightB
  sumB <~ sumB + (t * histogram[t])
  sumF <~ sumF + (t+1)* histogram[t+1])
  MeanB <~ sumB / weightB
  MeanF <~ (sumF - sumB) / weightF
  ClassVariance <~ wB * wF * (mB - mF) * (mB - mF)
  if (ClassVariance > TempVar) then
    TempVar <~ ClassVariance
    threshold <~ t
    end if
end for
for i <~ 0 to 255 do
for j <~ 0 to 255 do
                if grayscale[ i , j ]  > threshold then
                binaryImage [ i , j ] <~ 1
                else
                binaryImage [ i , j ] <~ 0
                end for
end for
Procedure Calculate (input: st, l, output : new_area, perimtr, eccentri, matric)
        i : Integer
        for i ← 1 to length(l) do
                bd ← l{i}
                delt ← diff(bd).^2
                perimtr←sum(sqrt(sum(delt,2)))
                new_area ←  st(i).Area
                eccentri ← st(i).Eccentri
                matric ← 4*pi*new_area/perimtr^2
        endfor
Procedure identification (input: metric, output : string)
        if metric > 0.8 then print"string"
        else
        endif
```

FIGURE 3. Algorithm used in retrieving the shape features of an image

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```
Algorithm: Color Extraction
Type color : recond  (Grean, Blue, Red : Integer)
Type color space : record (Hue, Value, Saturation : Integer)
Procedure Segmentation (input RGB : color, output HSV : color space)
Value_Max (R,G,B) : integer
Value_Min (R,G,B) : integer
Read RGB
If (value_max(R,G,B) = R and G>=B) then
        H< 60*((G-B) then
Else
        If(value_max(R,G,B) = G) then
                H < 60*((2+(B-R)/(S*V))
        Else
                If(value_max(R,G,B) =B) then
                        H <60*((4+(R-B)/(S*V))
                Else
                        If (value_max(R,G,B) = R and G < B) then
                                H < 60*((6+(R-B)/(S*V))
                        Endif
                Endif
        Endif
Endif
S < ((value_max(R,G,B))/((value_max(R,G,B))
V < (value_max(R,G,B))
Write HSV
```

FIGURE 4. Algorithm for extracting retinal images based on pattern

Texture feature is an important feature in an image which is information in the form of arrangement of the surface structure of an image. In this study, the *Gray Level Co-Occurrence Matrix* (GLCM) method is used as a matrix to retrieve gray values for an image. The following steps are used in retrieving the texture features of an image, an algorithm for extracting retinal images based on texture patterns as follow,

```
Algorithm: Texture Extraction
Type pixels : Record < R, G, B: integer >
        color      : pixels
        grayscale : pixels
Procedure Gray (Input: color, Output: grayscale ) :
        grayscale ← 0.3289 × R + 0.5870 × G + 0.11j+40 × B
pixelBaru ← setPixel (255,  grayscale.R,  grayscale.G,  grayscale.B )
for i=1 to 16 do
        segmenPixel [ i ] ← pixelBaru [ i ] .grayscale / 16
endfor
{pixel with orientations 0°, 45°, 90° , and 135° }
Value_Pixel [ i     , j+1 ] .grayscale
Value_Pixel [ i+1 , j+1 ] .grayscale
Value_Pixel [ i-1  , j     ] .grayscale
Value_Pixel [ i-1  , j-1  ] .grayscale
Procedure Contrast (Input: Pixel, Output: Value)
for k to kMAX do
        Value[ k ] ← 0
        sum ← 0
        for i to iMAX do
                for j to jMAX do
                        sum ← sum + Pixel [ i , j ]
                endfor
        endfor
        Value[ k ] ← k^2 × sum
endfor
Procedure Correlation (Input: Pixel, Output: Value)
Value ← 0
for i to iMAX do
                for j to jMAX do
                sum ← 1
                sum ← ( ( i – μi )( j – μj ) × Pixel [ i , j ] ) / ( σi ×σj )
                Value ← Value + sum
                endfor
endfor
Procedure Energy (Input: Pixel, Output: Value)
Value ← 0
for i to iMAX do
                for j to jMAX do
                sum ← 1
                sum ← Pixel [ i , j ]  × Pixel [ i , j ]
                Value ← Value + sum
                endfor
endfor
Procedure Homogeneity (Input: Pixel, Output: Value)
Value ← 0
for i to iMAX do
                for j to jMAX do
                sum ← 1
                sum ← Pixel [ i , j ]  / ( 1+ | i – j |  )
                Value ← Value + sum
                endfor
endfor
```

FIGURE 5. Algorithm for extracting retinal images based on texture patterns

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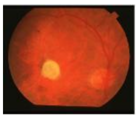
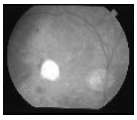
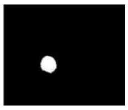
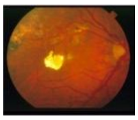
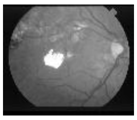
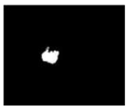
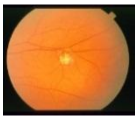
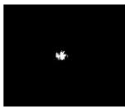
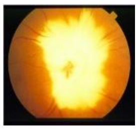
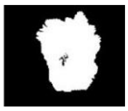
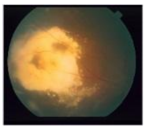
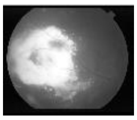
5. RESULTS

Table 1 is the result of enhancement and segmentation processes to identify retinal abnormalities in the human eye. The enhancement process uses a low-pass filter technique because it is useful for removing small noise on objects so that the results of segmentation are better. Then the segmentation phase uses the Otsu thresholding method because this technique is able to automatically select the threshold value so that the foreground separation is perfect. In Table 1, a low light RGB image on the edge of the object is improved by stretching contrast techniques. This technique results in the addition of light to smoother objects and objects. The results of segmentation using the Otsu method, clearly visible in the results of this study the technique is able to distinguish objects with background retina and have noise with grayscale approaching the color of the object so that there is no noise around the object in the segmentation results.

TABLE 1.
The results of the enhancement and the retinal segmentation, RGB image for each type of disease carried out stretching contrast techniques for the process of image enhancement while the segmentation process using the Otsu method

Diseases	RGB image	Results	
		Enhancement	Segmentation
Choroidal Neovascularization			
Branch Retinal Vein Occlusion			
Histoplasmosis			
Myelinated Nerve Fibers			
Coats			

The Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) values are used to show the performance of the image quality improvement process presented in Table 2. PSNR value on contrast stretching is intended for noise information on the image quality improvement. MSE in the stretching contrast information on the mean square error value, if the MSE value is smaller, the better the image quality improvement results, it can be formulated as follows with equation (1) and equation (2):

$$PSNR = 20log_{10}\left(\frac{255}{RMSE}\right) \quad (1)$$

$$MSE = \frac{\sum_{i=1}^{ro}\sum_{j=1}^{co}(I_0^c(i,j)-I_{th}^c(i,j))}{row\ x\ col} \quad (2)$$

where: I_0^c = original image; I_{th}^c= segmented image row x col = Total amount of image rows and columns

Because the higher the contrast of the image, the retinal abnormality object can be segmented properly and vice versa, if the contrast value is low, the object will be difficult to segment, especially on the edges of the object. The results showed that the improvement of the image in Myelinated Nerve disease was the best result from the image of other diseases.

TABLE 2.
The performance of the proposed method is in the process of enhancement and segmentation

Diseases	Parameters	Values(dB)
Choroidal Neovascularization	PSNR	17.0867
	MSE	0.0196
Branch Retinal Vein Occlusion	PSNR	22.5154
	MSE	0.0056
Histoplasmosis	PSNR	12.4245
	MSE	0.0572
Myelinated Nerve Fibers	PSNR	35.4933
	MSE	0.0003
Coats	PSNR	22.2594
	MSE	0.0059

In Table 3 the results of form extraction for retinal abnormalities, there is 1 disorder that has a round shape with a value of 0.89626. In the matrix measurement results below 0.7, the program will recognize a non-round shape like the 4 retinal abnormalities above. The results of the calculation of parameter values for form extraction can be seen in Figure 6.a. For color extraction is not so different from form extraction, which is detected is a macula object. But, in Coats color retinal abnormalities that are extracted exceeds the shape pattern object, because lighting spreads outside the object, this is due to poor enhancement stages.

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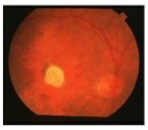
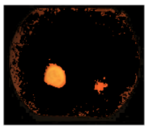
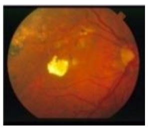
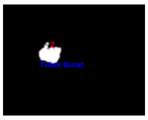
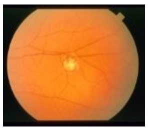
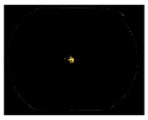
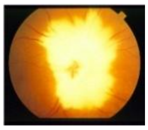
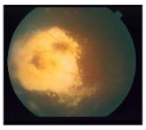
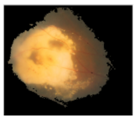
TABLE 3.
The results of feature extraction based on shape and color, retinal image of each type of disease are extracted with algorithms designed

Diseases	RGB image	Shape Extraction	Color Extraction
Choroidal Neovascularization			
Branch Retinal Vein Occlusion			
Histoplasmosis			
Myelinated Nerve Fibers			
Coats			

Histogram of an image is a graphical representation of the color distribution of digital images that can describe pixel intensity values and the results obtained from color feature extraction, namely retinal abnormalities of Branch Retinal Vein Occlusion and Histoplasmosis have numbers of Red Max, Green max, and Blue max quite large compared to the three other diseases, 42000 to 43000 pixels, this can be seen because the color of the disease is more striking and a smaller area than the other three diseases. While Choroidal Neovascularization disease, Myelinated Nerve Fiber, and Coats have different color characteristics with large sizes so that it can be seen in the values of Red Max, Green Max, and Blue Max having pixel values of 20000 to 26000, the color extraction graph is presented in Figure 6.b.

In texture analysis, orientation is formed in four angular directions with angular intervals of 45° that is 0°, 45°, 90°, and 135°. While the distance between pixels is usually set at 1 pixel. The results of the texture extraction calculations for each angle orientation and different parameters are presented in Table 4.

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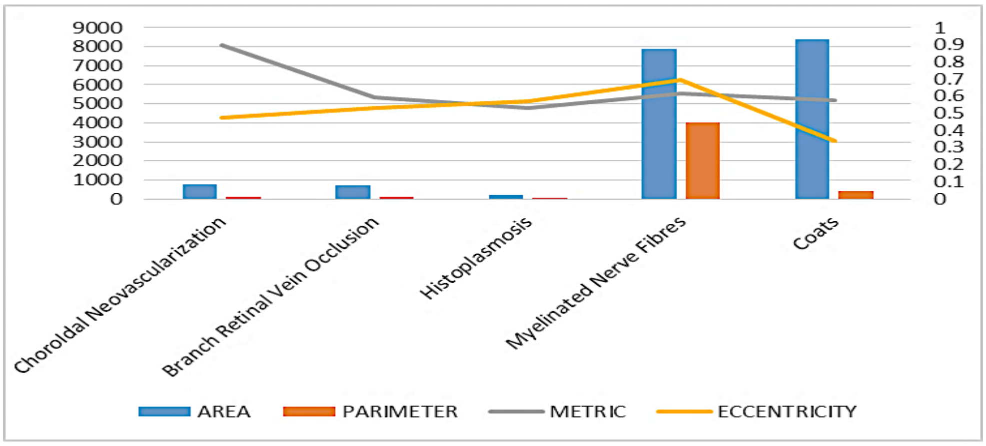
TABLE 4.
Feature extraction results based on texture with 4 different orientations for θ= 0 °, θ = 45 °, θ = 90 °, and θ = 135 °, with a radius of δ = 1, retinal image of each type of disease extracted by an algorithm designed

No.	Diseases	Texture Feature					
			0^0	45^0	90^0	135^0	Average
1	Choroidal Neovascularization	Contrast	0.0211	0.0277	0.0189	0.0281	0.0239
		Correlation	0.9724	0.9639	0.9754	0.9634	0.9688
		Energy	0.5992	0.5939	0.5992	0.5936	0.5965
		Homogeneity	0.9895	0.9862	0.9906	0.9859	0.9880
2	Branch Retinal Vein Occlusion	Contrast	0.0459	0.0601	0.04178	0.0637	0.0528
		Correlation	0.9847	0.9799	0.9861	0.9788	0.9824
		Energy	0.3755	0.3697	0.3784	0.3677	0.3728
		Homogeneity	0.9771	0.9704	0.9792	0.9687	0.9738
3	Histoplasmosis	Contrast	0.0367	0.0529	0.0392	0.0529	0.0455
		Correlation	0.9774	0.9674	0.9759	0.9674	0.9720
		Energy	0.3048	0.2956	0.3037	0.2953	0.2999
		Homogeneity	0.9817	0.9735	0.9804	0.9735	0.9773
4	Myelinated Nerve Fibers	Contrast	0.0393	0.0554	0.0386	0.0543	0.0469
		Correlation	0.9918	0.9883	0.9919	0.9885	0.9901
		Energy	0.3013	0.2981	0.3018	0.2985	0.2999
		Homogeneity	0.9808	0.9738	0.9814	0.9743	0.9776
5	Coats	Contrast	0.0344	0.0526	0.0373	0.0486	0.0432
		Correlation	0.9943	0.9913	0.9938	0.9919	0.9928
		Energy	0.1880	0.1823	0.1864	0.1835	0.1850
		Homogeneity	0.9832	0.9743	0.9813	0.9762	0.9788

From the results, risk parameters of the GLCM statistical feature calculation indicate that the average values of the five retinal images show the same response, starting with the Contrast parameters of the five retinal diseases such as Choroidal Neovascularization, Branch Retinal Vein Occlusion, Histoplasmosis, Myelinated Nerve Fibers and Coats which have an average value 0.0239, 0.0528, 0.0454, 0.0469 and 0.0432. Five retinal diseases had an increase with an average value of 0.9. Energy parameters of the five retinal diseases decreased with mean values of 0.5965, 0.3728, 0.2999, 0.2999 and 0.1850. While the homogeneity value of the five retinal diseases also increased with an average value of 0.9. Figure 6c. shows a graph of the measurement results of the texture extraction parameters.



(a)

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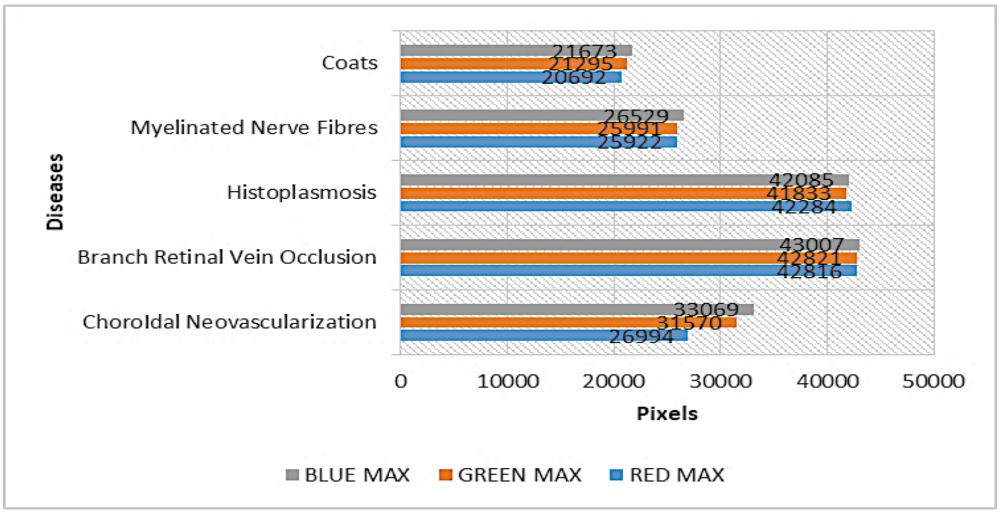
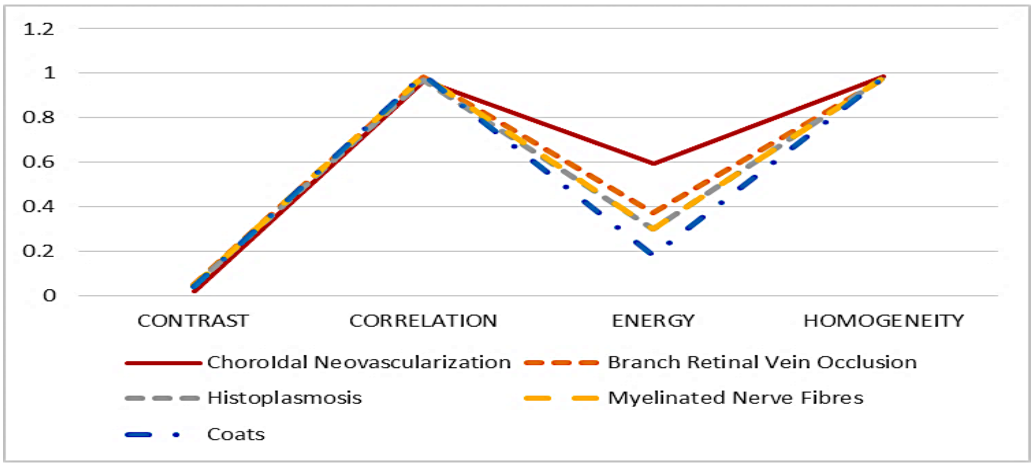


(b)



(c)

FIGURE 6. Graph of measurement of extraction parameters, a. shape extraction, b. color extraction, and c. texture extraction by comparing the extraction results with the reference image.

The metrics in contingency tables are usually used to measure the performance of an algorithm. The measurement of sensitivity values, specifications, and accuracy are the most frequently used. In this study, the new function was proposed [24] called Quality Evaluation Function (QEF). The functions of connectivity, area, and length of blood vessel extraction are the functions measured by QEF. Evaluate the function Denoting S as an image of the segmentation results that will be evaluated and S_G is a reference image, defined in the interval [0, 1]. The evaluation function is in accordance with Equation (3) as follow;

$$f(C, A, L) = C * A * L \qquad (3)$$

Measurement of the success or failure rate with this metric is obtained by comparing the pixels between the segmentation results automatically with manually labeled reference image pixels (ground-truth). Therefore, pixel pixels with special features such as vessels become not part of the vascular structure. This function evaluates the characteristics of the vascular structure as a connected segment into area and length measurements.

The purpose of evaluating this QEF function is using the Stare dataset. This dataset provides 20 retinal images resulting from two manual segmentations obtained from two different specialist experts so that it is possible to compare between images labeled by human observations with automatic segmentation results. The manual segmentation image performed by the second observer is accepted as a reference image by many literature, in this study is used as a reference image and the dataset produced by the second observer is used as a result of segmentation that will be evaluated. Area parameter values are calculated by the average approach of the last 15 images of 20 first observer segmentation images. The same procedure is also done to calculate the length and connectivity parameters.

TABLE 5.
The Comparative performance of blood vessel segmentation methods in retinal images from the Stare dataset

Methods	Connectivity	Area	Length	C*A*L
Manual	0.9998	0.8476	0.8600	0.7288
[25]	0.9986	0.7828	0.8007	0.6259
[26]	0.9914	0.7903	0.8082	0.6332
[11]	0.9992	0.8238	0.8375	0.6893
our method	0.9585	0.8271	0.8109	0.7132

Evaluation of the quality of blood vessel segmentation in the retina is automatically carried out with the mathematical function of the distortion between the results of the segmentation and the proposed method and the reference image of the ground truth. The segmentation result image by the observer has a high subjective value caused by the difference in the label results given by the expert on an image, especially occurs in the observation of narrow and smooth vessels. The result of QEF measurements for vessel segmentation for STARE datasets and compared with the results performed [25], [26] and [11] presented in Table 5. This result shows that the proposed segmentation method produces the highest QEF.

Table 5 shows the performance of the segmentation results from the proposed method with the Stare dataset as test data. The CAL calculation results reach a value of 71.32% which is a higher result than the previous methods with the same dataset and mathematical functions. In the table, the results of segmentation carried out by Zhang and Nguyen are still lower because the results of vessel segmentation are still incorrect in determining blood vessels, while the results obtained from Yin occur broken pixels. The segmentation results of thin and wide vessels for the proposed method is get better results compared to the three methods. For some cases, the proposed method’s ability which was extracting thin vessels is get more results and provides a more accurate vascular structure, although there are many extraction errors in the area around the pathologies. Exudation and bright lesions cause visualization of features that will complicate determination of vessels.

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6. CONCLUSION

Image of retinal eye abnormalities is carried out enhancement and segmentation processes, then the image is reprocessed using feature extraction method to get the final information. Area, perimeter, metric and eccentricity values of human eye retinal abnormalities from the extraction process feature the shape and size of retinal abnormalities. The maximum values of red, green and blue levels are obtained from the extraction of color features while the extraction of the texture results in the value of the parameters of contrast, correlation, energy, and homogeneity. The improved image on Myelinated Nerve Fiber disease is the best result from the image of other diseases with a value of the PSNR of 35.4933 dB and MSE of 0.0003 means that the technique is able to repair objects well. Testing of segmentation results shows the improvements based on the proposed method compared to other methods.

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