I.J. Image, Graphics and Signal Processing, **2022, 1, 26-39**
Published Online February 2022 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijigsp.2022.01.03

A Novel Approach for Early Detection of Neovascular Glaucoma Using Fractal Geometry

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Received: 17 November 2021; Revised: 14 December 2021; Accepted: 02 January 2022; Published: 08 February 2022

Abstract: Neovascular glaucoma (NVG) is a human eye disease due to diabetes that leads to permanent vision loss. Early detection and treatment of it prevent further vision loss. Hence the development of an automated system is more essential to help the ophthalmologist in detecting NVG at an earlier stage. In this paper, a novel approach is used for detection of Neovascular glaucoma using fractal geometry concepts. Fractal geometry is a branch of mathematics. It is useful in computing fractal features of irregular, asymmetrical, and complex natural objects. In this work, fractal feature-based Neovascular glaucoma detection from fundus images has been proposed. It utilizes the image adjustment enhancement technique as a preprocessing method to improve the accuracy of NVG detection and the box-counting technique of Fractal geometry to estimate the fractal dimension. The proposed system is tested over MESSIDOR and KMC datasets and yields an average accuracy of 98%.

Index Terms: Glaucoma, Fractal Dimension (FD), Box Counting, Segmentation, Texture Features, Retina.

1. Introduction

According to ophthalmology, Glaucoma is a neurodegenerative disease concerned with the human eye. The main cause of glaucoma is the loss or death of retinal ganglion cells and their axons. Continuous loss of retinal ganglion cells leads to permanent vision loss. Glaucoma is primarily classified into two categories as primary glaucoma and secondary glaucoma. Further, Primary glaucoma is classified into two types as open-angle and angle-closure glaucoma. The most commonly found glaucoma is open-angle glaucoma and it is due to structural damage to the optic nerve head and visual abnormalities. Structural damages in the optic disc of an eye are mainly because of loss of optic nerve fiber layers, thinning of the neuroretinal rim, and continuous cupping of the optic disc. The main cause for Angle Closure Glaucoma is due to blockage of the aqueous fluid to the trabecular meshwork because of forwarded iris. This leads to a rise in intraocular pressure. The sudden increase in pressure causes damages to the optic nerve head which leads to Angle Closure Glaucoma.

The main causes for secondary glaucoma are eye injury, tumor, and inflammation. Other reasons are diabetes, consumption of certain drugs such as steroids, and advanced contrast. Diabetes is the primary cause of glaucoma and according to Wild et al. [1], the diabetic patients in the universal raised from 171 million to 366 million by 2030 with an extreme increase in India. Therefore it is important to develop a feasible method to detect secondary glaucoma called Neovascular Glaucoma in the early stage to prevent further vision loss. Proposed work presents the early detection of Neovascular glaucoma and it works on the box-counting fractal dimension method to detect the NVG using fundus images. The box-counting method calculates the fractal dimension (FD) by constructing the slope of the line. “The slope of the line estimated by plotting the value of log(N) on the Y-axis against the value of log(r) on the X-axis. The same equation is used to define the fractal dimension (FD). Where, N is the number of boxes that cover the pattern, and r is the magnification or the inverse of the box size.”

Xiao hui Zhang et al. [2] used the Fuzzy C-Means approach to improve the segmentation step to detect the optic disc part using fundus images. The SVM classifier is used to classify the image into three levels. They are no Diabetic retinopathy (DR), mild DR, and severe DR. The proposed method includes three steps: Image preprocessing, retinal structure extraction, and features classification. In image preprocessing, Fuzzy Filtering is performed on green channel to increase the quality of the image. The second step focused on the detection of OD, blood vessels, macula, and fovea from retinal fundus images. Finally, the authors performed feature classification using machine learning algorithms. Classification algorithms used in the proposed method are SVM Naive-Bayes, RBF Kernel, k-NN, polynomial Kernel SVM and achieved the accuracy 0.75, 0.93, 0.93, 0.93, and 0.7 respectively

Jôrg Meier et al. [3] developed an approach to detect glaucoma using Principal component analysis (PCA) using fundus images. Steps proposed in this approach are the non-uniform illumination correction, blood vessels in painting, and the RoI normalization. The PCA extracts the features from the RoI then calculated features are submitted to the support vector machine for classification. The accuracy achieved by the method is 81%. Mvoulana et al. [4] established a computerized glaucoma detection technique. The system works on template matching and brightness criterion techniques. These techniques detect the optic disc as RoI and segment the OD from the image. The clinical parameter cup to disc ratio (CDR) is calculated to classify the glaucomatous and healthy patients. The authors used the binary classifier for image classification and the performance of the proposed method is evaluated on the DRISHTI-GS1 dataset. The method achieved the 98% of accuracy on DRISHTI-GS1dataset. Like CDR, there are some parameters to identify glaucoma, and these parameters are estimated by using image processing techniques [12-16].

Mookiah et al. [5] established an automatic glaucoma detection technique called AMD detection system. Steps involved in the approach are the acquisition of fundus image, image preprocessing, Discrete Wavelet Transform (DWT), features extraction, features ranking, features selection, and classification. The authors, Ayushi Agarwal et al.[6], proposed the method to calculate the rim to disc ratio and cup to disc ratio from retinal fundus images. Steps involved in the identification of glaucoma disease are RoI extraction, Red channel extraction, optic disc extraction, optic cup extraction, NRR calculation, cup to disc ratio calculation, and the rim to disc ratio calculation. The authors used the images collected from the Venu eye research center, New Delhi. The accuracy obtained from the proposed method is 90%. The cup and disc parts are segmented using threshold values calculated by the following formula

Tdisc=1.2*sum(mean, SD) and Tcup=1.25*(Tdisc)+diff(mean, SD)

The authors calculated the CDR value by computing the disc and cup area and used CDR in glaucoma detection.

R. Ali et al.[7], presented fuzzy broad learning system-based technique for glaucoma identification. The authors considered the fundus images to detect glaucoma. Glaucoma assessment based on Optic Disc and Optic Cup extraction. Steps involved in the approach are a region of interest extraction, red-green, and blue channel images extraction, segmentation of OD and OC using red and green channel images. The authors used the fuzzy broad learning system-based neural networks for OD and OC extraction and finally calculated CDR. Sreemol S et al [8], proposed the method to extract the texture features and VCDR calculation using the Gabor filter. The proposed computer-aided diagnosis system is simulated on HRF and DRISHTI GS1 datasets using Python 3. The accuracy is evaluated using classifiers Logistic regression, Random forest SVM, and KNN.

A. S. Ghorab et all [9], proposed the new algorithm for finding glaucoma in fundus eye images. Proposed method extracted the optic nerve head from retinal images to calculate the cup to disc ratio (CDR), and the ISNT ratio. Results obtained from the proposed method illustrated that the average sensitivity for optic disc extraction is 94% while for the optic cup is 83%. The average specificity for the optic disc extraction and for an optic cup is 96%. The authors tested the ISNT ratio using a t-test and obtained the significant feature. F. Z. Zulfira et al [10], developed the active contour snake based approach to multi-class glaucoma detection. The proposed method estimated the optic disc and optic cup area values to measure the CDR. A support vector machine (SVM) algorithm is used to classify the images into glaucomatous and non-glaucomatous. The proposed method evaluated 210 retinal fundus images and achieved accuracies of 95%. M. Aljazaeri et al [11], established a deep learning method to estimate the CDR for the finding Glaucoma. The developed method used the Self-attention and Atrous Convolution mechanisms for image regions extractions. The authors evaluated the method on the REFUGE dataset.

This work presents the most relevant contributions from a health psychology perspective for the assessment and treatment of Neovascular glaucoma, which is emerging in the field of psycho-ophthalmology. This work presents the following contributions to ophthalmology field.

1. Using proposed method ophthalmologist can detect Neovascular glaucoma at the earlier stage
2. Introduced new clinical parameter called fractal dimension to diagnose Neovascular glaucoma
3. Illustrated how to use mathematical concepts in health care technology

2. Methodology

The detection of Neovascular glaucoma using the fractal geometry is a new research area in the field of ophthalmology. From literature survey it is found that accuracy of most of the existing approaches is very less. This motivates to develop the new approach. Figure 1 shown below represents the flow chart of proposed system. It describes the estimation of FD and feature extraction from healthy and unhealthy retinal images for early detection Neovascular Glaucoma. Initially red, green and blue channels are extracted from the color input image. Red and green channel images are used to estimate the FD values from complete retinal image and blood vessels respectively. Blue Channel is not considered due to the lower blue components in the color image. The fuzzy C means clustering algorithm is applied on Green Channel image to extract the blood vessels. Later, FD is calculated using Box Counting method. On the other side, texture features and FD are extracted from the red channel image.

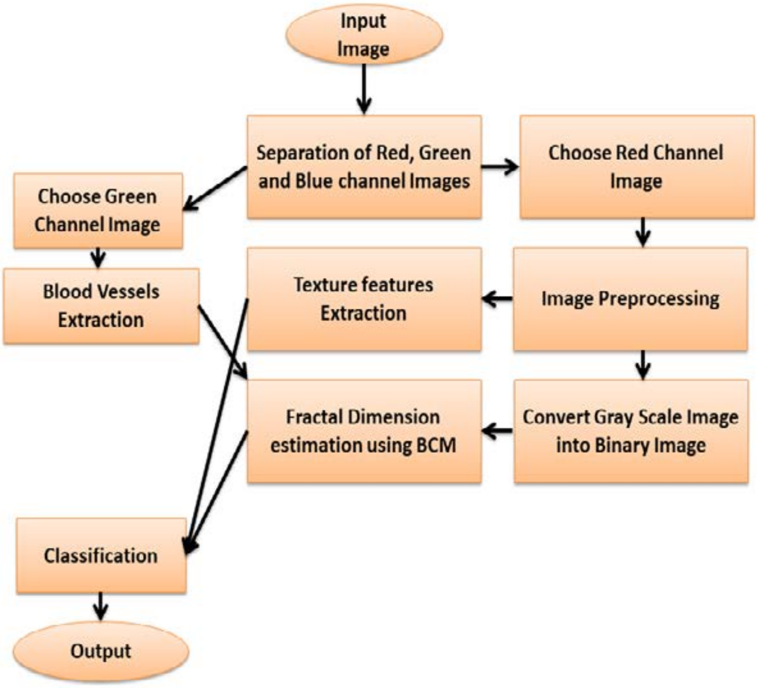


Fig.1. A flow chart of Proposed System.

2.1. Fractal dimension estimation from retinal fundus image

The input color image is resized to 512X512 pixels to standardize the process. The RGB channels are extracted from the resized image to select the red channel image for further processing because it has high intensities compared to other two channel images. These intensities support the identification of percentage of affected area in the retina. The red channel image is converted into grayscale image. Later, grayscale image is converted into binary image by applying the specified threshold value. Range of threshold values from 0.2 to 0.35 with the difference of 0.05 are consider for evaluation of algorithm for both NVG and healthy. If the pixel is greater than the threshold value (on 0 to 1 scale) then pixel in the binary image is white or value 1 otherwise pixel is set to black or value 0.

Algorithm 1 Algorithm for FD Estimation and Texture Features Extraction from Retinal fundus image

Input : Color Retinal fundus image, I
Threshold values, T=[0.20,0.25,0.30, 0.35]

Output : Average FD Value, Contrast, Energy, Entropy, Homogeneity, Kurtosis, Mean, RMS, Skewness, SD, Variance

1: Read Retinal fundus image, I
2: Separate the Red (R), Green(G) and Blue (B) Channels from I
3: Choose the Red Channel Image, R
4: Preprocess R using normalization to remove noises
5: Initialize T=0.2 as initial threshold value and Initialize array A to empty
6: **for** T $\leq$0.35 **then**
7: Convert R to binary image, B
8: Calculate FD using Box counting Method
9: Add the calculated FD value to array A
10: Add 0.05 to T
11: Go to step 6

12: **end for**
13: Estimate mean of FD using the array values
14: Extract the texture features: Contrast, Energy, Entropy, Homogeneity, Kurtosis, Mean, RMS, Skewness, SD, Variance

2.2. Frctal dimension estimation from blood vessels of retinal fundus image

The green channel is chosen for blood vessels extraction from input image because it has highest contrast in blood vessels areas compared to other two channels. The Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied on green channel image to increase the contrast of image which in turns supports the better detection of blood vessels in later stages. The CLAHE algorithm combines the neighboring tiles to remove the artificial boundaries present in the image using bilinear interpolation. The Morphological Open operations 1) Structuring Element with ball of radius 8 and height 8 is used to remove optic disc from the image. 2) Structuring Element with disk of radius 100 is applied on median filtered-disc removed image to eliminate Background. Finally, Fuzzy C-means algorithm is used to extract the blood vessels from the image.

Algorithm 1 Algorithm for FD Estimation from blood vessels
Input : Color Retinal fundus image, I
Output : FD Value

1: Read Retinal fundus image, I
2: Separate the Red (R), Green(G) and Blue (B) Channels from I
3: Choose the Green Channel Image, G
4: Apply CLAHE algorithm on G to get Cimage
5: Apply Morphological Open Operation on Cimage using strel('ball',8,8) to get OpenCimage
6: Subtract Cimage from OpenCimage to obtain Optic Disk removed image Nodisc
7: Generate Background image, Bimage, by applying Morphological Open Operation strel('disk',100) on Nodisc image
8: Subtract Nodisc from Bimage to obtain No Background image, NoBimage
9: Apply Fuzzy C-means algorithm on NoBimage to generate BloodVesselimage
10: Calculate FD using Box counting Method on BloodVesselimage

3. Results and Discussion

The proposed method evaluated on Messidor and KMC Database images. Messidor Database has 1200 images with dimensions of 1440*960, 2240*1488 or 2304*1536 pixels acquired by 3 ophthalmologic departments. KMC (private) dataset has 24 images with dimensions of 1440*960 pixels. Messidor database has 400 healthy images and 800 neo vascular images. The hospital dataset has 12 healthy images and 12 neo vascular images. All Images are converted into binary images of size 512 × 512. Algorithms are implemented and tested on database images. Results obtained from the method are two binary images which are generated from the red channel and green grayscale images. Figure 2 a) Illustrates the important anatomical structures present in the retinal image [19-20]. Figure 2 b) Illustrates the healthy fundus image (blood vessels are clear). Figure 2 c) illustrates the neovascular image (blood vessels are damaged due to diabetes). Figure 2 d) shows the Histogram of healthy retina. It is not uniform due to randomly distributed pixels. X-axis represents pixels that set of values which the measurements fall under. The Y-axis represents number of times that the values appeared within the pixels. Figure 2 e) shows the Histogram of neovascular image. The abnormal growth of blood vessels in retinas introduces the maximum red components in image and maximum pixels are belongs to specified range. Therefore, histogram is almost uniform in NVG images.

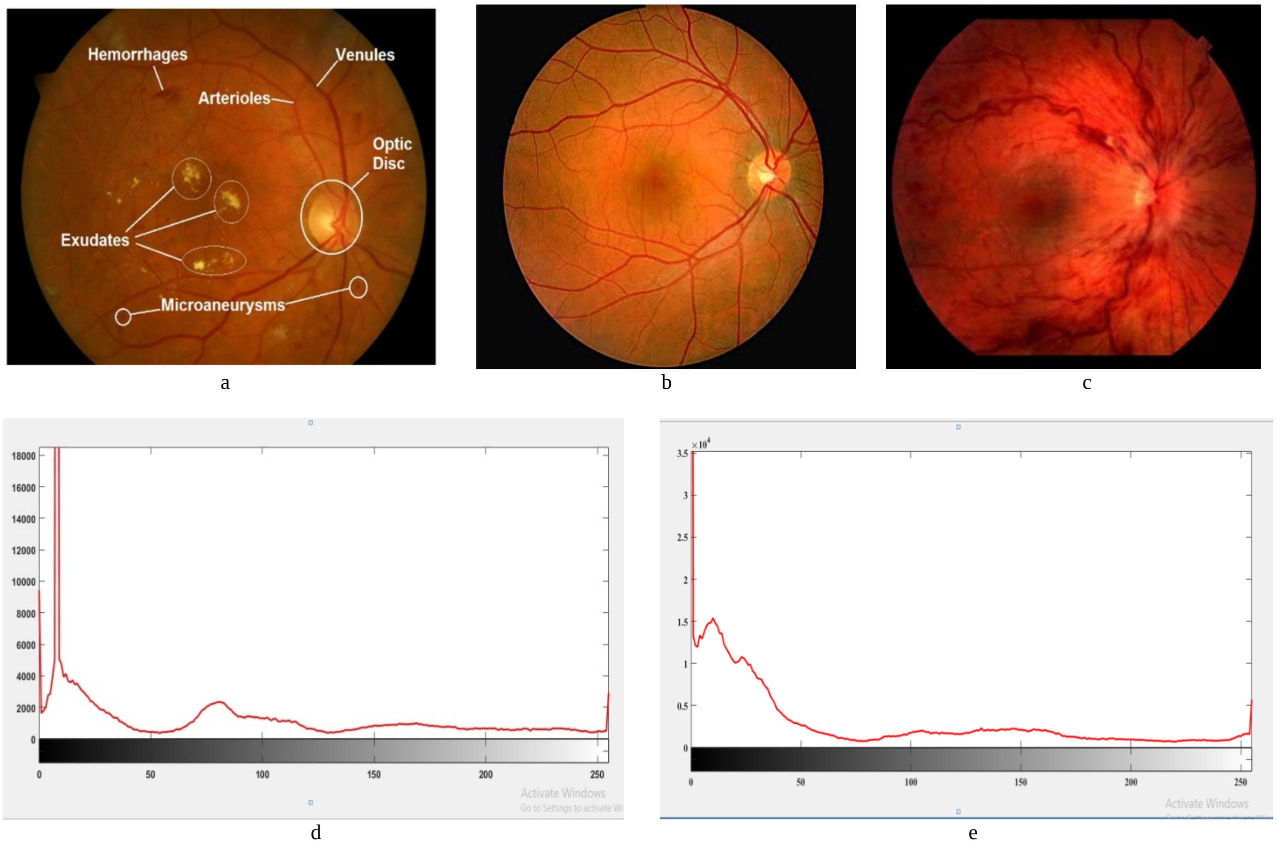
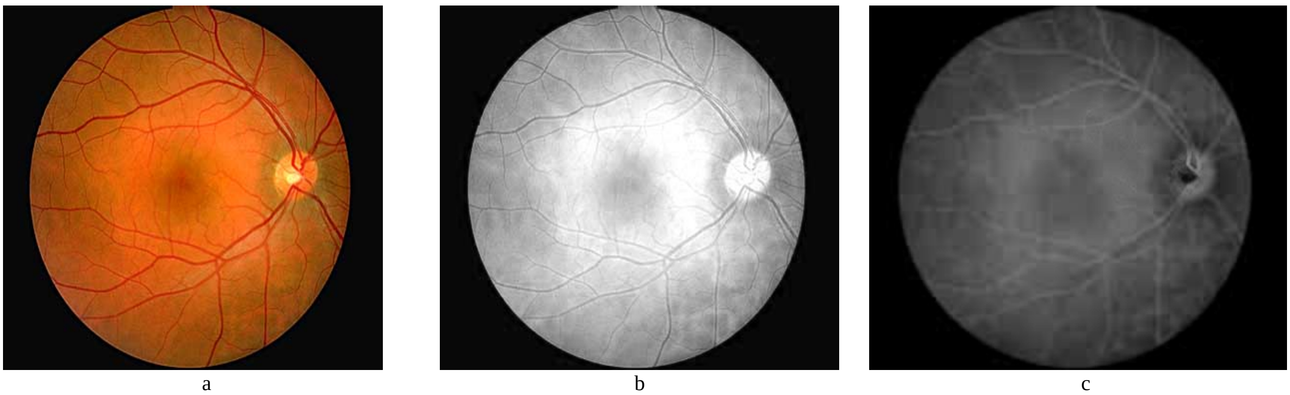


Fig. 2. Input Images and Related Information.

3.1. Fractal dimension estimation from retinal fundus image

Figure 3 illustrates the process of conversion of RGB image to grayscale image, grayscale to binary and calculation of FD using Box Counting method. Steps involved in the estimation of FD values are (a) provide fundus image to software as input. (b) Extract the red channel image. (c) Preprocess the red channel image using normalization method. (d) Generation of binary image using simple thresholding method with threshold value of 0.25. (e) FD value estimation by considering slope of plot log(# boxes) vs log(pixel length). Figure a, b, c, d, and e represents the outputs generated from proposed method on healthy fundus image. Figure f, g, h, i and j represents the same process as a, b, c, d, and e respectively on NVG images.



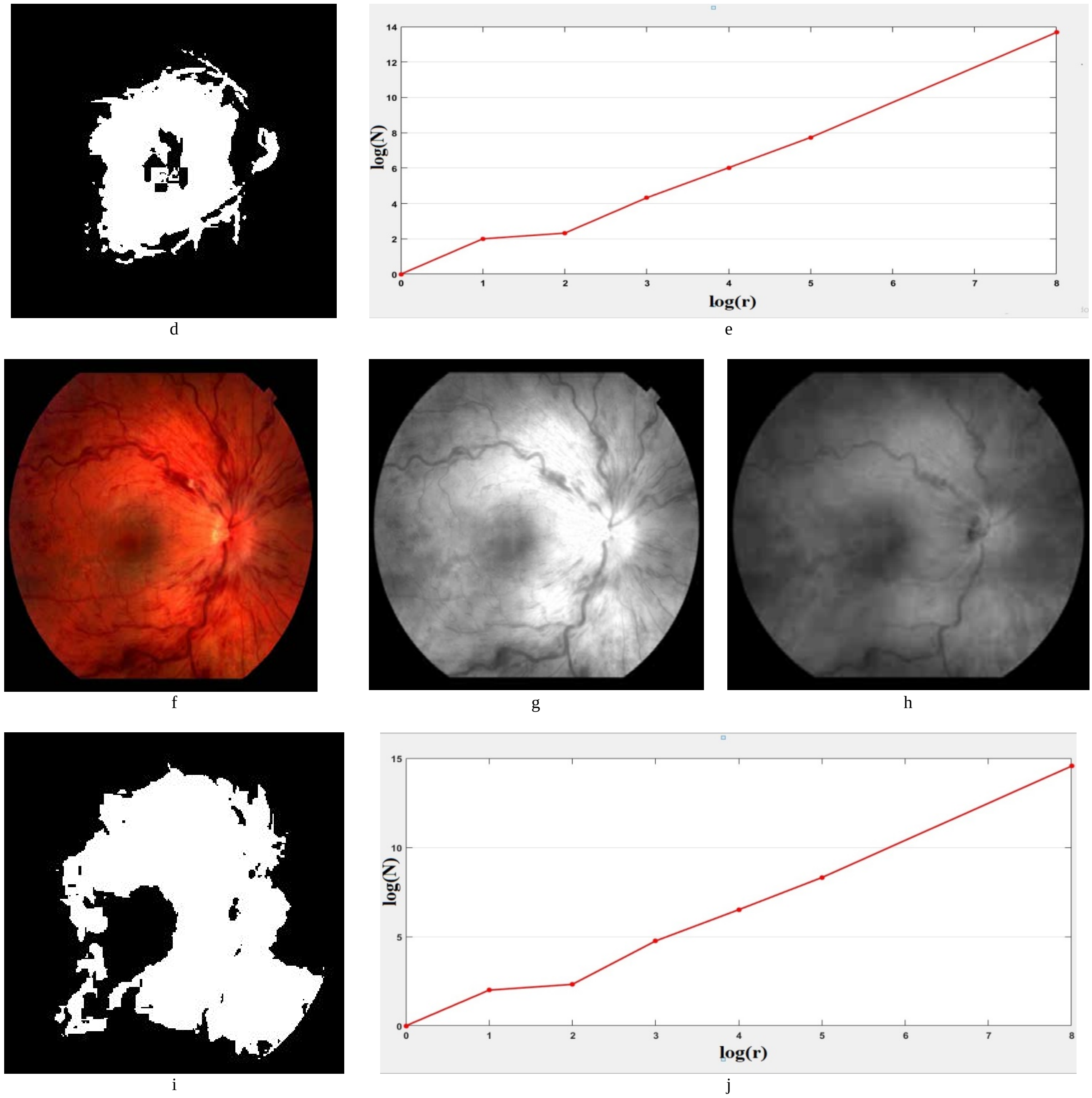


Fig.3. FD Calculation from Retinal Fundus images.

Similar process is carried out for 4 different threshold values, for each threshold value the box counting method is executed 5 iterations by considering the side lengths 2, 4, 8, 16 and 32. For side length 2 image is divided into 2X2=4 blocks. Same is applied to side lengths 4, 8, 16 and 32. The plot is drawn as shown in figure 3 (j) by considering the side lengths and number of boxes occupied the white areas. The obtained FD values are tabulated as shown in the table 1. The graph is plotted for 5 iterations results and obtained FD values. It shows that FD values decreases with increases in threshold values because of increase in similarity among pixels due to the highest threshold value. Finally, mean is computed for all four cases and tabulated in Table 1. The mean FD obtained for healthy retina and NVG images (shown in figure 3 (a) and (f)) are 1.5502 and 1.7869 respectively. Same operations are carried out on remaining healthy and NVG retinal images. Obtained mean FD is in the range of 1.06 to 1.62 for healthy image and above 1.62 for NVG images.

Table 1. Mean FD Values for Retina images with Different Threshold Values

SL. No	Cases	Threshold Values	Healthy Retina FD Values	NVG FD Values
1	Case1	0.20	1.9121	1.9058
2	Case2	0.25	1.7300	1.7900
3	Case3	0.30	1.3389	1.7459
4	Case4	0.35	1.2198	1.7059
Mean		0.275	1.5502	1.7869

Results obtained from the proposed method are illustrated in Figure 4. Figure 4 (a) illustrates the FD values obtained on healthy images of Messidor Database and Figure 4 (b) illustrates the FD values obtained on NVG images of Messidor Database. The Table 2 illustrates the mean Fractal Dimension and Margin of Error calculation on Messidor and KMC datasets. From Table 2, it is observed that Feasible FD value of Healthy Retina is range from 1.30±0.04977 to 1.40±0.04977 and NVG range from 1.7±0.02358 to 1.8±0.02358.

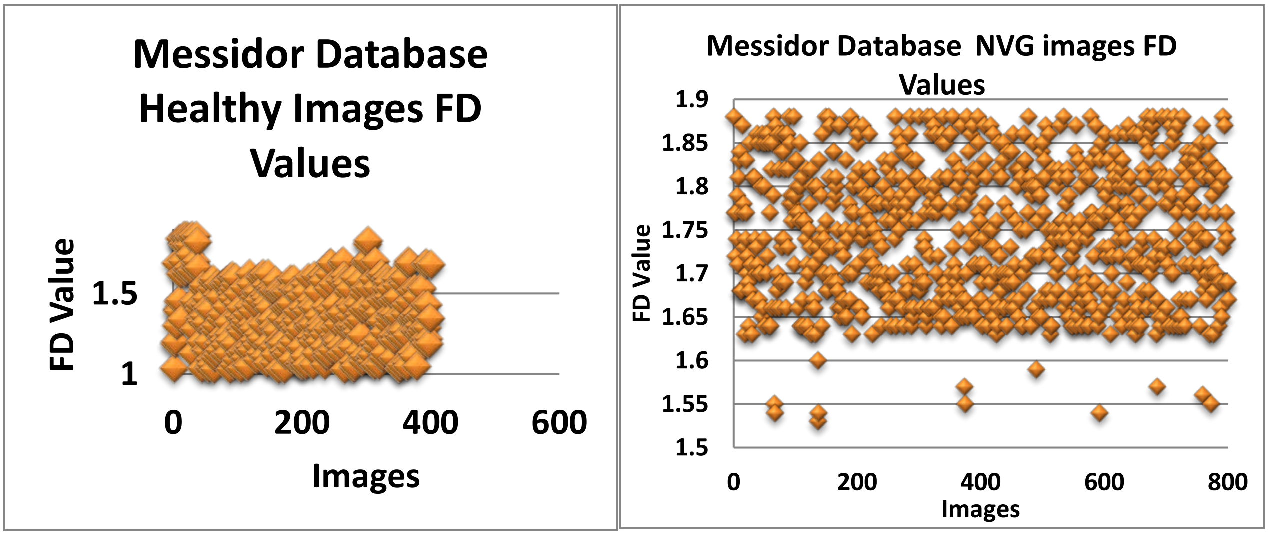
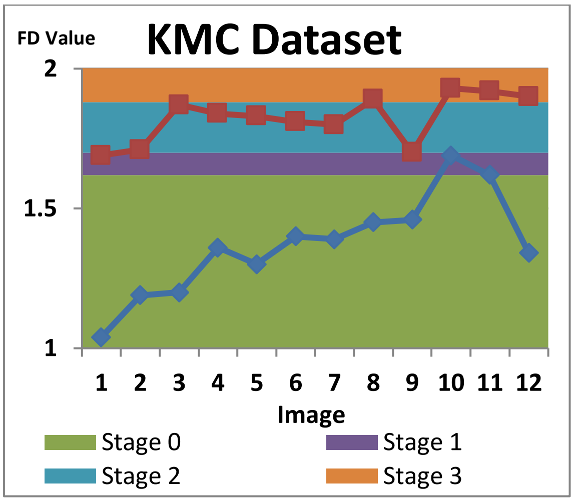


Fig.4. FD values of Messidor dataset Retinal Fundus images.

Table 2. Mean FD Values and Margin of Errors calculation for Retina images for Messidor and KMC Datasets

SL. No.	Parameter	Non-NeoVascular Glaucoma/Healthy Images		NeoVascular Glaucoma Images	
		Messidor Dataset	KMC Dataset	Messidor Dataset	KMC Dataset
1	Count, N	400	12	800	12
2	Sum, Σx	534.78	16.44	1398.5	21.89
3	Mean, μ	1.33695	1.37	1.74812	1.82416
4	Variance, σ2	0.03344	0.02973	0.00617	0.00667
5	Standard Deviation, σ	0.18286	0.17243	0.07855	0.08169
6	Margin of Error $\sigma_{\bar{x}} = \sigma/\sqrt{N}$	0.00914	0.04977	0.00277	0.02358

From the results, it is noticed that out of 400 healthy images in Messidor Dataset, 360 are identified as healthy, and out of 800 neovascular images, 788 identified as neovascular glaucoma. In KMC Dataset, out of 12 healthy images, 11 are identified as healthy, and out of 12 neovascular images, 12 identified as neovascular glaucoma. FD values and corresponding NVG stage of all images are illustrated in the graphs shown in the figure 5 and possible stages identified by the ophthalmologist are healthy, mild, medium, and severe. Considering FD values, images are classified into the healthy retina (Stage 0), mild NVG (Stage 1), medium NVG (Stage2), and severe NVG (Stage 3). From the Figure 5, it is observed that FD is less than 1.62 denoting stage 0, for stage 1 FD is in between 1.62 to 1.70, for stage 2 FD is in between 1.70 to 1.88, and for stage 3 FD is greater than 1.88. Mean and Standard Deviation (SD) values are also calculated on databases. For healthy retina obtained mean value is 1.3358 and Standard Deviation value is 0.1833. For Healthy images, FD is ranges from 1.06 to 1.62, whereas for neovascular glaucoma, FD is above 1.62. Table 3 illustrates mean values of Texture Features extracted from the image. Later, these features are used in artificial neural network (ANN) algorithm to classify the image. By observing the obtained Texture Features values, it shows that these Features help in the identification of NVG.



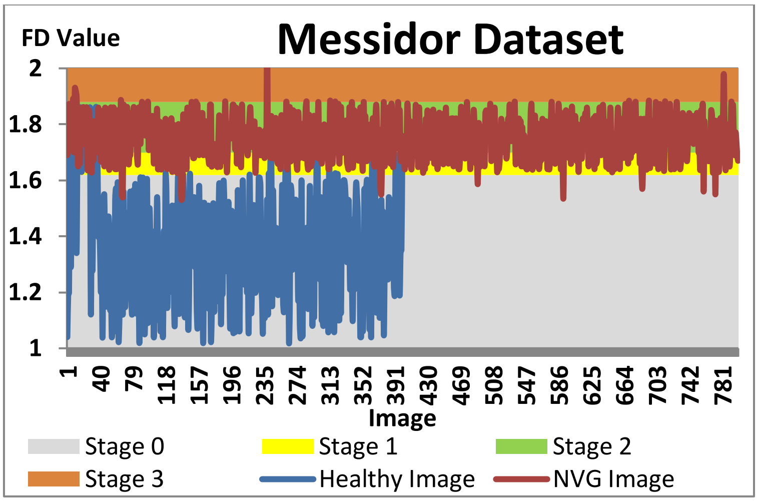


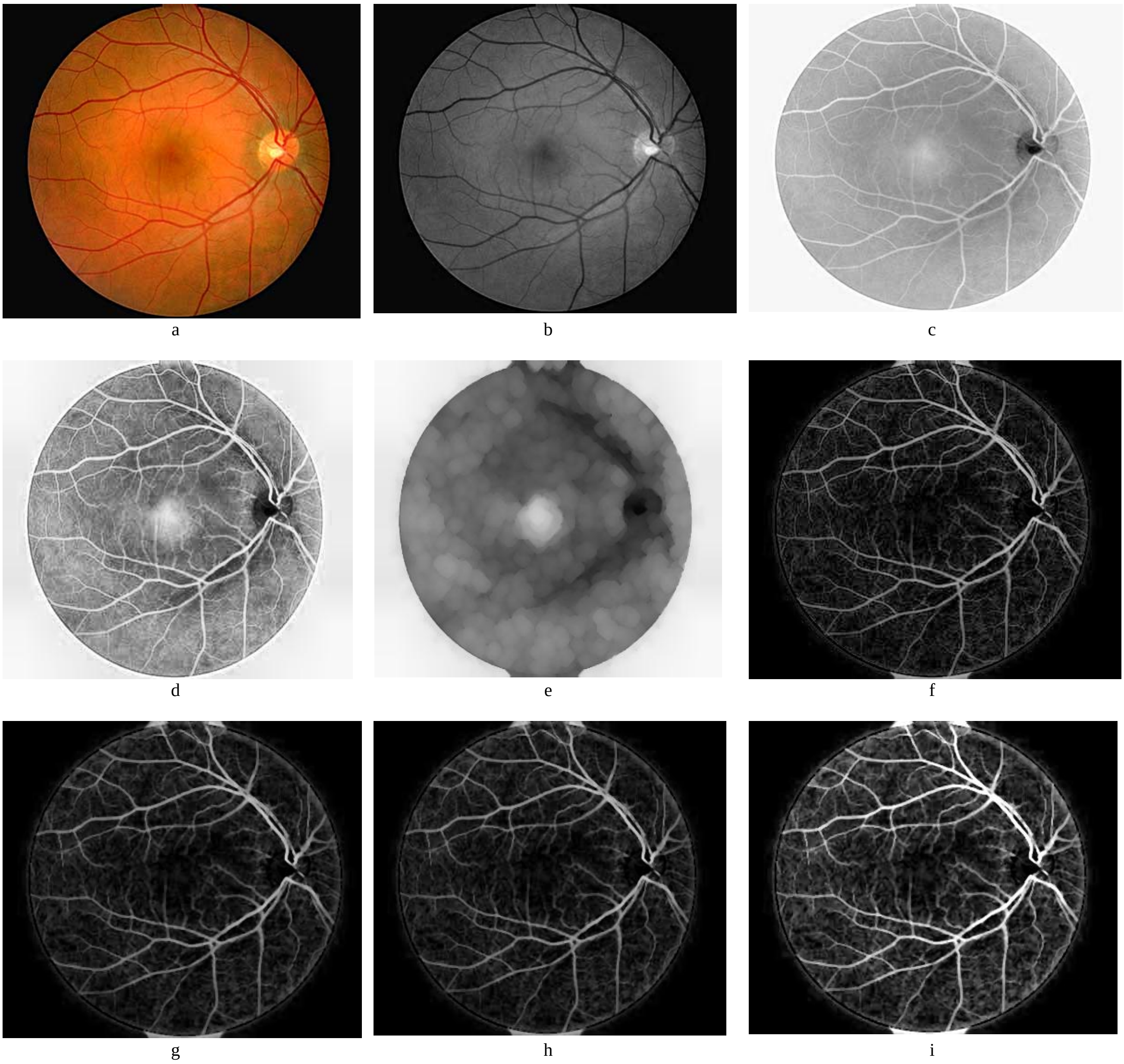
Fig.5. Stages of NVG.

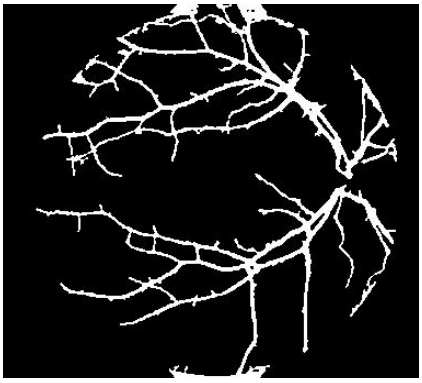
Table 3. Texture Features Extracted from Retinal images of Messidor and KMC Datasets

SL. No.	Texture Features (Average)	Healthy Images		NeoVascular Glaucoma Images	
		Messidor Dataset	KMC Dataset	Messidor Dataset	KMC Dataset
1	Count	400	12	800	12
2	Contrast	0.11±0.04	0.14±0.04	0.03±0.04	0.03±0.04
3	Correlation	0.95±0.02	0.99±0.02	0.98±0.02	1.00±0.02
4	Energy	0.22±0.04	0.28±0.04	0.29±0.04	0.35±0.04
5	Entropy	6.00±0.4	9.00±0.4	6.80±0.4	9.60±0.4
6	Homogeneity	0.94±0.1	1.24±0.1	0.98±0.1	1.31±0.1
7	Kurtosis	2.40±0.3	2.80±0.3	1.90±0.3	2.40±0.3
8	Mean	67±6	72±6	82±6	86±6

3.2. Fractal dimension estimation from blood vessels of fundus image

The process of extraction of blood vessels from fundus image and calculation of FD using Box Counting illustrated in Figure 6. Steps involved in the estimation of FD values are (a) provide color fundus image to software as input (b) extract the green channel image (c) complement the green channel image. The complement of a grayscale is obtained by subtracting each pixel (intensity) from the maximum intensity supported by the class to increase the contrast level. (d) Apply CLAHE to complemented image to improve the contrast of the grayscale image by changing the values. (e) Apply Morphological Open operation on CLAHE generated image to identify the optic disc part in the image. (f) Remove Optic Disk by subtraction Morphological Open operation generated image from CLAHE generated image. (g) apply 2D Median Filter on disc removed image to remove noises from image (h) generate background image by applying Morphological Open operation on median filtered image (i) apply image adjust method to enhance the image to supports segmentation process in later stage. (j) Perform Segmentation of blood vessels Using Fuzzy C-means (k) shows the blood vessels detected by the proposed method. (l) illustrates FD value estimation by considering slope of plot log(# boxes) vs log(pixel length). The m,n,o,p,q,r,s,t,u,v,w, and x represents the same process as a, b, c, d, e,f,g,h,i,j,k and l respectively on NVG images.





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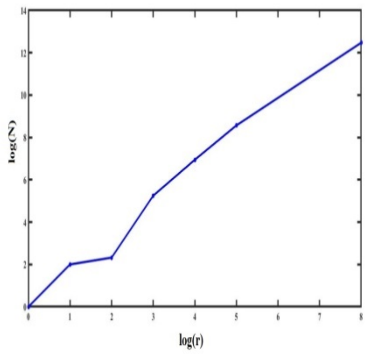

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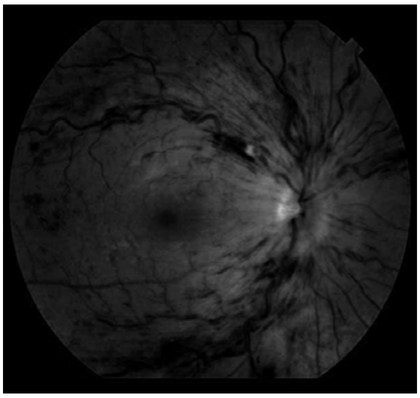

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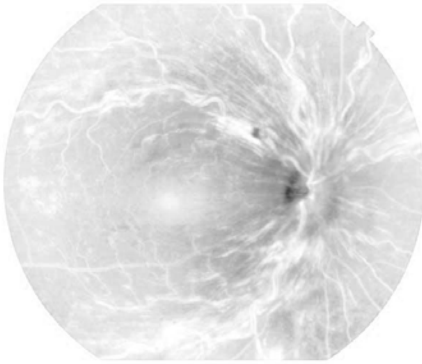

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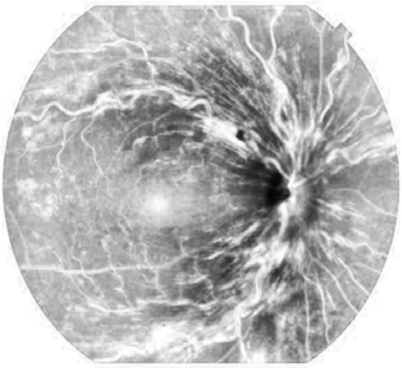

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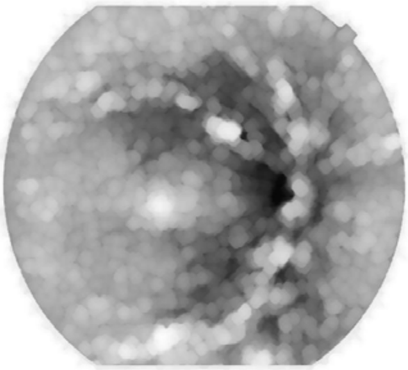

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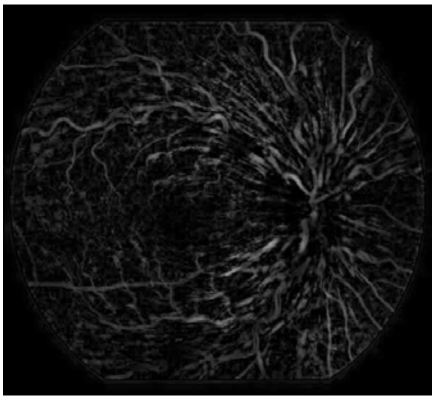

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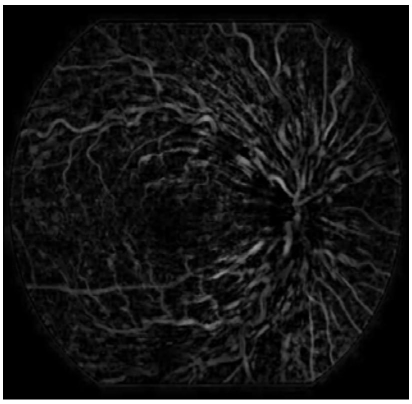

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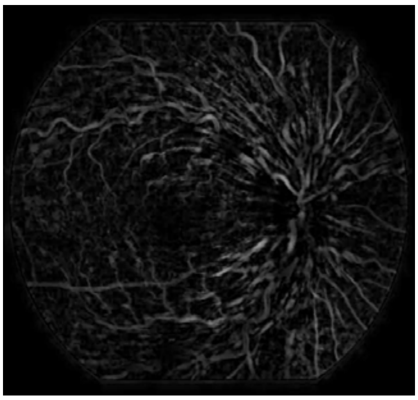

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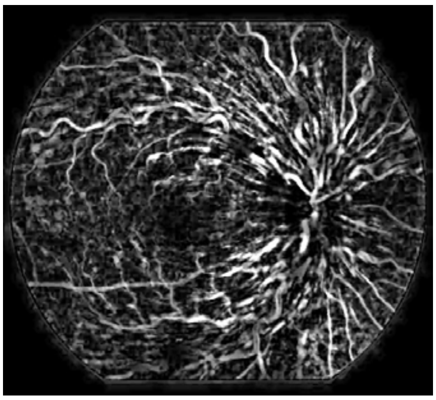

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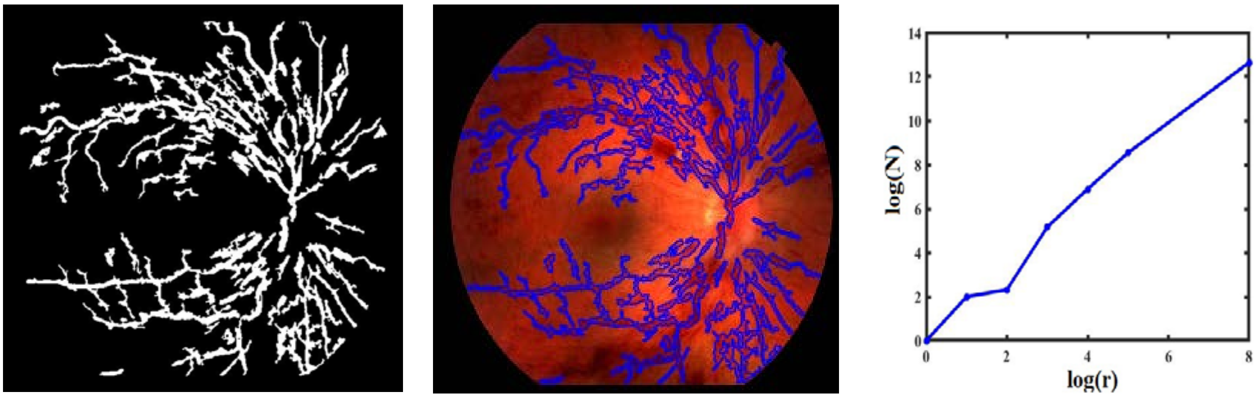

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Fig.6. FD Calculation from blood vessels of Retinal Fundus images.

The FD obtained for healthy retina and NVG images as shown in figure 6 (a) and (m) are 1.5977 and 1.7152 respectively. Same operations are carried out on remaining healthy and NVG retinal images. Obtained FD is in the range of 1.00 to 1.63 for healthy image and above 1.63 for NVG images [22]. From the results, it is noticed that out of 400 healthy images in Messidor Dataset, 346 are identified as healthy, and out of 800 neovascular images, 726 identified as neovascular glaucoma. In KMC Dataset, out of 12 healthy images, 10 are identified as healthy, and out of 12 neovascular images, 11 identified as neovascular glaucoma.

3.3. Performance measure

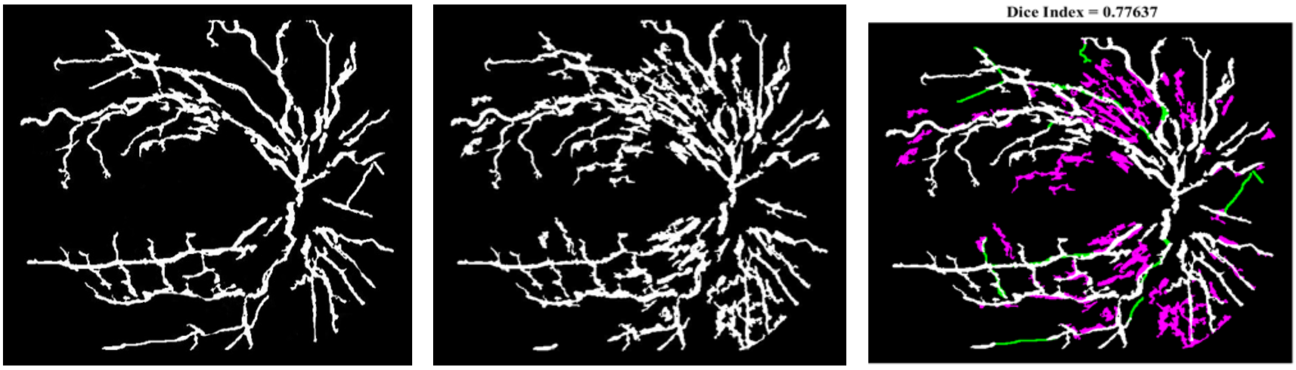
Performance of blood vessel segmentation approach is evaluated by two methods 1) Dice Coefficient 2) Accuracy calculation. Dice coefficient estimate the similarity between two images ‘A’ and ‘B’. Assume image ‘A’ represents the result obtained by the proposed method and ‘B’ represents the ground truth image generated by the ophthalmologist. The Dice coefficient value ranges from 0 to 1. A higher coefficient value (near to 1) means higher the accuracy of the proposed method.

$$Dice=(2*Area(A \cap B))/(Area(A)+Area(B)) \quad (1)$$

In accuracy calculation method pixels of the image ‘A’ compared with pixels of image ‘B’. **True positive (TP)** represents the number of cases correctly identified as 1. **False positive (FP)** represents the number of cases incorrectly identified as 1. **True negative (TN)** represents the number of cases correctly identified as 0. **False negative (FN)** represents the number of cases incorrectly identified as 0. The accuracy of a method is represents the ability of a method to differentiate 1 and 0 cases in the images correctly. Mathematically, it is represented as:

$$Accuracy=TP+TN/TP+TN+FP+FN \quad (2)$$

a b c



d e f

Fig.7. Dice Index Calculation using Equation (1) from blood vessels of Retinal Fundus images.

The similarity index calculation for Healthy Image and Neovascular Glaucoma images is illustrated in Figure 7. Figure 7 a) represents the ophthalmologist marked blood vessels areas of Healthy Image. Figure 7 b) blood vessels extracted from the proposed method. Figure 7 c) illustrates the similarity index value obtained by comparing proposed system generated image with ground truth image (ophthalmologist generated image). The similarity value obtained is 92%, same operation is carried out on Messidor and KMC Datasets images and obtained 90% and 88% similarity respectively on healthy images. This illustrates, proposed method works efficiently for healthy images because of clear blood vessels in images. Figure 7 d), e) and f) illustrates same operations as 7 a), b) and c) respectively on Neovascular Glaucoma image. The similarity value obtained is 77%, same operation is carried out on Messidor and KMC Datasets images and obtained 74% and 71% similarity respectively on Neovascular Glaucoma images. Similarity index values for Neovascular Glaucoma images are very low because of more damages to blood vessels and optic disc area. Even in these images, the proposed method discovered the blood vessels in an efficient way by considering the damaged areas. Table 4 illustrates the accuracy table for Healthy and Neovascular Glaucoma images. This algorithm yields an accuracy of 95% on Messidor and KMC Datasets.

Table 4. Accuracy estimation using Equation (2) of Healthy Image and Neovascular Glaucoma images.

	Healthy Image	Neovascular Glaucoma
TP	88	1093
FP	408	12123
TN	102828	237295
FN	3002	6777
Accuracy	98.97	92.65

Finally all the values (Retinal Image FD, Blood Vessels FD, Count, Contrast, Correlation, Energy, Entropy, Homogeneity, Kurtosis, and Mean) are feed to ANN classifier to improve glaucoma detection accuracy by splitting the data into approximately 70% for training and 30% for testing. The Levenberg-Marquardt activation function is used with 10 neurons in two layers. The epoch of 1000 iterations is considered for Training the data. Out of 1224 images (Messidor and KMC Datasets), 856 are considered as training images and 368 are considered as testing images. Out of 368 images the ANN predicted 361 images correctly. Therefore, the accuracy of proposed work is 98.08%. Table 5 illustrates the Accuracy comparison of proposed framework with existing approaches. Where proposed System achieved the better accuracy compared to existing approaches.

Table 5 Accuracy of the proposed frame work and existing approaches.

Year/author	**Method**	**Accuracy**
2019/Amed Mvoulana [4]	Texture and Model-based Approach	98%
2014/Xiao hui Zhang et al. [2]	k-NN Polynomial Kernel SVM RBF Kernel SVM Naive Bayes	93% 70% 93% 75%
2007/Jôrg Meier et al. [3]	Principal Component Analysis	81%
2015/Mookiah et al. [5]	KLD ranking and SVM Classifier	93.70%
2011/Liye Guo et al. [15]	Multiclass Discriminant Analysis	90.9%
2015/Agarwal et al. [6]	Support Vector Machine	95%
2010/Bock et al. [17]	Support Vector Machine	88%
2014/Kotowski et al. [18]	Support Vector Machine	88%
2015/Septiarini and Harjoko et al. [19]	Support Vector Machine	95%
2015/Singh et al. [20]	ANN	94.7%
2011/Acharya et al. [21]	Random Forest Classifier	91%
Proposed Method	**FD and Texture features Technique**	**98%**

4. Conclusion

The Early detection of glaucoma using fundus images is an important research area. In this work, a novel approach for the early detection of glaucoma using fractal geometry is proposed. Two techniques have been presented for an examination of fundus images: 1) FD estimation from retinal fundus image and 2) FD estimation from blood vessels of retinal fundus image. It deals with neovascular glaucoma by combining the results of both approaches. The texture features are also considered for better NVG detection. This method has given significantly better outcomes as compared to existing approaches. The system is tested on Messidor and KMC Datasets. The results obtained from the proposed method are correlated with the results of the ophthalmologist and provided average accuracy of 98%. Therefore, the proposed system can be used for early detection of glaucoma and as the decision support system for ophthalmologists. From statistical analysis of results, it is observed that, for Healthy images, FD is ranges from 1.06 to 1.62, whereas for neovascular glaucoma, FD is above 1.62 on fundus images. The range of 1.00 to 1.63 for healthy images and above 1.63 for NVG images on blood vessels. Further, this approach is used to detect FD values of optic cup, disc and exudates to achieve still better accuracy. Proposed system tested only on two data sets and obtained moderate similarity index. One limitation related to proposed work is, the system generates less similarity index for highly damaged retinal images. In future work, additional image pre and post processing techniques are used to enhance the similarity index. FD values of perimeter of cup and disc areas are calculated using different fractal algorithm and finally, power spectral fractal dimension technique is applied on fundus images to support glaucoma analysis. Further, Same techniques are used on primary glaucoma images and results are analyzed.

Acknowledgment

We would like to thank Dr. Neetha, Assistant Professor, Dept of Ophthalmology, KMC, Manipal, for their expert advice and support to carry out this work.

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How to cite this paper: Chandrappa S, Dharmanna L, Basavaraj Anami, " A Novel Approach for Early Detection of Neovascular Glaucoma Using Fractal Geometry", International Journal of Image, Graphics and Signal Processing(IJIGSP), Vol.14, No.1, pp. 26-39, 2022.DOI: 10.5815/ijigsp.2022.01.03