ISSN 2063-5346

AUTOMATIC DETECTION OF NEOVASCULARIZATION AND DAMAGED BLOOD VESSELS FOR THE DIAGNOSIS OF DIABETIC RETINOPATHY FROM DIGITAL FUNDUS IMAGES USING ADVANCED MACHINE-LEARNING TECHNIQUES

Aldrin karunaharan. K, Abdul Hameed. K

Article History: Received: 01.02.2023 Revised: 07.03.2023 Accepted: 10.04.2023

Abstract

Diabetic retinopathy is a leading cause of blindness in people with diabetes. Proliferative diabetic retinopathy is characterized by neovascularization of the retina as a result of a severe vascular problem. The automatic detection of such new vessels would be helpful in assessing the severity of diabetic retinopathy, and it is an important element of the screening procedure to identify those who may have the disease. Their diabetic retinopathy necessitates rapid care. The early and precise identification of proliferative diabetic retinopathy is critical for the patient's eyesight protection. Automated techniques for detecting proliferative diabetic retinopathy in digital retinal images should be able to distinguish between normal and pathological vessels. Using a multivariate m-Mediods-based classifier, statistical texture analysis (STA), high order spectrum analysis (HOS), and fractal analysis (FA), we suggested a new method for detecting aberrant blood vessels and evaluating proliferative diabetic retinopathy in this paper. The system extracts the vascular pattern and optic disc, using a multilayered thresholding technique and the Hough transform.

Keywords: **Diabetic retinopathy, Fundus Photographs, Automated detection, Blood vessel area, Hemorrhage, Exudate**.

International Maritime College Oman
aldrin@imco.edu.om, abdul-hameed@imco.edu.om

DOI:10.31838/ecb/2023.12.s1-B.286

1.0 INTRODUCTION

The retinal vasculature is an observable circulatory system in the eye [1–4] that provides useful information on the body's microcirculation without requiring invasive procedures. Proliferative diabetic retinopathy is characterized by neovascularization, which is a pathogenetic marker. During repeated follow-up visits or telemedicine consultations, effective computer assistance could improve the sensitivity and consistency of neovascularization detection. Patients would be less likely to lose out on early and effective laser treatment if detection was more reliable. Unlike microaneurysms, the shape and size of neovascularization vary, posing additional challenges and requirements for the development of automated detection methods. One of the hallmarks of proliferative diabetic retinopathy is neovascularization. It's a process in which vasogenic factors react to hypoxia, forming new blood vessels. The new vessels are faulty, leaking fluid (edema/true exudates) as well as red cells (hemorrhages). As a result, connective tissue growth is stimulated. One of the hallmarks of proliferative diabetic retinopathy is neovascularization. It's a process in which vasogenic factors react to hypoxia, forming new blood vessels. The new vessels are faulty, leaking fluid (edema/true exudates) as well as red cells (hemorrhages). As a result, connective tissue growth is stimulated. One of the hallmarks of proliferative diabetic retinopathy is neovascularization. It's a process in which vasogenic factors react to hypoxia, forming new blood vessels. The new vessels are faulty, leaking fluid (edema/true exudates) as well as red cells (hemorrhages). As a result, connective tissue growth is stimulated. One of the hallmarks of proliferative diabetic retinopathy is neovascularization. It's a process in which vasogenic factors react to hypoxia, forming new blood vessels. The new vessels are faulty, leaking fluid (edema/true exudates) as well as red cells (hemorrhages). As a result, connective tissue growth is stimulated.

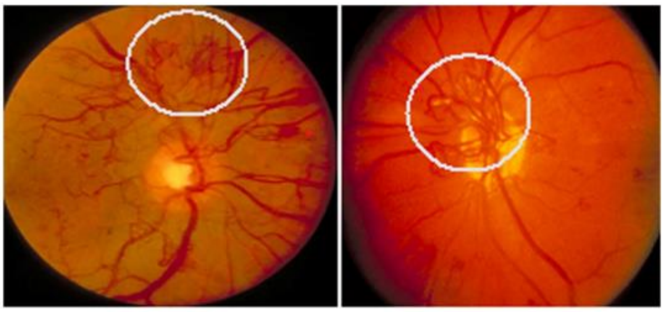

Fig 1 a) New vessels elsewhere NVE b) NEW vessels on the edge NVD

Fig 2 Damaged blood vessels

One of the characteristics of proliferative diabetic retinopathy is neovascularization. It is a process by which the vasogenic factors react to hypoxia, forming new vessels. Red blood cells and fluid (edema/true exudates) seep from the faulty new vessels (hemorrhages). This in turn encourages the formation of connective tissue. Neovascularization must be present for a referral to an ophthalmologist or retina specialist to be made, whether it be neovascularization on the disc (NVD) or neovascularization elsewhere (NVE). Figure 1 displays an NVD and NVE case study. Numerous studies have offered an automatic diagnosis of retinal abnormalities for small hemorrhages, hard exudates, cotton wool spots, and microaneurysms.

2.0 LITERATURE SURVEY

Using image analysis techniques, Singh and Chandra reported a method in 2010 for automating the early diagnosis of diabetic retinopathy. So that the patient could be identified early and directed to the specialist well in advance for future intervention, the automated diabetic retinopathy diagnosis system was utilized to various lesions of the retina, such as exudates, microaneurysms, and hemorrhages, their count size, and location.[1]. When there are no or few diseases, such as bright exudates, Santhinatha explored a method for locating and segmenting the area in the image with high grey level variation to find the optic disk works well. In 2001, Walter and Klein identified the position of the optic disk and subsequently extracted its contours using the watershed transform. [2] In order to locate the optic disk, Hoover and Goldbaum employed a fuzzy voting approach in 2003.[3] The majority of the parts overlap in the optic disk. A technique to locate the optic disk based on the overall orientation of the vasculature was also presented by Foracchia et al. in 2004 [4]. Welfer in 2010 [6] proposed a method for exudate detection based on mathematical morphology. Sopharak et al. employed fuzzy C-means clustering in 2009 to segment exudates before classifying them using morphological principles. Garcia et al. in 2009 [8] classified exudates using three neural network classifiers after segmenting exudates using a combination of the local and global thresholds. While W. Reza, C. Eswaran, and K, Dumyat, "in 2009 [7] proposed a methodology based on mixture models to discriminate between hard and soft exudates after separating exudates from the background. The image was adjusted using a geometrical model of the average retinal vessel orientation in relation to the position of the optic disk. A method based on segmenting the picture into 64 sub-images and then using a mix of regional growth and edge detection to detect exudates was proposed by H.Li in 2004 [8].

2.0 PREPROCESSING & PROPOSED SYSTEM

There have been many investigations on noninvasive, retinal image-based methods for detecting new vasculature. For instance, when Saranya et al. used the FCM technique to segment vessels, they used features like gradient, gradient variation, gray level coefficient of variation, moment invariants-based features, and tortuosity, which primarily depend on the shape, contrast, and brightness of the segmented vessels. Sadly, this method is not entirely automatic. New vessels near the optic disc are one of the 15 characteristics of

proliferative retinopathy that can be seen. This method only found

new vessels on the optic disc (NVD), and the sample size was somewhat limited. This method employed elements that were primarily dependent on various vascular characteristics, such as vessel density, edge magnitude, etc. Energy, mean gradient, standard deviation gradient, mean intensity, and intensity variation were some of the features they used. Compared to earlier approaches, this strategy had higher accuracy in identifying new vessels but required larger sample size.

All of the images used in this investigation were chosen from online benchmark retinal databases. Therefore, information about the patient enrollment or selection processes can be found on the websites for each. A set of standards were established to select an appropriate neovascularization image. Only 130 of the photographs from these two internet databases were used in our study because we removed any that were unclear or had low resolution, as well as any ground truth unrelated to a diabetes condition. We primarily concentrate on extracting all potentially important risk indicators that are strongly correlated with new vessels, with particular attention paid to the vessel-related characteristics. Since retinal images almost always contain saturation in the red channel and very little contrast in the blue channel, we chose the green channel for all of our activities. Fig. 2 presents the system's complete layout. Preprocessing and contrast enhancement are used to get rid of any artifacts that appear during the capture of retinal images. To preprocess the raw photos, we used the following techniques.

1. Transform the RGB-colored image into a green channel image, then apply contrast and enhancement. The contrast stretch is arguably one of the most fundamental improvement methods. By enhancing the disparities in hue, we used the decorrelation stretching approach. This method produces superior results for the microvasculature in retinal images.

2. Then, to distinguish vessels from other objects, we used the hybrid median filtering technique. With this method, impulse noise may be easily removed while edges are preserved thanks to a windowed nonlinear filter (during vessel segmentation). Each pixel is initially given a ranking in several sub-neighborhoods, and the final ranking is then determined by taking the median values from all of those rankings. With this method, the small details are better preserved while the noise is eliminated.

Due to the varied surface textures of the objects and the shadows cast by the various light source orientations, non-uniform illumination in an image frequently results in reduced structures and inhomogeneous intensities. One of the most crucial elements that affects how a picture looks, especially when it comes to biological imaging. We use morphological procedures to adjust for non-uniform light. The following is the main concept: Under the premise that the vessels maintain primarily in local linear orientation, we first display the background approximation as a surface and then choose a line structure to generate a morphological filter for vessel segmentation. Segmentation, noise removal, and edge recognition at picture points use local and global spectral information. Segmentation is a crucial step in describing the fundamental processes of an individual. Filtering is one of the often employed methods, however this method's main drawback is the loss of precision brought on by prior filtering.

An alternative strategy is to use the image as a gauge for the fixed resolution. Multifractal analysis can be used to investigate this measure's irregularities. First, several capacities and metrics are defined from images having a gray level. Following that, enabling and global information must be determined for the matching multifractal spectrum.

The first stage in constructing the optic disk is to identify its center, which is the lighter and brighter area in the retinal image. In order to locate the optic disk and define its center, this property investment will compute the red and green channels from the original RGB color retinal image. We must ascertain the maximum value of in order to obtain all of the light and bright regions in the image (D). The experiment demonstrated that the center of the optical disk is represented by pixels with intensity value. It will then compute the red-to-green channel ratio (R/G) to obtain all the light and bright places in the image. D is calculated for every pixel

$$D = R/G$$

$$\text{Max}(D) \leq x \leq 255$$

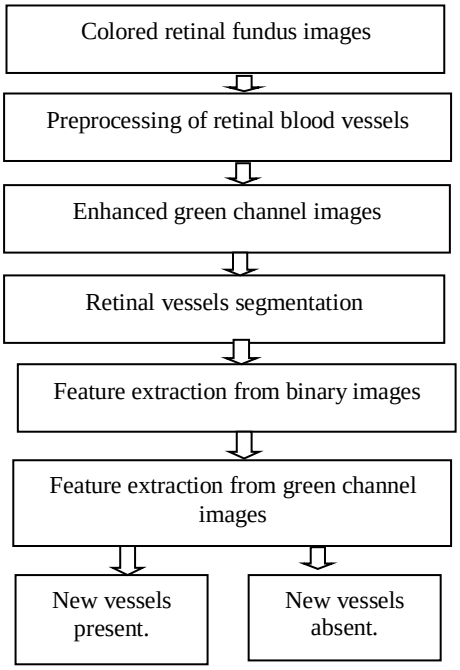

Fig 3 Proposed system for vessel detection

3.0 SEGMENTATION

There are two sorts of exudates in images: actual exudates and false exudates (which are any areas that resemble exudates, including light dots). For automatically identifying the optic disk and exudates in retinal pictures, a proposed method was built. The algorithm was created using fundus photographs. Exudates were the sort of DR visible in the pictures. The purpose of the paper is to identify exudates, which are the nom-proliferative stage of DR, so that the illness can be effectively controlled to reduce the likelihood of vision impairment. The goal of the paper is to recognize exudates, the nom-proliferative stage of DR, in order to properly manage the condition and lessen the possibility of visual impairment. The representation of an image in RGB color space enables the analysis of the various spectral response channels independently. Each of the three channels, red, green, and blue, has an intensity value between 0 and 255.

By scanning all image pixels, applying placeholder labels to nonzero pixels, and noting label equivalences in a union-find table, the binary picture's components will all be labeled using the image label algorithm. The union-find procedure is then used to maintain a number of non-overlapping sets from a finite universe of elements to resolve the equivalence classes. Relabel the pixels based on the clarified equivalence classes at the end. The retinal image's labeled regions are all computed for texture as the last step. Quantifying a region's texture content is a key step in describing it. The statistical aspects of the intensity histogram are used in this paper's method for computing texture based on the statistical measure. We propose six texture metrics for each location, including average intensity (mean), average contrast (standard deviation), smoothness, third moment, uniformity, and entropy. One class of such measure is based on statistical moments. Exudates were eliminated by re-labeling them using the union-find algorithm, edge detection, and size determination before segmenting them. Each fake exudate is removed based on its size and location. Only genuine exudates are still visible in the image. After locating the center, we must determine the radius of the optic disk. To do this, we must examine and count each pixel's intensity as it moves in four directions—two horizontally and the other two vertically—away from the optic disk edge, which marks the boundary between two regions of contrasting color intensity.

The right radius is obtained by calculating the four radiuses in the four directions. The optic disk is covered with a black circle with the same optic disk radius after determining the center and radius. The following step is to identify every exudate in the retinal image. To do this, use the green channel of the retinal image . The "bright" portion of the retinal image is typically represented with high numbers in terms of intensities; each pixel in the image has an intensity value ranging from 0 (the darkest pixel) to 255. (Light pixel). Due to their designation as image objects, the portions of an image with high and low intensities may include very significant features. The tops of the items in an image of several objects may be represented by spots of high intensity; maxima can be used to recognize things in an image. There is only one global maximum in an image that has intensities greater than or equal to the threshold (the band of exudates) and has a comparable specified texture. An image can have several regional maxima in terms of intensity and texture. By turning each pixel equal to or greater than the threshold to white color with value 1, and the other pixel changing to black color with value 0, this procedure turns the image into a binary image.

The white pixels in the binary image created by this method stand in for exudates, while all other image details are altered to a background black color. Parameters mean, smoothness, standard deviation, uniformity, and entropy are given below where (x_i) is a variable that represents the amount of intensity at location (i), $P(x_i)$ is a histogram of the intensity levels in a region, and L is the total number of intensity levels that can be used. In this situation, the contrast and average intensity are also genuine, and the false exudates' entropy is higher than that of the other (real) exudates. The ratings for smoothness and uniformity, on the other hand, show that this region is the least uniform and least smooth. As stated in table 1, measurements of each region's texture will make a clear distinction between the actual and fake exudates. Therefore, an algorithm is created for the automatic recognition of the optic disk before looking for exudates based on their yellow hue. The optic disk often holds the majority of the highest green intensities on an image, and the color yellow corresponds to high intensity in the green channel.

Mean (m) = $\sum_{i=0}^{L-1} (x_i)P(x_i)$

Smoothness = R = 1- $\frac{1}{1-\sigma^2}$

Standard deviation = σ = $\sqrt{\mu\,(x)}$

Uniformity U = $\sum_{i=0}^{L-1} P^2(x_i)$

Entropy = $\sum_{i=0}^{L-1} (P(x_i)\ log_2 P(x_i)$

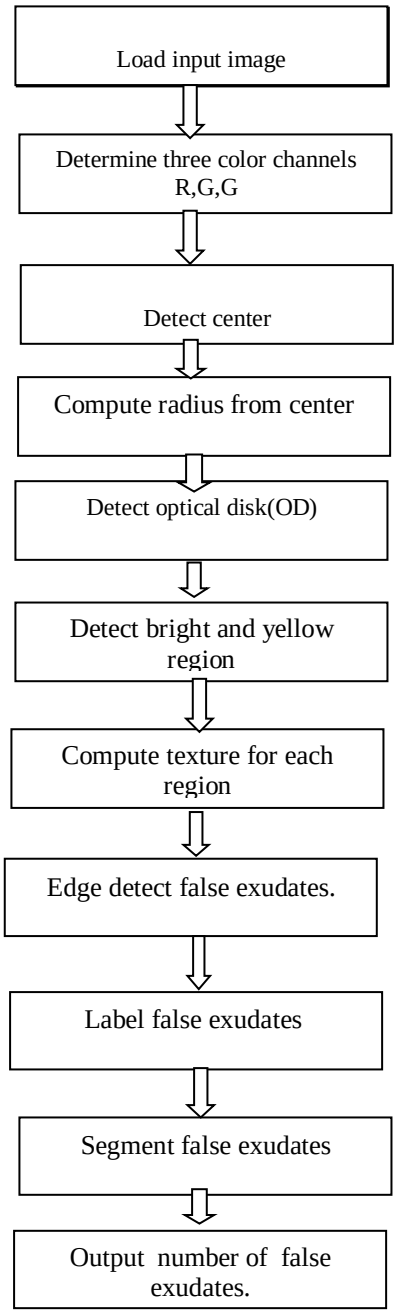

Fig. 4 Algorithm for detection

4.0 MULTIFRACTAL ANALYSIS (MFA), HIGHER ORDER SPECTRAL ANALYSIS(HOSA) & STATISTICAL TEXTURE ANALYSIS (STA)

It is possible to think fractal model (analysis) as a model-based texture analysis. It can be divided into mono-fractal and multi-fractal categories. Fractals are geometric objects that, when magnified, reveal ever-increasing features that statistically or precisely mirror the entire entity (self-similarity). Due to the fact that certain of their physical qualities (such as length, mass, area, and volume) are mainly reliant on the measurement's magnification, such fractal objects are difficult to describe as "measurable" in traditional geometric terms. The parameters such as slope and intercept were derived based on the comparable FFD approach that we modified.

Since the multifractal spectrum can describe the evolution of the probability distribution of fractal structures, we applied it last. Multifractals are distinguished from simple fractals (or monofractals) by a hierarchy of exponents as opposed to a single fractal dimension. The box-counting method was applied in this study to characterize various spectra. This indicates that the fractal object's surface is frequently complicated and that any patterns found there may be mixed with various physical properties. Fractal dimension is a notion that may be used to represent the incompleteness or fragmentation of entirety and can be used to illustrate the varied complexity of fractals.

Recent studies also demonstrate that such surface complexity of an image may be described by its multifractal spectra, which is a mathematical description of a surface that can accurately reflect its features, in addition to its fractal dimension. This is consistent with the various theoretical models that relate to surface structures. Thus, we may use multifractal spectra to gain more comprehensive information than is feasible with the fractal dimension alone, and we can apply fractal analysis to calculate the surface complexity, which is evaluated on the grayscale. Recently, retinal vasculature investigation has made extensive use of this kind of approach. Recall that scale invariance, a property of fractals, is what gives them their characteristic degree of space-covering (shape). Scale invariance's appearance is unique to the structure under consideration and can be described by a single number, the fractal dimension (FD). The multifractal main parameter is given by

$$\alpha = \frac{log\ \mu(box)}{log£}$$

Where μ(box) represents the dimension of the box and £ represents the dimension of the longitude of the box.

The non-integer value FD represents the "convoluteness" of the structure. There are other places where fractal analysis is introduced quite well. Fractal analysis has also been suggested as a potential tool for detecting diabetic retinopathy. The fractal dimension is anticipated to be a natural way to gauge the development of new blood vessels because the retinal vasculature is a fractal that adheres to the principles of fractal geometry. Additionally, it has been demonstrated that the new vessel creation modifies the vessel pattern's fractal dimension. The results were unaffected by the picture preprocessing with regard to the representation of the individual vessel thickness, however, the fractal dimension demonstrates a high degree of sensitivity with respect to new vessel development. The fractal dimension might be employed for automatic detection because it seems to be the "natural" way to measure proliferative changes.

One method of addressing abnormalities is to use fractal and multifractal analysis (MFA), which has advantages over "traditional" signal analysis. While the "traditional" technique frequently observes LF (low-pass filter) filtered versions, with varying filtering depths for abnormalities noticing and noise repressing, MFA attempts to extract the information straight from the singularity. In the original signal, a homogeneity point can be separated based on particular values of a and f(a). Any of the known ways can be extracted by picture pixel extraction, which satisfies the specified value of the parameter and or spectrum f(a). The local singularity exponent is used as one of the inputs to calculate the multifractal spectrum, which characterizes the distribution of singularity exponents across different scales and positions in the image.

a. Calculate the partition function, Z(q), for a range of q values:

$$Z(q) = \sum(|f(i)|^{q})$$

where f(i) is the local singularity exponent at pixel i, and the sum is taken over all pixels in the image.

b. Calculate the singularity spectrum, f(α), using the Legendre transform of the partition function:

$$f(\alpha) = q\alpha - \log(Z(q))$$

where alpha is the singularity exponent, and q is the moment order.

c. Calculate the multifractal spectrum, D(h), which is the derivative of the singularity spectrum with respect to the singularity exponent:

$$D(h) = \alpha(h) + hf(\alpha\ (h))$$

where h is the Holder exponent, and α(h) is the value of the singularity exponent that maximizes the multifractal spectrum for a given h.

An additional benefit of this segmentation is that the beginning image is not degraded; all pixel interactions remain constant, preserving all of the image's information. We must look at fractal characteristics in order to characterize rapidly changing signals (small area) of retinal images and to communicate variability. The application of traditional statistical techniques in this situation (mean values) may result in valuation errors. Multifractality of the process indicates significant singularities. Further insight of the mechanisms underlying complicated changes is provided by the conclusion that the fractal dimension is a descriptor of early changes in diseased vascular modifications. Fractals play a significant role in both pathology and medicine. In our investigation, the multifractal analysis produced five parameters: three from local (a) and two from global (f(a)).

In order to find patterns or features that might not be obvious in the lower order moments, a technique called higher-order spectral analysis (HOSA) includes estimating higher order moments of the signal. Via an examination of the intricate wavelet transform of the retinal image, HOSA has been utilized for the detection of retinal blood vessels. The complex wavelet coefficients' higher-order moments are estimated. You can accomplish this by utilizing techniques like poly spectra and cumulants. Higher-order moments can show patterns or features that may not be apparent in lower-order moments because they represent statistical interdependence between the coefficients at various scales and orientations. The higher order moments are used to construct a spectral correlation matrix, which captures the spectral correlations between the complex wavelet coefficients. The spectral correlation matrix is defined as:

$$R(m,n) = E[W(m) \times W(n)]$$

where W(m) and W(n) are the complex wavelet coefficients at scales m and n, respectively, and E[.] denotes the expected value. The eigenvalues and eigenvectors of the spectral correlation matrix are separated out. The spectral correlations' spatial organization is captured by the eigenvectors, while their strength is captured by the eigenvalues. The characteristics corresponding to the blood vessels in the image are extracted using the eigenvalues and eigenvectors. Techniques like clustering, thresholding, or principal component analysis can be used to accomplish this (PCA). The blood vessels are then separated from the backdrop using the extracted features.

5.0 RESULTS AND DISCUSSION

.

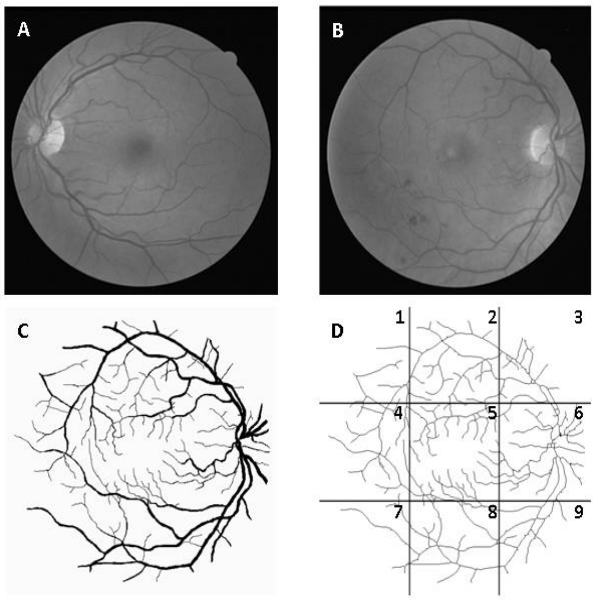

Fig 5

An overview of the procedures for employing multifractal analysis to find retinal blood vessels is given as follows. The segmented binary image is subjected to multifractal analysis in order to determine how complex the retinal vessels are. It is possible to smooth the vessel boundaries and remove isolated tiny areas once the blood vascular segmentation has been done. Techniques like morphological operations, linked component analysis, or curve fitting can be used for this. This is a general description of the algorithm for STA-based segmentation of retinal blood vessels. The particular implementation may depend on the techniques chosen for classification and post-processing, feature extraction and selection, and selection of features. Many multifractal analytic techniques, including the multifractal spectrum, singularity spectrum, and wavelet-based techniques, can be used to accomplish this. The outcomes of the multifractal analysis are used to extract features that help to discriminate between vascular and non-vessel regions. The singularity or multifractal spectra mean and variance, as well as other statistical and textural aspects, can be included in this list of characteristics. Overall, multifractal analysis can be an effective approach for identifying retinal blood vessels, especially when used in conjunction with other image analysis methods. The specific dataset and application may, however, dictate the choice of particular methods and parameters.

6.0 CONCLUSION

Based on image processing techniques that make use of colour, intensity gradients, and picture textures in fundus photos, automatic approaches for screening exudates have been created. The methods were tested on many photos from a common database. According to table 1, all actual exudates have identical texture measures, yet they all differ greatly from the texture measurements of fraudulent exudates. The key component that causes confusion with exudates is eliminated and novel techniques for implementing the optic disk are presented in this research. This algorithm's output shows great promise and accurately detects all exudates in the image. Prior research has sought to measure minute variations in the human retinal vasculature that are not immediately visible to the naked eye and serve as an early disease signal [35–37]. Although mono-fractal analysis can be used to detect vascular change, it has had only sporadic success since retinal vessels can differ in their features depending on where they are found or how they are measured. Consider the retinal vascular pattern to be multifractal, defined by a hierarchy of exponents rather than a single fractal dimension, for greater reported success. The Fourier fractal dimension (FFD) approach, which has been proposed by FFD, has been utilized to quantify the grayscale images projected on to 3-D fractal surface. We first applied the box-counting algorithm approach to calculate fractal dimension in binary kind of image (segmentation of vessels). With FFD, picture segmentation is not necessary because it computes the fractal dimension of grayscale images. Additionally, it has been discovered to be comparatively noise-insensitive, and it is thought to function well with data that has a low signal-to-noise ratio. We modified an FFD strategy that was similar.

6.0 REFERENCES

1) S. Neera, and R. Chandra, “Automated early detection of diabetic retinopathy using image analysis techniques”, International Journal of Computer Applications (0975 – 8887), Vol. 8, No.2, October 2010.

2) Thomas Walter and Jean-Claude Klein, “Segmentation of Color Fundus Images of the Human Retina: Detection of the Optic Disc and the Vascular Tree Using Morphological Techniques”, J. Crespo, V. Maojo, and F. Martin (Eds.): ISMDA 2001, LNCS 2199, pp. 282–287, 2001. @ Springer-Verlag Berlin Heidelberg 2001.

3) A. Hoover and M. Goldbaum, “Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels,” IEEE Trans. Med. Imag., Vol. 22, No. 8, pp. 951–958, Aug. 2003.

4) M. Foracchia, E. Grisan, and A. Ruggeri, “Detection of optic disk in retinal images by means of a geometrical model of vessel structure,” IEEE Trans. Med. Imag., Vol. 23, No. 10, pp. 1189–1195, Oct. 2004.

5) M. Garcia, C. I. Sanchez, M. I. Lopez, D. Abasolo and R. Hornero, “Neural network basad detección of hard exudates in retinal images,” Computer Methods and Programs in Biomedicine, Vol. 93, pp. 9-19, 2009.

6) Sopharak and B. Uyyanonvara, “Automatic Exudates Detection from Non-dilated Diabetic Retinopathy Retinal

Images Using Fuzzy C-means Clustering," Sensor, Vol. 9, No. 3, pp. 2148-2161, 2009.

7) W. Reza, C. Eswaran and K, Dimyati, "Diagnosis of Diabetic Retinopathy: Automatic Extraction of Optic Disc and Exudates from Retinal Images Using Marker-controlled Watershed Transformation," Springer, J Med. Syst., online Jan. 2010.

8) H.Li, O. Chutatape, "Automated feature extraction in color retinal images by a model-based approach," IEEE Trans. on Medical Engineering, Vol. 51, pp. 246-254, 2004.

9) F. Mendels, C. Heneghan, and J.-P. Thiran, "Identification of the optic disk boundary in retinal images using active contours," in Proc. Irish Machine Vision Image Processing Conf. (IMVIP'99), pp. 103– 115, Sept. 1999