

CLASSIFYING NORMALITY, ABNORMALITY OF DIABETIC RETINOPATHY FUNDUS IMAGES BY DETECTING AND ANALYZING THE OD AND VASCULAR

¹C.A.SATHIYAMOORTHY,²Dr.G.KULANTHAIVEL

¹Research Scholar.,Sathyabama University, Chennai, India

²Professor.,NITTTR, Tharamani, Chennai, India

E-mail: ¹satya.cas@gmail.com , ²gkvel@rediffmail.com

ABSTRACT

The Assessment of the Blood Vessels in a Retinal Image is one of the significant jobs for diagnosing the ophthalmic pathology. The main objective of this paper is to classify the normal and abnormal images in diabetic retinal fundus images. This paper carry out the sequence of processes (i) detect Optic Disc, (ii) Extract the Blood vessels and (iii) classify whether the DR is normal or abnormal due to the stages of Optic Disc and Blood Vessels. The investigational results of an automated method for image-based classification of diabetic retinopathy have been presented. The process is divided into three stages: Image Pre-processing, Image-Segmentation & Extraction, feature extraction and then image classification. In the first stage two image processing techniques are used in order to enhance their features. Then, the second stage reduces the dimensionality of the images and obtains features using the statistical method of principal component analysis. Finally, in the third stage the images are classified using SVM classifier as normal or abnormal. The suggested algorithm is checked on the database DRIVE and the average value of sensitivity is about 83% with the average value of accuracy reaching 98%. Huge number of vessels is differentiated by a standard Thresholding for their good contrast and brightness. Then some thin vessel segments are identified with bad contrast and brightness. This proposed method reduces the more computational complexity and hand simulation work.

Keywords: *Optic Disc; Blood Vessels; Diabetic Retinopathy; Vascular; Normality–Abnormality; Detection and Classification.*

1. INTRODUCTION

Presently the blindness in pupil has increased gradually in most of the countries particularly due to diabetic disease. From the report by WHO – [World Health Organization] there are 285.56 million public people nearly with visually lessened worldwide, 39 million people are blind and other 247 million have low vision.

A reason for this upturn is the diabetic retinopathy, which is a dangerous eye illness which can be stared as a display of diabetes on retina. One way to recognize the existence of diabetic retinopathy is by examining the retina using fundus images, which led the experts to find irregularities such as vessel discontinuity, micro-aneurysms, soft exudates, hard exudates and hemorrhages. This credentialization procedure is done physically and regularly, but however, this is not stress-free because it necessitates skill and experience, and also a time-consuming task. Additionally, automatic

approaches are more neutral than humans, i.e. they are not subject to the conscious and unconscious pre judies that may affect humans when they are looking at the medical images [1].Numerous mechanisms using machine learning and image handling methods have been projected in order to categorize some types of eye illnesses. A principal approach using image investigation and statistical grouping was projected in 2000 by Ege B.M. *et al* [2]. In their research they described the initial progress of a tool to provide automatic investigation of digital images of diabetic retinopathy. They verified numerous statistical classifiers, including a Bayesian, a Mahalanobis and KNN. Their greatest results were acquired with the Mahalanobis classifier. Osareh A. *et al* [11] projected a mindless method to identify exudate regions.

The entire image enhancement, improving background, segmentation, clustering and classification of the regions into non-

exudates, exudates can be achieved by fuzzy-c-means clustering method and ANN respectively.

2. RELATED WORKS

A correlation filter is introduced to detect approximately the center of the optic disc from diabetic retinal images [9]. A point distribution model is applied to detect the retinal structure but it is a cost optimized automated method [10]. Sopharak et al. [17] introduced morphological approaches to detect the optic disk in retinal images. Fleming et al. [3] used semi-ellipsis to spot the optic disk center. On [12] the author proposes an automated method for identifying the blood vessels in color images of the retina. On [14] the author presents a novel method for detecting the blood vessels in digital retinal images.

This method employs a scheme of neural network (NN) for classifying the pixels and calculates a vector of seven dimensions comprising features of gray-level and moment invariants for representation of pixels. On [24] the author introduced an extraction technique to gain the universal characteristics of the fundus images and differentiate the normal images from DME images. *Diabetic Macular Edema* (DME) due to diabetes is a highly complicated disease which can create irreversible loss of sight [14]. The prior detection of even a small sign of DME is important as it may also appear with no external symptoms. The solutions such as tele-screening using permanent and mobile units have been proposed to enable checking of retinal disorders in remote areas [19].

3. SYSTEM MODEL

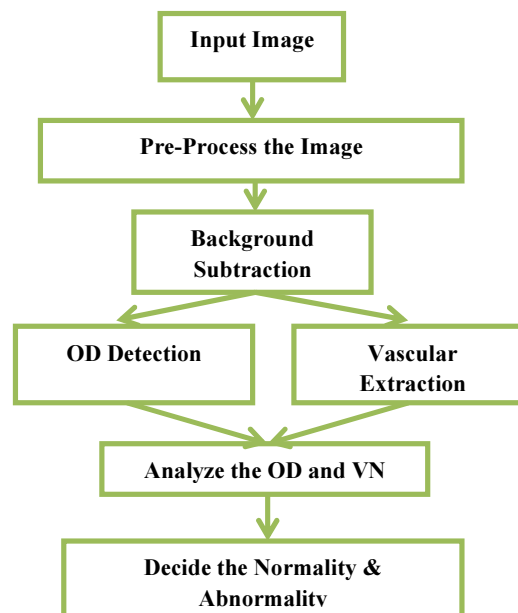


Fig 1: System Model

The step wise functionality of the proposed approach is depicted clearly in Figure 1 and the explanation with the experiment is given below.

3.1 Input Image

The input image for experimenting and evaluating the proposed approach is any type of diabetic retinopathy fundus image from Internet, Hospitals or any benchmark database like STARE, DRIVE, DIABETV1.0 etc. In this paper the database DRIVE is taken for performance evaluation and some of the images taken real-time from Hospital. Since, the conditions of the real-time images are unknown and they belong to normal or abnormal, the experimental images can also be compared with the Ground-Truth variable. Our proposed technique was tested on two databases of retinal images available on the Internet. One of the databases is DRIVE [19], and the other is DIARETDB1 [8].

3.2 Pre-Processing

In this paper the image pre-processing can be obtained by smoothing the image where smoothing is a set of local-preprocessing technique having the aim of removing the noise by redundancy in the image data.

Since the sources of the images are different, the DR image needs to be preprocessed

before image processing. Also the image can be enhanced due to the level of the brightness or contrast to emboss the structure of the DR image. In this paper the LAB color space is used to improve the brightness structure associated with optic disc and then the same image is smoothed for the same.

In this scenario, the bilateral smoothing filter that has combination of geometric closeness and photometric similarity is given as:

$$h(x) = k^{-1}(x) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\xi) c(\xi, x) s(f(\xi); f(x)) d\xi$$

--- Equation [1]

with the normalization factor which improve the brightness and re move the noise.

$$k(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\xi, x) s(f(\xi); f(x)) d\xi$$

----- Equation [2]

Where

$f(x)$ – retinal image under study

$c(\xi, x)$ & $s(f(\xi), f(x))$

– geometric closeness, photometric similarity,

among the neighborhood center

& the nearby point ξ .

$c(\xi, x)$ & $s(f(\xi), f(x))$ are the gaussian functions

The output of the Gaussian filter provides the noise removed, brightness increased image is $x = f(x)$.

3.3 Background Subtraction

Background subtraction is a significant work in image processing based on videos, to detect and track the objects in a video sequence. This method determines whether the pixel belongs to background or foreground. After deleting the background in any image, processing on the foreground is very easy and accurate which can regularize the information about the pixels in the image.

Table 1: Algorithm: Background Subtraction In An Image

```

1.  $w \leftarrow \text{width}(I); h \leftarrow \text{height}(I);$ 
2.  $\text{for } i \leftarrow 1 \text{ to } w; \text{ for } j \leftarrow 1 \text{ to } h$ 
3.  $\text{Threshold } TH(i, j) \leftarrow \frac{1}{c} [M(i, j) + N(i, j)]$ 
4.  $TL(i, j) \leftarrow M(i, j) - TH(i, j)$ 
5.  $TU(i, j) \leftarrow N(i, j) + TH(i, j)$ 
6.  $\text{if } [TL(i, j) \leq I(i, j) \leq TU(i, j)] \text{ then}$ 
7.  $BI(i, j) \leftarrow 0$ 
8.  $\text{else}$ 
9.  $FI(i, j) \leftarrow 1$ 
10.  $\text{endfor}$ 

```

The proposed approach follows simple and easiest way for subtracting the background in the image, where the different thresholds can be obtained for the image background and foreground, then subtract the background image which has different threshold value than the foreground. The original image is converted into gray-scale image from RGB, categorize the image pixels as stationary and non-stationary by calculating their derivations from the mean value. Then the background is taken as the collection of stationary pixels in the image and the range of values can be defined [111]. The background subtraction algorithm is given above.

Once the background is subtracted from the image, the foreground is in FI (I, j) where the optic disc of the DR image can be obtained easily from the image FI.

3.4 OD Detection

After the receiving the foreground of the image, the morphological operations are applied sequentially to detect and extract the OD. In general the morphological operations are used to analyze the shape of the objects in an image. The mathematical model of the morphological operations can be obtained by certain assumptions and calculations.

Let I_f is the subset of IM^2 and

Threshold TH

$= \{TH_{min} \dots \dots, TH_{max}\}$ as the arranged set of gray level in I_f

The gray level image I_g can be defined as a function-

$I_g = I_f \subset IM^2 \rightarrow TH = \{TH_{min}, \dots, TH_{max}\}$.

Also let MI be a subset of IM^2 and $size \in IM$ is representing the scaling factor, and $sizeMI$ is the element delivers the structured element MI with the size “size”, Ig is the maker and k is the mask. Using these components of the image the mathematical form of the morphological operations can be written as given in Table 2.

Table 2: The Morphological Operations In Mathematical Form

Operation Name	LHS of the Mathematical Equation	RHS of the Mathematical Equation
Dilation	$[\delta^{sizeMI}(f)](x)$	$=max_{b \in sizeMI} f(x - b)$
Erosion	$[\epsilon^{sizeMI}(f)](x)$	$=min_{b \in sizeMI} f(x - b)$
Opening	$\gamma^{sizeMI}(f)$	$=\delta^{sizeMI}[\epsilon^{sizeMI}(f)]$
Closing	$\phi^{sizeMI}(f)$	$=\epsilon^{sizeMI}[\delta^{sizeMI}(f)]$
Reconstruction	$R_g(f)$ $= \delta_g^i(f) \text{ with } \delta_g^i(f)$ $\delta_g^n(f) = \delta_g^{n-1}(f) \text{ with } \delta_g^i(f) = \delta^b(f) \wedge g.$	$= \delta_g^{i+1}(f),$

The morphological operation will do step by step operations where initially the image will be splitted into two portions, one is the portion of image to be dilated and the other one is set of co-ordinate points as structuring elements. Then the entire structured elements will be exposed and extracted from the image and those elements are called as connected components in the image. These connected components are dilated and eroded by the threshold value of the image foreground.

3.5 Vascular Extraction

Mostly filters are applied to extract an expected signal from noise combined interference where their techniques are based firmly on frequency based domain concepts. But the WF – [Wiener Filter] filter is used in time domain based concepts and it will reduce the MSE – [Mean Square Error] among the input and the expected output. The performance of the wiener filter may be appraised by snooping to signals and noise. By applying WF filter the DR image extract the vascular vessels after normalize the pixel value in brightness level wise.

3.6 Analization of OD, BV

After optic disc detection and the vascular network extraction, the size, shape of the optic disc, the continuity and connectivity of the vascular can be verified. It is well known and advice from aOphthalmologist, the OD should be in

circular shape, with a minim of 1.49 mm to maximum of 1.78 mm for the diameter of the OD. Also there are no heavy breaks in the vascular network [travel path]. The normality, abnormality of the OD can be obtained from [yy] and measurement of the diameter of the optic disc is depicted clearly in Figure 2.

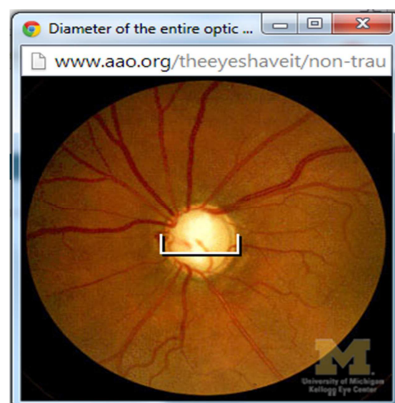


Fig 2: Normal Od Diameter

The complete step by step process of the proposed approach can be written in the form of pseudo code for further implementation in any language.

Table 3: Pseudo Code – [The Proposed Approach]

1. Read the image I from DRIVE DB
2. Remove noise by Gaussian filter and normalizing the noise into unit value
3. Compute the min, max threshold and separate the background and foreground in the image
4. Subtract the background
5. Apply morphological operations and detect, extract the OD
6. Using Wiener filter extract the vascular network
7. Check the shape, size, diameter of the OD and check the vascular network connectivity and continuity
8. Categorize the DR image is normal image or abnormal image.

The classification of the Diabetic retinal image can be obtained by extracting the features and fed into SVM technique. The features are the measurements of OD that is the area, contrast,

homogeneity and these are fed into SVM classifier for automatic classification.

This pseudo code converted is into Mat lab script [using MATLAB 2012a software] and the proposed approach is experimented and evaluated to find the accuracy. The performance evaluation can be obtained by comparatively using the DRIVE, Ground Truth and General Hospital images to find out the TPR, FPR –[True Positive Rate, False Positive Rate]. According to the TPR, FPR, the proposed approach is evaluated.

4. EXPERIMENTAL RESULTS

The performance of the proposed approach can be evaluated on the DRIVE, Ground-Truth images and on a data set composed from a local eye hospital as part of a continuing experimental study. It contains 70 normal and 30 abnormal (total of 100) images of size 1504*1000. The images are occupied under a stable procedure with 30-degree field of view highlighted on the OD. Ground truth (GT) patterns for OD and vascular are provided by a glaucoma expert and STARE-DRIVE experts.

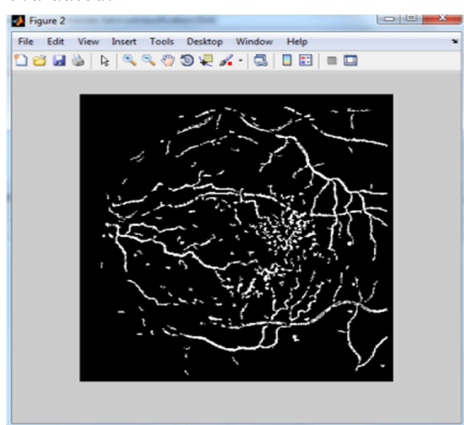


Fig 3a

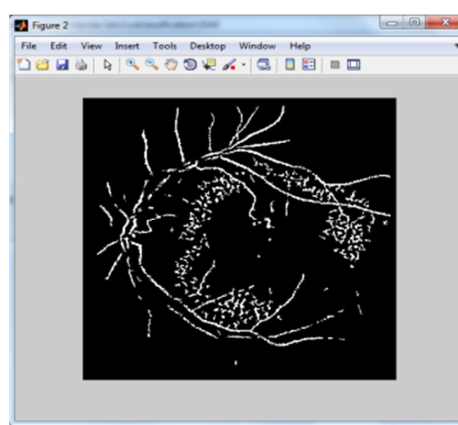


Fig 4a



Fig 3b



Fig 4b

This image is normal by analyzing the shape , connectivity of the vascular network. The network connectivity is good and the OD looks like circular.

This image is normal due to the circular OD shape and the vascular network connect is also ok.

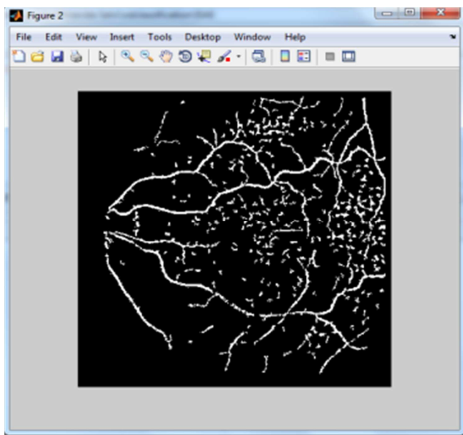


Fig 5a



Fig 5b

This image is normal by analyzing the shape , connectivity of the vascular network. The network connectivity is good and the OD looks like circular.

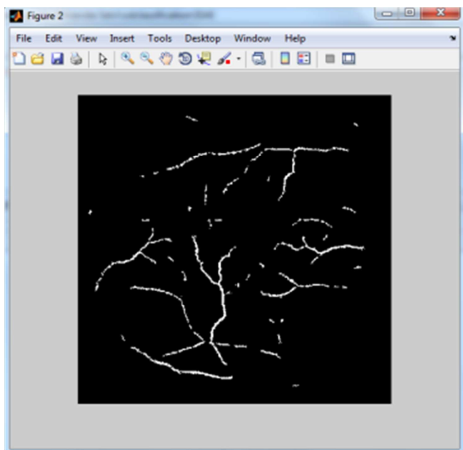


Fig 6a



Fig 6b

This image is abnormal due the size and shape of the OD and the dis-continuity of the vascular networks.

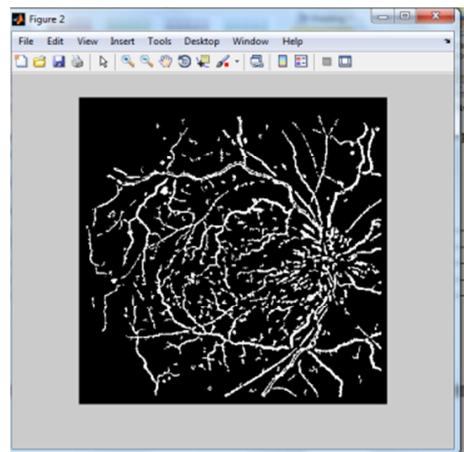


Fig 7a

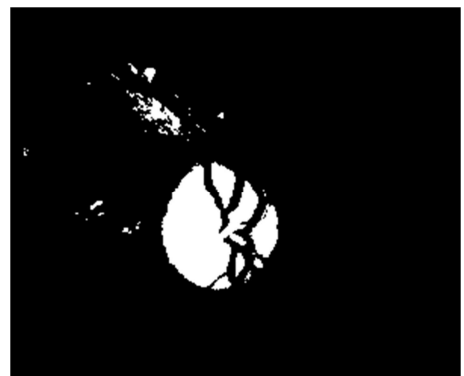


Fig 7b

This image is normal by analyzing the shape , connectivity of the vascular network. The network connectivity is good and the OD looks like circular.

$$Homogeneity = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (P_{ij} / (1 + |i - j|))$$

The experimented results of the proposed approach are given in Figure 3. The first column says a series of Image taken from the data base, the second column shows the vascular extracted from the image using Wiener filter, the third column shows the Optic Disc detected using morphological binary operation and the fourth columns says whether the input image is Normal or Abnormal due to the conditions of the OD and vascular network.

The contrast and homogeneity is obtained using the following equation as:

$$contrast = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (I - J)^2 P_{ij}$$

where P_{ij} is the elements of the co-occurrence matrix.

Table-4: Classification of DRFI using SVM

Classes	Training Image	Testing Images	Correctly classified	Classification (%)
Normal	145	100	96	96%
Abnormal	155	125	97	97%
Average				96.5%

The input image space is mapped with the high dimensional feature space. Then the separation margin among classes that provides maximization of the margin is constructed. The very nearer points for the decision surface are named as support vectors.

The result of the SVM classifier classifies 96.5% accurately than 100%.

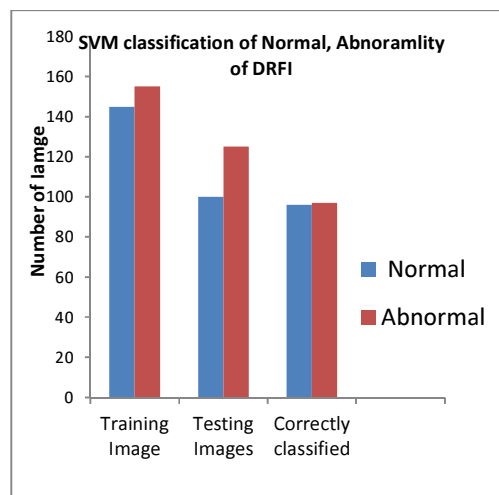


Fig 8: Normality, Abnormality classification using SVM

For improved evaluation on the performance of the proposed approach on taken dataset, we employed cross-validation for multiple runs, and then count the normal and abnormal images from the DB report and the experimental report. The results are summarized in Table 5 and in Fig 9.

Table 5: Existing Classified Data Vs. Proposed Classification

	DRIVE		GT		Local Hospital	
	NL	ANL	NL	ANL	NL	ANL
DB Result	60	40	50	50	35	65
Proposed Approach Result	58	39	50	48	34	62

In the database, available normal images are 60, 50 and 35 in DRIVE, GT and local Hospital dataset respectively. The abnormal images available are 40, 50 and 65 in DRIVE, GT and local hospital data set respectively. In the experiment the

proposed approach detects and classifies 58 images as normal out of 60, classifies 39 abnormal images out of 40 in Drive database, it also detects and classifies 50 images as normal out of 50, classifies 48 abnormal images out of 50 in GT database and also detects and classifies

34 images as normal out of 35, classifies 62 abnormal images out of 65 in local Hospital data set image.

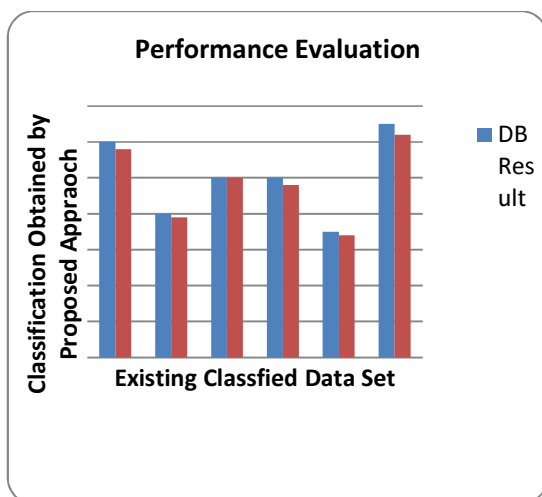


Fig 9: Performance Evaluation Of The Proposed Approach

The performance evaluation of the proposed approach is also represented in graph form in Figure 3. The performance of the proposed approach can also be measured in metrics like TPR, FPR – [True Positive Rate, False Positive Rate].

$$TPR = \frac{\text{Number of images detected and classified correctly}}{\text{Total Number of Images in particular class}}$$

$$FPR = \frac{\text{Number of images detected and classified Not Correctly}}{\text{Total number of Images in particular class}}$$

$$TPR = \frac{60 + 50 + 35}{58 + 50 + 34} = \frac{145}{142} = 98\%$$

$$FPR = \frac{40 + 50 + 65}{39 + 48 + 62} = \frac{6}{39 + 48 + 62} = \frac{6}{149} = 4.13\%$$

5. CONCLUSION

In general the morphological operations alone are applied for OD detection and vascular extraction. In this paper, the proposed approach uses step wise image processing technique [including preprocessing] using mathematical morphology function which structures the elements in disk shape and detects and classifies the OD.

The proposed approach shows the better result than the SVM.

The Retinal Vascular is extracted by the Wiener filter and the continuity and connectivity of the vascular network is analyzed. From the better values of TPR and FPR in Figure 3 and Figure 4 values it is concluded that the proposed approach is efficient than the existing approaches.

In this paper the proposed approach is efficient in classifying the diabetic retinopathy fundus images in terms of OD and BV.

But there are various causes still to be analyzed like Exudates, hemorrhages, Microaneurysms etc.

The limitation of the proposed approach is the normality and abnormality of the images can be classified only by checking the conditions of the optic disc and blood vessels continuity network. it is assumed that the OD shape is circular and Blood vessels are continuous networks in the image.

REFERENCES:

- [1] J. Davidson, T. Ciulla, J. McGill, K. Kles, and P. Anderson, "How the diabetic eye loses vision," *Endocrine*, vol. 32, pp. 107–116, Nov. 2007.
- [2] Ege B.M., Hejlesen O.K., Larsen O.V., Moller K., Jennings B., Kerr D., Cavan D.A. "Screening for diabetic retinopathy using computer based image analysis and statistical classification." *Computer Methods and Programs in Biomedicine*, Jul, 62(3):165-175, (2000).
- [3] D.Fleming, K.A.Goatman, S.Philip, J.A. Olson, P.F.Sharp, "Automatic detection of retinal anatomy to assist diabetic retinopathy screening" *Physics in Medicine and Biology* 52(2)(2007)331–345.
- [4] L. Giancardo, F. Meriaudeau, T. Karnowski, K. Tobin, E. Grisan, P. Favaro, A. Ruggeri, and E. Chaum, "Texture-less macula swelling detection with multiple retinal fundus images," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 3, pp. 795–799, Mar. 2011.
- [5] L. Giancardo, F. Meriaudeau, T. P. Karnowski, Y. Li, K. W. Tobin, Jr., and E. Chaum, "Automatic retina exudates segmentation without a manually labelled training set," in *Proc. 2011 IEEE Int. Symp. Biomed. Imag. From Nano to Macro*, Mar. 2011, pp. 1396–1400.



- [6] M. R. Hee, C. A. Puliafito, C. Wong, J. S. Duker, E. Reichel, B. Rutledge, J. S. Schuman, E. A. Swanson, and J. G. Fujimoto, "Quantitative assessment of macular edema with optical coherence tomography," *Arch. Ophthalmol.*, vol. 113, no. 8, pp. 1019–1029, Aug. 1995.
- [7] Kalyan Kumar Hati, Pankaj Kumar Sa, and Banshidhar Majhi, "Intensity Range Based Background Subtraction for Effective Object Detection", *IEEE SIGNAL PROCESSING LETTERS*, VOL. 20, NO. 8, AUGUST 2013 759.
- [8] T. Kauppi, V. Kalesnykiene, J.-K. Kamarainen, L. Lensu, I. Sorri, A. Raninen, R. Voutilainen, H. Uusitalo, H. Kalviainen, J. Pietila, "DIARETDB1: diabetic retinopathy database and evaluation protocol, in *Medical Image Understanding and Analysis*" (MIUA), 2007, pp. 61–65.
- [9] J. Lowell, A. Hunter, D. Steel, A. Basu, R. Ryder, E. Fletcher, L. Kennedy, "Optic nerve head segmentation", *IEEE Transactions on Medical Imaging* 23(2)(2004) 256–264.
- [10] M. Niemeijer, M. D. Abramoff, B. V. Ginneken, "Segmentation of the optic disc, macula and vascular arch in fundus photographs" *IEEE Transactions on Medical Imaging* 26(2007) 116–127.
- [11] Osareh, A., et al. "Automatic recognition of exudative Maculopathy using fuzzy c-means clustering and neural networks." *Medical image understanding and analysis*, 3:49–52, (2001).
- [12] A. Osareh and B. Shadgar, "Automatic Blood Vessel Segmentation In Color Images Of Retina", Vol. 33, No. B2, pp 191-206, Printed in The Islamic Republic of Iran, 2009
- [13] Pilar Pérez Conde, Jorge de la Calleja, Antonio Benitez, Ma. Auxilio Medina, "Image-Based Classification of Diabetic Retinopathy uses Machine Learning", 2012 IEEE.
- [14] K. Sai Deepak* and Jayanthi Sivaswamy, *Member, IEEE*, "Automatic Assessment of Macular Edema From Color Retinal Images", *IEEE TRANSACTIONS ON MEDICAL IMAGING*, VOL. 31, NO. 3, MARCH 2012.
- [15] R. F. N. Silberman, K. Ahlrich, and L. Subramanian, "Case for automated detection of diabetic retinopathy," *Proc. AAAI Artif. Intell. Development (AI-D'10)*, pp. 85–90, Mar. 2010.
- [16] Sophara, A., et al. , "Automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods". *Computerized medical imaging and graphics*, 32:720–727, (2008)
- [17] A. Sopharak, B. Uyyanonvara, S. Barmanb, T. H. Williamson, "Automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods", *Computerized Medical Imaging and Graphics* 32(2008)720–727.
- [18] M. Verma, R. Raman, and R. E. Mohan, "Application of teleophthalmology in remote diagnosis and management of adnexal and orbital diseases," *Indian J. Ophthalmol.*, vol. 57, no. 5, pp. 381–384, Jul. 2009.
- [19] DRIVE: Digital Retinal Images for Vessel Extraction. URL: <http://www.isi.uu.nl/Research/Databases/DRIVE/S>.