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A Novel Approach For Detection Of Diabetic Retinopathy Using Kohonen Clustering Network

Sreelakshmi K P, Jais John

***Abstract*— this paper presents an automated blood vessel detection method Using Morphological Operator and Kohonen Clustering. The method first performs some basic image preprocessing tasks on the green channel of the retinal image. Currently the issue due to the complications of diabetes is day to day increasing with diabetic retinopathy being ocular degeneration of diabetes. Retinal vessel segmentation is really useful for generation of retinal maps for curing age related muscular degeneration. A combination of morphological operations like top- hat and bottom-hat transformations are applied on the preprocessed image to highlight the blood vessels. Finally, the Kohonen neural network is applied to cluster the input image into two clusters namely vessel and non-vessel .The performance of the proposed method is tested by applying it on fundus images. The sensitivity and accuracy of the proposed method is found to be higher than the other methods which imply that the proposed method is more efficient and accurate.**

***Index Terms*— Top Hat Transform; Bottom Hat Transform; KCN**

I. INTRODUCTION

Highlight a section In the present era diabetes has been an increasing distress for people due to the uncontrolled insulin level in the blood. Diabetic retinopathy is caused by complications of diabetes, which can in due course lead to blindness and can be termed as an ocular manifestation of diabetes. Based on recent surveys, diabetic retinopathy is the principal cause of new blindness in persons aged 25-74 years in the United States. The exact cause by which diabetes causes retinopathy remains imprecise, but numerous theories have been postulated to elucidate the typical course and history of the disease. Glaucoma and cataract are also such manifestations cuased by diabetes . In India, it is estimated that 8-20% of the population is diabetic,and the prevalence is increasing. Although population-based studies suggest that diabetic retinopathy is not a major cause of blindness in India at present, this is likely to change in the future. Early detection and treatment could reduce the development of severe vision loss or blindness by half. Diabetic retinopathy does not reduce vision in its early stages, when treatment is most effective. Examination of fundus photographs helps to detect the disease pathology in its early stages. DRIVE and STARE databases are intended to provide digital fundus images solely for research works collected on behalf of the diabetic screening program held in Netherlands.

Digital image proceesing and segmentation has indeed tremendously proved to be a efficient and diagonistic tool in the automatic generation of retinal maps for curing age related muscular degeneration, retinal image mosaic synthesis, extraction of characteristic points of the retinal vasculature. Retina functions as a light-sensitive layer of tissue, lining the inner surface of the eye .The various components present in the human retina such as the central portion of the retina as macula, the central part of macula as fovea, optic disc (OD) and blood vessels are shown in fig 1. There are two phases of diabetic retinopathy, these are non-proliferate diabetic retinopathy (NPDR) and proliferate diabetic retinopathy (PDR). NPDR being the mildest exhibits no warning signs where patients tend to have 20/20 vision. The lesions in the retina at the stage of NPDR are within the retina and include microaneurysms, small dot and blood hemorrhages, intraretinal micro vascular abnormalities (IRMA) and cotton wool spots. These symptoms progressively become distinct and as abnormal new blood vessels form at the back of the eye as a part of proliferative diabetic retinopathy, which could results in bursting and bleeding of new abnormal blood vessels.

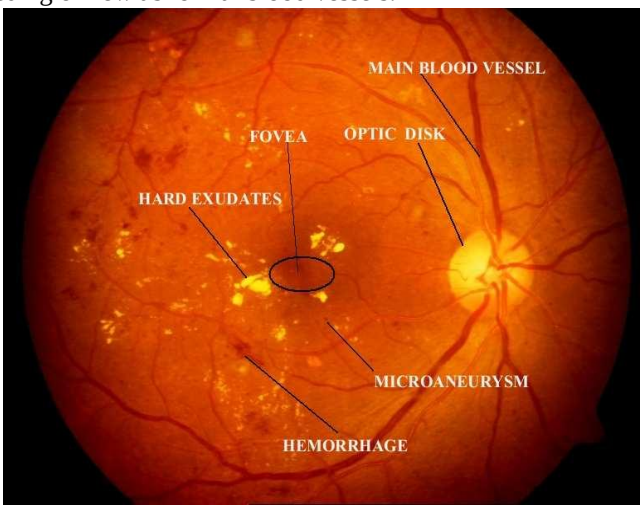

Fig. 1: Main components of Retina

The detection and measurement of retinal vessels can be used to enumerate the severity of disease, as part of the process of automated diagnosis of disease or in the assessment of the progression of therapy. Retinal blood vessels have been shown to have measurable changes in diameter, branching angles, length, as a result of a disease. Thus a reliable method of vessel segmentation would be

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***Sreelakshmi K P**, PG Scholar, Electronics and Communication Dept Nehru College of Engineering and Research Center, Thrissur, India.*

***Jais john**, Assistant Professor, Electronics and Communication Dept Nehru College of Engineering and Research Center*

valuable for the early detection and characterization of changes due to such diseases. Several algorithms and diagnostic methods have been developed for the retinal screening and early diagnosis of the disease. Different approaches for automated vessel segmentation have been proposed. Methods based on colored retinal image vessel segmentation technique that enhances and sharpens the vascular pattern using 2-D Gabor wavelet and sharpening filters. A method based on h-maxima transformation and multilevel thresholding for blood vessel detection is also prevalent. Another significant method is the blood vessel detection based on edge and object classification.

The proposed method is based on green channel feature extraction of the blood vessels by Kohonen clustering network. Hence a neural mapping algorithm is used for vessel segmentation after the preprocessing techniques which includes smoothing and contrast enhancement. A set of morphological operations which are the top hat and bottom hat transformations are applied on the preprocessed image before segmentation. Digital fundus images are obtained from medical practitioners and also several database images are readily available.

II. PROPOSED METHOD

The method herein presented can be schematically described by the functional block diagram in Fig. 2, where we identify five main processing phases: 1) preprocessing, for green channel extraction 2) Gaussian smoothing and filtering 3) contrast enrichment 4) morphological operations for defining minute blood vessels and 5) neural mapping by using Kohonen networks. These phases are further subdivided in quite a few steps, as follows:

A. Input Stage

Digital fundus images here used are of 2196 x 1958 pixel resolution obtained from eye care hospitals. Several databases such as the DRIVE and STARE can also facilitate with adequate images which are taken from various diabetic screening programs held in European countries. The DRIVE (Digital Retinal Images for Vessel Extraction) database is a collection of 40 retinal images, 7 of which contain pathological indicators, obtained from a screening program at the University Medical Centre Utrecht, Netherlands. This set was originally compressed in JPEG-format captured by a Canon CR5 non-mydriatic 3CCD camera with a 45° field of view, which produced images 540 pixels in diameter. Typically, there is wide variation in the color of fundus from different patients that is strongly correlated to the person's race and iris color. Therefore, we put our data through preprocessing steps before commencing the detection of blood vessels.

B. Green Band Processing

The green channel is considered as the natural basis for vessel segmentation because it normally presents a higher contrast between vessels and retinal background. To switch the RGB image to its green channel form, it is essential to estimate the values of its red, green, and blue primaries by means of linear intensity encoding and gamma expansion. If the output image is I and the red, green, and blue components are R, G, and B, respectively, then,

$$I = 0.33R + 0.5G + 0.166B \quad (1)$$

Also the input image can be written as a combined form of all 3 channels as,

$$I = [\, I_R + I_G + I_B \,] \quad (2)$$

Subsequently it will be made simpler if the single channel image is used. Conversely, the red and the blue bands are hardly used by automated applications since much information is not clearly displayed in these color bands. Thus, the green channel is extracted from the input image and stored in the matrix form.

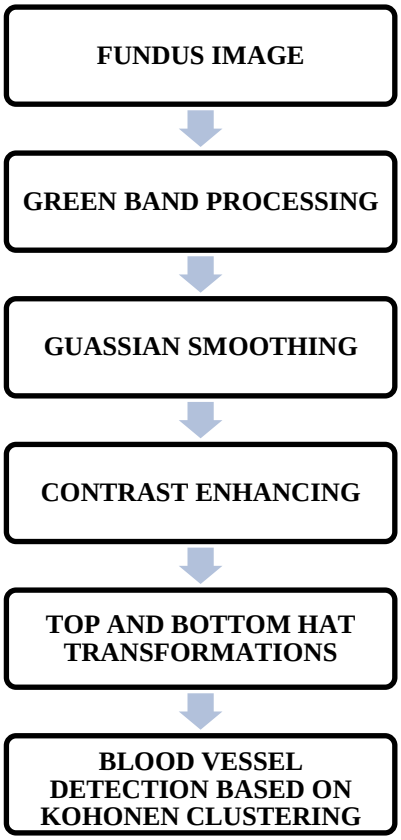


Fig. 2 Flow Chart Of Proposed Technique

C. Gaussian Smoothing

The Gaussian smoothing operator is a 2-D convolution operator that is used to `blur' images and remove detail and noise. The cause of Gaussian smoothing is to blur an image, in a comparable approach to the mean filter. The measure of smoothing is determined by the standard deviation value of the Gaussian function. This filtering not only has utility in engineering applications but is also attracting attention from computational biologists because it has been attributed with some amount of biological credibility, *e.g.* some cells in the visual pathways of the brain often have an approximately Gaussian response. In this case Gaussian smoothing is done to remove the Gaussian noise in the retinal fundus images. Using a Gaussian Blur filter before

edge detection it aims to reduce the intensity of noise in the image, which improves the result of the subsequent edge-detection algorithm.

$$I_{ga}(x, y) = I_G(x, y) * g(x, y) \quad (3)$$

Where * denotes convolution and g(x,y) is a Gaussian function represented by

$$g(x, y) = \frac{1}{2\pi\sigma^2} * \frac{-x^2+y^2}{2\sigma^2} \quad (4)$$

Where σ is the standard deviation and (x,y) represents the pixel coordinates of the input image.

D. Contrast Enhancement

The contrast of images is very important characteristics by which the quality of images can be judged as good or poor. The contrast enhancement techniques are commonly used in various applications where subjective quality of image is very important. The objective of image enhancement is to improve visual quality of image depending on the application circumstances. Low contrast images could crop up often due to a number of reasons, such as reduced or non-uniform lighting circumstance, nonlinearity or minute dynamic range of the imaging sensor, i.e., illumination is dispersed non-uniformly within the image. An equalization algorithm is useful in improving the contrast of the image.

$$I_E = 255 \frac{I_{ga} - I_{ga,max}}{I_{ga,max} - I_{ga,min}} \quad (5)$$

Where I_E is the enhanced image, I_{ga} is the smoothed image, $I_{ga,max}$ and $I_{ga,min}$ are the maximum and minimum pixel value of the image I_{ga}.

E. Top Hat and Bottom Hat Morphological Operations

In digital image processing, morphological operation is an operation that extracts small elements and details from given images. A morphological operation generally has a structuring element applied to the image, creating an output image of the same size. In this operation, the assessment of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors.

The hat-transforms represent an important class of morphological transforms used for detail extraction from signals or images. This procedure involves the subsequent steps:

- *Step 1:* The top hat transform of the enhanced image I_E is calculated using equation (5).

$$F_T = I_E - (I_E \circ Є_i) \quad (6)$$

$Є_i$ is a disk shaped structuring element. Then the green component (I_G) of the original image is added to the top-hat transform image (F_T), given as,

$$I_D = F_T + I_G \quad (7)$$

- *Step 2:* The result obtained in step-1 is subtracted from the bottom-hat transformed image. The bottom-hat transformation is represented as,

$$F_B = (I_E \bullet Є_i) - I_E \quad (8)$$

Then I_D is subtracted from I_B which results in enhanced blood vessels in the resultant image,

$$I_\psi = F_B - I_D \quad (9)$$

Where I_ψ represents the resultant image.

F. Kohonen Neural Network

Kohonen neural networks are well known for their cluster analysis. Kohonen clusters are unsupervised schemes which find the best set of weights for hard clusters in an iterative and sequential manner. The arrangement of kohonen clustering network consists of two layers an input layer and an output which is a competitive layer. The neuron closest to the input vector in terms of Euclidean distance is the winner neuron. The approximation of the winner and its predefined neighbors are updated using an unsupervised learning rule. The final change map is formed by a clustering technique in which the input image is dispatched into two clusters of changed and unchanged using Kohonen Clustering Network (KCN). The network used for clustering in this paper is shown in Fig.3.The steps involved in KCN clustering are as follows: Let the pixels of I_ψ be represented by $I_{\psi,j} \in (I_{\psi,1}, I_{\psi,2}, \ldots I_{\psi,n})$.

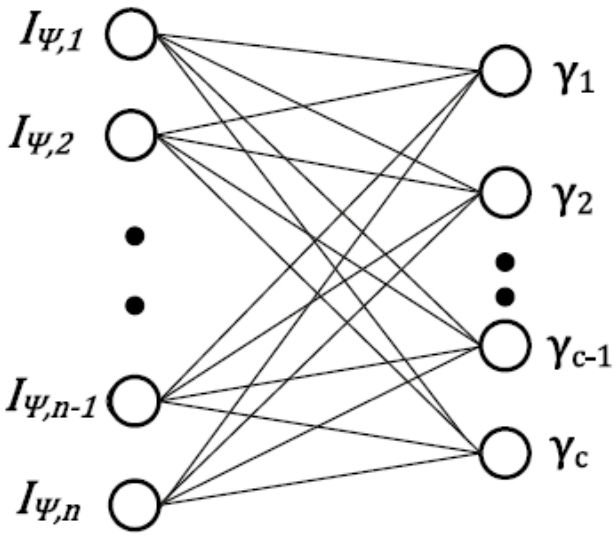


Fig. 3 Architecture of KCN

Where n= pq is the total number of pixels in the image. These pixels are given as input to the KCN network. Centers of the clusters formed are denoted by $\gamma_{i,t.}$

Step 1.Initialization: the first step is to initialize the cluster center as $\gamma_{i,0}$ $(i \leq 0 \leq c)$, and the learning rate, $\beta_{i\,j,t}$ $(0 < \beta_{i\,j,t} < 1)$, threshold $Ɛ$($Ɛ > 0$) and topological neighborhood parameters. Set t = 1 and maximum iteration limit $t_{max.}$

Step 2.Selection of winner: Calculate the squared Euclidean distance:

$$d^2_{ij,t} = \| I_{\psi,j} - \gamma_{i,t} \|^2 \text{ for } j= 1,2,\ldots n \text{ and } i= 1,2,..c \quad (10)$$

Winning output neuron is decided by,

$$\min \{ d^2_{ij,t} \} \text{ for } j= 1,2,\ldots n \text{ and } i= 1,2,\ldots c \quad (11)$$

Step 3.Weight Updating: The weight of the winner neuron is updated by

$$\gamma_{i,t} = \gamma_{i,t-1} + \beta_{i\,j,t} (I_{\psi,j} - \gamma_{i,t-1}) \quad (12)$$

Where $\beta_{i\,j,t}$ is learning rate.

Step 4. If $\| \gamma_{i,t} - \gamma_{i,t-1} \| > \varepsilon$ set t = t + 1, update learning rate and go to step 2 else stop. Two cluster centers are obtained by applying KCN denoted by γ_{wc} and γ_{wu} for clusters W_v and W_b representing blood vessel and non-blood vessel clusters respectively. Each pixel of the fused image I_ψ is assigned to one of the two clusters formed using eq. (12). Based on the distance of each pixel from the cluster center, the pixels are assigned to the cluster having minimum distance. Final binary image (I_{vessel}) is created as

$$I_{vessel} = \begin{cases} 1, & \| I_\varphi(x,y) - \gamma_{wc} \| \leq \| I_\varphi(x,y) - \gamma_{wu} \| \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

Where $\| \|$ is the Euclidean distance. The image consists of zeros and ones indicating "non-blood vessel" and "blood vessels" respectively.

III. Experimental Results

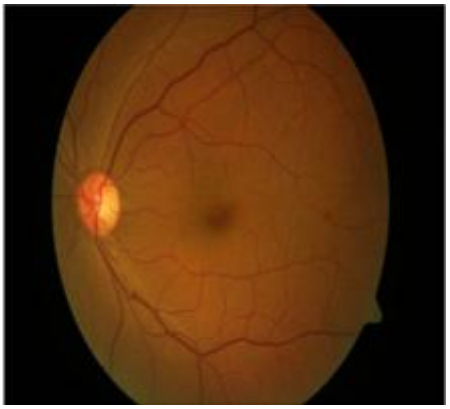
The proposed technique is implemented in MatlabR2010.The parameters used are σ = 0.56 which is the Gaussian function for Gaussian smoothing, the learning rate β = 0.5 which determines a threshold level for the kohonen networking, and maximum number of iterations is given by t_{max} = 90.The results obtained at various steps are shown in fig.4. The degree of dominance of retinopathy can be scaled in factors of false positive rate and true negative rates. This in turn can be enhanced for the quantitative analysis of sensitivity and precision of the whole scheme.

- True Positive Rate (TPR): actual blood vessel pixels classified correctly as blood vessel pixels in the image.
- True Negative Rate (TNR): actual values of non blood vessel pixels distinguished as non-blood vessel pixels.
- False Positive Rate (FPR): blood vessel pixels incorrectly classified as non-blood vessel pixels.
- False Negative Rate (FNR): number of non-blood vessel pixels incorrectly determined as blood vessel pixels.

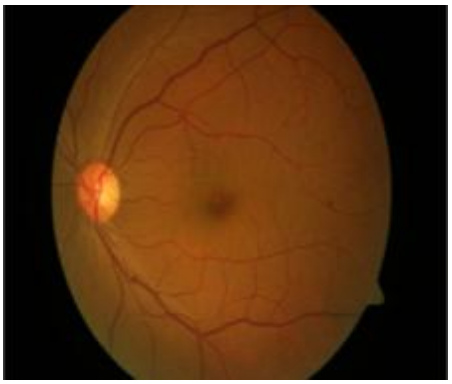
It can be defined that accuracy and sensitivity are results of statistical analysis of performance of kohonen self organizing map herein used. The grade of the disease can be monitored by using false positive ratio (FPR) which analysis the ratio of falsely detected blood vessels to overall non-blood vessels.

	FPR	accuracy	sensitivity
centerline	0.0183	0.9452	0.7344
Object classification	0.0371	0.9653	0.8431
proposed	0.0415	0.9802	0.9912

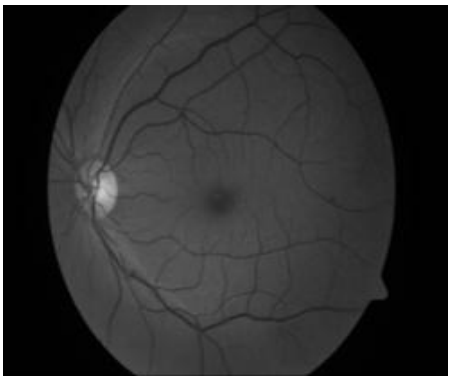
Table 1. Statistical study of various techniques



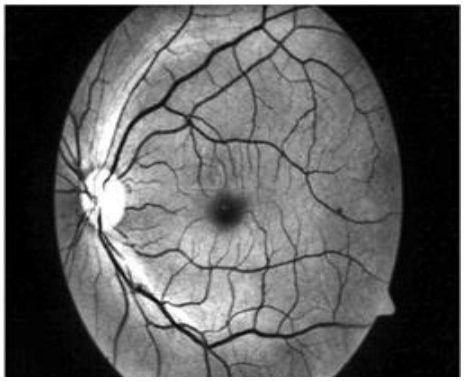
(a) Input fundus image



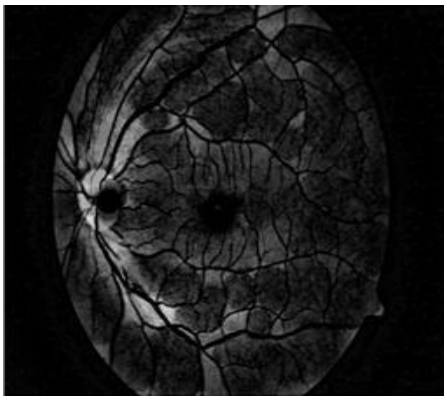
(b) Smoothed image



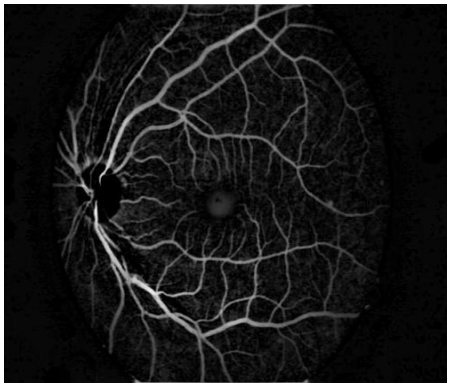
(c) Green channel image



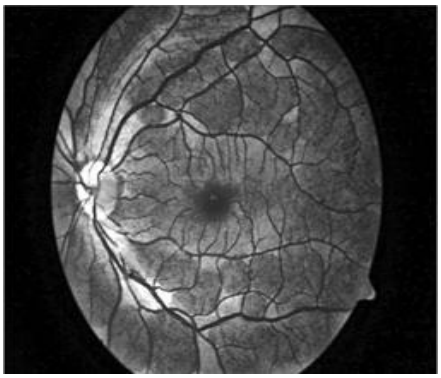
(d) Contrast enhanced image



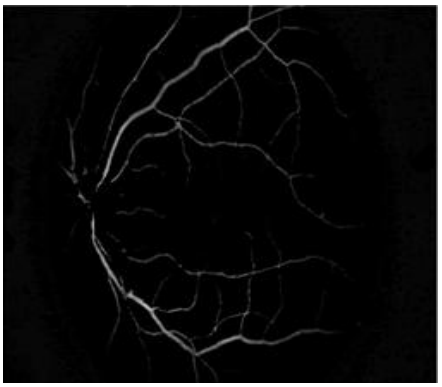
(e) Top hat transformed



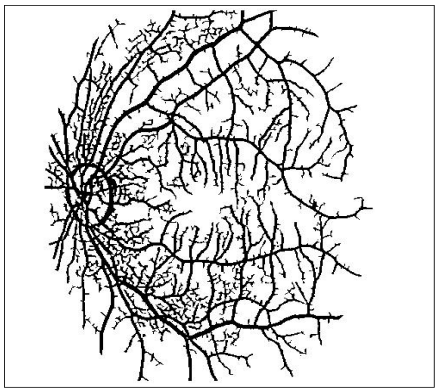
(f) Bottom hat transformed



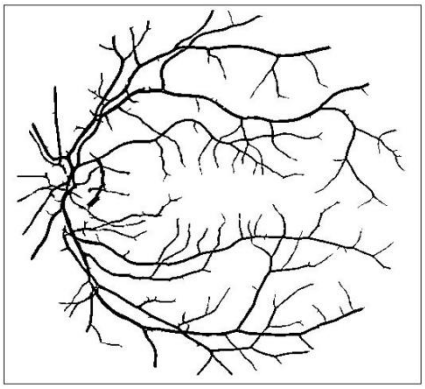
(g) Image I_D



(h) Image I_Ψ



(i) Blood vessel extracted for an abnormal fundus



(j) Blood vessel extracted for a normal fundus
Fig 4 (a) to (j) shows the results of different stages of the proposed method

The morphological transformed images are formed by top hat and bottom transformations. The final fused image after the KCN clustering is depicted for both abnormal and normal fundus. This illustrate that the severity of the disease causes the normal blood vessels to leak and swell resulting in weak and abnormal new blood vessels. This paper presents a novel approach for analysing the abnormal blood vessel patterns efficiently and more precisely by representing the exact variations and size of the vessels. The self organizing Kohonen clustering network is an automated technique which is well and most popular hence it is often used in neurobiology. The proposed method is tested on fundus

image with abnormal behaviour of new sprouting blood vessels and also a normal fundus image is also segmented.

IV. CONCLUSION

In this paper, a new technique based on morphological operations and kohonen clustering is presented for automatic extraction of blood vessels in the fundus image. In the future the work could be extended for the purpose of detecting and classifying exudates pathologies of DR. The performance of the proposed approach is evaluated by comparing fundus photographs provided by expert medical practitioners. The results obtained from this study show that the proposed algorithm is a powerful technique compared to other well-known methods. However, one of the major fundamental problems in the field of biomedical image analysis is the shortage of accurate and efficient computer-aided diagnostic tool to assist the fundus image extraction and evaluation process. From the medical perspective, the projected method can be helpful to aid the ophthalmologists while assessing or analyzing the fundus images. In the future, the proposed approach can be applied for image registration purposes to track the changes in retinal images for monitoring DR.

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REFERENCES

[1] David Yorston FRCS FRCOphth, Specialist Registrar Moorfields Eye Hospital City Road London EC1V 2PD UK, Retinal Diseases and VISION 2020

[2] K Viswanath, MS DO MSc ,Head of the Department of Ophthalmology Osmania Medical College Deputy Medical Superintendent Regional Institute of Ophthalmology Sarojini Devi Eye Hospital Hyderabad, Diabetic Retinopathy: Clinical Findings and Management.

[3] S.Tripathi,K.K.Singh,B.K.Singh andA.Mehrotra, "Automatic Detection of Exudates in Retinal Fundus Images using Differential Morphological Profile", International Journal of Engineering & Technology,vol.5,no.3,2013,pp.2024-2029.

[4] A. Osareh, B. Shadgar and R. Markham, " A computational-intelligence based approach for detection of exudates in diabetic retinopathy images," Information Technology in Biomedicine, IEEE Transactions on, vol. 13, no.4,2009,pp. 535-545.

[5] R.M. Rangayyan, F. Oloumi, F. Oloumi, P. Eshghzadeh-Zanjani and F. J. Ayres, " Detection of Blood Vessels in the Retina using Gabor Filters,"In Proc. IEEE Electrical and Computer Engineering (CCECE) Canadian Conference, April,2007,pp.717-720.

[6] Saleh MD, Eswaran C: An efficient algorithm for retinal blood vessel segmentation using h-maxima transform and multilevelthresholding. Computer Methods in Biomechanics andBiomedical Engineering 15(5):517–525, 2012.

[7] Mendonca AM, Campilho A: Segmentation of retinal blood vesselsby combining the detection of centerlines and morphological reconstruction. IEEE Trans. Med. Imag. 25(9):1200–1213, 2006.

[8] ShahriarBadsha, Ahmed Wasif Reza, Kim Geok Tan, Kaharudin, " A New Vessel Extraction Technique Using Edge Enhancement and Object Classification", Springer, march 2013.

[9] K.K. Singh, A. Mehrotra, M.J.Nigam and K. Pal, "A Novel Edge Preserving Filter For Impulse Noise Removal," In Proc. IEEE Multimedia, Signal Processing and Communication Technologies (IMPACT) International Conference, December,2011,pp. 103-106.

[10] T. Kohonen Self-Organization and Associative Memory (3rd Edn.)Springer, Berlin 1989

[11] Dr. M Turhan Turner, Rock solid images, Kohonen's Self Organizing Maps and their use in Interpretation.