International Journal of Engineering Research in Electronic and Communication Engineering (IJERECE) Vol 3, Issue 5, May 2016

Automatic Retinal Disorder Identification In Diabetic Retinopathy And Maculopathy Using Neural Network

[1] Sandeep M S [2] Dr Chandrashekar M Patil
[1] PG Scholar [2] Professor
Dept. of Electronics and Communication
Vidya Vardhaka College of Engineering
[1] sandeep8881@gmail.com [2] patilcm@gmail.com

***Abstract*— Computational methodologies have become a significant part of the real time applications. One specification application which highly depends on the computing techniques is the medical led ophthalmology is a significant branch of biomedical led which requires computer aided automated techniques for pathology identification in human eyes. Eye is the most essential part of the entire creature in this world for vision. So the main intention of carrying this work is to reduce retinal disorders in younger generation. This work proceeds with detecting the disorder present in human eye based on Diabetic retinopathy and other parameter and develops an efficient algorithm to detect retinal disorder using MATLAB.**

I. INTRODUCTION

Diabetic retinopathy (DR) is the most common cause of blindness and vision defects in developed countries [1]. Due to its prevalence and clinical significance the research community has attempted to improve its diagnosis and treatment by developing algorithms to perform retinal image analysis, fundus image enhancement [2-4], and monitoring [5]. Of special significance is automatic image analysis algorithms designed to detect hard exudates (HEs) [6]. Early detection enables laser therapy to be performed to prevent or delay visual loss and may be used to encourage improvement in diabetic control. Current methods of detection and assessment of diabetic retinopathy are manual, expensive and require trained ophthalmologists. Exudates are one of the primary signs of diabetic retinopathy [7,8]. Automatic exudates detection would be helpful for diabetic retinopathy screening process. The eye is an organ associated with vision. The eye is housed in a socket of bone called the orbit and is protected from the external air by the eyelids [9]. A cross section of the eye is shown in Figure 1. Light entering the eye through the pupil is focused on the retina. The retina is a multi-layered sensory tissue that lines the back of the eye. It contains millions of photoreceptors that capture light rays and convert them into electrical impulses [10]. These impulses travel along the optic nerve to the brain where they are turned into images. In a normal FI, the optic disk is brighter than any part of the retina and is normally circular in shape. It is also the entry and exit point for nerves entering and leaving the retina to and from the brain. A typical retina fundus image looks like the one shown in Figure 2. The bright optic disc and the vascular network can clearly be seen in the image.

II. LITERATURE SURVEY

1"Automated Extraction Of Blood Vessels In Retinal Image", J.Sivakumar and J.Jeno [1]. Here in this paper we are meant to address the problem of nding the true blood vessels automatically by overcoming the problems caused by the bifurcation and crossover points using the tracing method. It separates the true blood vessels and false blood vessels, and identi es multiple numbers of vessels and properties simultaneously one at a time.

2."Automatic diagnosis of retinal diseases from color retinal images", D.Jayanthi, N.Devi and S.SwarnaParvathi [2]. The proposed system will diagnose the disease present in the retina using a neural network based classi er.The extent of the disease spread in the retina can be identi ed by extracting the textural features of the retina. This system will diagnose the following type of diseases: Diabetic Retinopathy and Drusen.

3."Retinal Vessel Extraction by Using Visual Cortical Filters", Davanamena Shivakr-ishna, R Raja Kishore and Dr. M Narsing Yadav [3]. In this paper we implement a visual cortical lter which is also called as 2D - Gabor lter in combination with linear model for retinal vessel extraction. By convoluting multiple Gabor lter with the image we try to detect the retinal blood vessels. Here we consider Gabor transformed image as independent variables and the location the vessels as dependent variables. This method is validate graphically and by calculating sensivity and speci city.

4."A Survey of Automated Techniques for Retinal Diseases Identi cation in Diabetic Retinopathy", Kade Mahesh k [4]. This paper focus on importance of understanding the motivation behind the retinopa-thy , its intricacies and the role of technology involved in it . It also gives information of available public data set on which algorithms are tested and trained 4"Imaging the Retina", Jos Cunha- Vaz [5]. In this paper, Spectral domain optical coherence tomography has revolutionized our understanding of retinal diseases and allowed close monitoring of changes in the retina. All these non- invasive procedures can, nally, be combined making multimodal imag-ing of the retina an extremely promising tool to improve the understanding of retinal disease.

5 "Detection of Diabetic Retinopathy with Feature Extraction using Image Processing", Meera Walvekar, Geeta Salunke [6]. In this paper, we will look at the extraction and outcome of important features, using image processing, and the severity of Diabetic Retinopathy. The datasets used for this study are DRIVE and STARE.

6."Study of Image Segmentation Techiques on Retinal Images for Health Care Manage-ment With Fast Computing",Srikanth Prabhu and N. Gopalakrishna Kini [7]. In this paper emphasis has been laid on segmentation of biometric retinal images to lter out the vessels explicitly for evaluating the bifurcation points and features for diabetic retinopathy. Segmentation on images is performed by calculating ridges or morphology. Ridges are those areas in the images where there is sharp contrast in features. Morphology targets the features using structuring elements.

7."Automatic Retina Exudates Segmentation Without A Manually Labelled Training Set" L. Giancardo, F. Meriaudeau, T.P. Karnowski, Y. Li K.W. Tobin Jr., E. Chaum [8]. In this work, two new methods for the detection of exudates are presented. The methods do not require a lesion training set so the need to ground-truth data is avoided with signicant time savings and independence from human error. They evaluated the algorithm with a new publicly available dataset from various ethnic groups and levels of DME. Also, compared the results with two recent exudate segmentation algorithms on the same dataset.

8."An E ective Automated Technique for Retinal Disease Identi cation in Diabetic Retinopathy without Manually Labeled Kit " Romana Naznin and Ipsita Parida [9]. In this work, new exudates detection method is given which has overcome the limita-tions of labeled lesion training sets such as: time consumption, complexity and more probability of error. In this project present a new concept to normalize the fundus im-age and directly compared the method with an implementation. Here, they introduce two variations of a new exudates segmentation method that comes under the category of thresholding methods and nd out the diabetics as well as other eye diseases.

9."Biometric Iris Recognition Based on Hybrid Technique", Khattab M. Ali Alheeti [10]. In this paper the iris recognition algorithm is implemented via histogram equalization and wavelet techniques. In this paper the iris recognition approach is implemented via many steps, these steps are concentrated on image capturing, enhancement and identi cation. Di erent types of edge detection mechanisms; Canny scheme, Prewitt scheme, Roberts scheme and Sobel scheme are used to detect iris boundaries in the eyes digital image. The implemented system gives adequate results via di erent types of iris images.

10."Iris Recognition using Feature Detection Techniques in Matlab Simulink Model Block-set", Adhyana Gupta and Dr.Pratistha Mathur [11]. In this paper, entirely biometric-based personal veri cation and identi cation methodshave gained much interest with an increasing accent on safety. Iris recognition using feature detection techniques in Matlab simulink model blockset. The iris texture pat-tern has no links with the genetic structure of an individual and since it is generated by chaotic processes externally visible patterns imaged from a distance. Iris patterns possess a high degree of randomness and uniqueness. Video and Image Processing Blockset is a tool used for the rapid design, prototyping, graphical simulation, and e cient code generation of video and image processing algorithms. The developed process involves object feature identi cation, detection

11."Arti cial Neural Networks for Iris Recognition System: Comparisons between Di er-ent Models, Architectures and Algorithms ", Omaima N. Ahmad AL-Allaf, Abdelfatah Aref Tamimi and Shahlla A. AbdAlKader [12]. In this research, an iris recognition system was suggested based on ve Arti cial Neu-ral Network (ANN) models separately: feed forward (FFBPNN), cascade forward (CFBPNN), function tting (FitNet), pattern recognition (PatternNet) and learning vector quantization (LVQNet). For each ANN model, two architectures were constructed sep-arately; 4 layers and 7 layers, each with di erent numbers ofhidden layer units (5, 10 and 15). Ten di erent ANN optimization training algorithms (LM, BFG, BR, CGF, GD, GDM, GDA, GDX, OSS and RP) were used to train each model separately.

12."E cient Iris Recognition Algorithm Using Method of Moments", Bimi Jain, Dr.M.K.Gupta and Prof.JyotiBharti [13]. This paper presents an e cient biometric algorithm for iris recognition using Fast Fourier Transform and moments. Biometric system provides automatic identi cation of an individual based on a unique feature or characteristic possessed by the individual. The Fast Fourier Transform converts image from spatial domain to frequency domain and also lters noise in the image giving more precise information. Moments are area descriptors used to characterize the shape and size of the image. The moments values are invariant to scale and orientation of the object under study, also insensitive to ro-tation and scale transformation. At last Euclidean distance formula is used for image matching.

13."Iris Recogntion Based on LBP and Combined LVQ Classi er", M. Z. Rashad, M. Y. Shams, O. Nomir, and R. M. El-Awady [14]. This paper proposes an algorithm for iris recognition and classi cation using a system based on Local Binary Pattern and histogram properties as a statistical approaches for feature extraction , and Combined Learning Vector Quantization Classi er as Neural Network approach for classi cation, in order to build a hybrid model depends on both features. The localization and segmentation techniques are presented using both Canny edge detection and Hough Circular Transform in order to isolate an iris from the whole eye image and for noise detection.

14."Iris Recognition using Wavelet Transformation", Amritpal Kaur [15]. This paper describes the segmentation and the normalization processing for biometric iris recognition system, implemented and validated in MATLAB Software. In this work we use the image database digitized in greyscale, where segmentation algorithms were implemented based on region growing using wavelet decomposition with Gabor lter, nally an alternative segmentation algorithm was designed and implemented, its performance was evaluated with satisfactory results.

III. RELATED WORK

Automatic exudates detection would be helpful for diabetic retinopathy screening process. Gardner et al. proposed an automatic detection of diabetic retinopathy using an artificial neural network. The exudates are identified from grey level images and the fundus image is analyzed using a back propagation neural network. The classification of a 20 × 20 region is used instead of a pixel level classification [11]. In the preprocessing step, adaptive, local, contrast enhancement is applied. The optic disc, blood vessels and fovea detection are also localized [12]. Wang et al. used color features on a Bayesian statistical classifier to classify each pixel into lesion

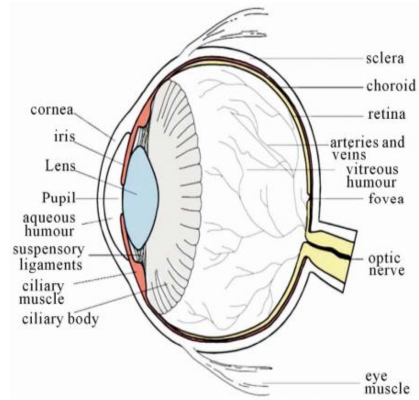


Fig. 1 Cross sectional diagram of human eye

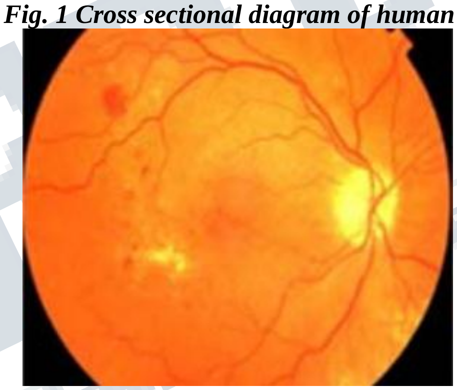
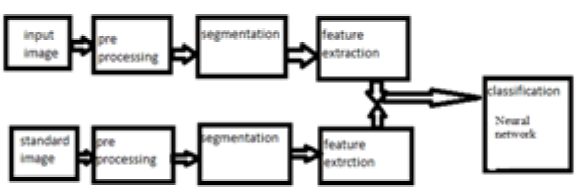


Fig. 2 Retinal fundus image

Or non-lesion classes [13]. Huiqi Li et al. proposed an exudates extraction technique by using a combination of region growing and edge detection techniques. The optic disc is also detected by Principal Component Analysis (PCA). The shape of the optic disc is detected using a modified active shape model [14]. Usher et al. detected the candidate exudates region by using a combination of RRGS and adaptive intensity thresholding [15]. Goh et al. used the minimum distance discriminated to detect the exudates. The spectrum feature center of exudates and background are computed and then the distance from each pixel to class center is calculated. The pixel is classified as exudate if it falls within the minimum distance [16]. Ege et al. used a median filter to remove noise. Bright lesions and dark lesions are separated by thresholding. A region growing algorithm is used to locate exudates. Bayesian, Mahalanobis and K-Nearest Neighbor classifier were tested. From these experiments, the Mahalanobis classifier was shown to yield the best results [17]. The comparative exudate classification using Support Vector Machines (SVM) and neural networks was also applied. They showed that SVM are more practical than the other approaches [18]. Many techniques have been performed for exudate detection, but they have limitations. Poor quality images affect the separation result of bright and dark lesions using thresholding and exudate feature extraction using the RRGS algorithm, while other classification techniques require intensive computing power for training and classification. Furthermore, based on experimental work report in the previous work, most of techniques mentioned above worked on images taken when the patient had dilated pupils. Good quality retinal images with large fields that are clear enough to show retinal detail are required to achieve good algorithm performance. Low quality images (non-uniform illumination, low contrast, blurred or faint images) do not give good results even when enhancement processes are included. The examination time and effect on the patient could be reduced if the automated system could succeed on non-dilated pupils. Tang et al. [19] used watershed algorithm for segmentation of splats, a collection of pixels with similar color and spatial location. The connected vasculatures were removed by automated vessels segmentation method. The KNN classifier was applied with 42 features in training and reduced to 7 features using forward feature selection method in testing stage. A set of 20 images from DRIVE database was used for training and then 1200 images from MESSIDOR database are used in testing. the bottom-up strategy to detection of bright lesions and the top-down strategy in dark lesions detection. In hemorrhage detection, hemorrhages are located in the ROI firstly by calculating the evidence value of every pixel using SVM. The kernel PCA and PCA are used to selection features. SVM Classifier with kernel yields 90.6% true positive while PCA is 89.1%.

Block Diagram



A. Image Pre-processing

Image pre-processing is the initial step in automated retinal pathology diagnosis. It includes techniques such as contrast enhancement, gray/green component, image de-noising, etc. In a binary image, white pixels are normally taken to represent foreground regions, while black pixels denote background. In case of Gray scale image, the intensity value represents height above a base plane. Thus, the Gray scale image represents a surface in three-dimensional Euclidean space

RGB to gray scale conversion

Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), fig 3 and in such cases they are monochromatic proper when only a given frequency is captured

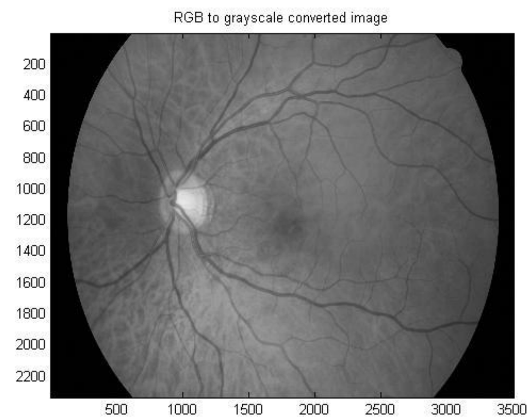


Fig:3

Edge Detector

The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images fig 4

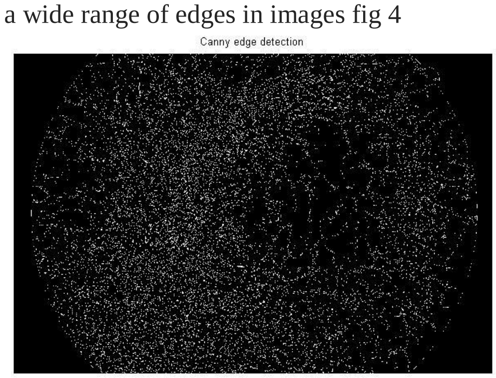


Fig:4

Optic disc: The image is filtered in order to eliminate large gray level variations within the papillary region. The vessels are filled applying a simple Closing operation. Classical Watershed transformation fig5 is applied to the gradient to detect contours of the optic disc.

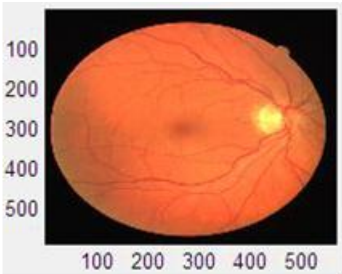


Fig:5

C. Disease severity:

The severity of the disease is measured depending on the area calculated from the pre-processing and feature extraction. Depending on the severity, there are three categories such as mild, moderate and severe stage. A treatment can also be based on the severity.

Output

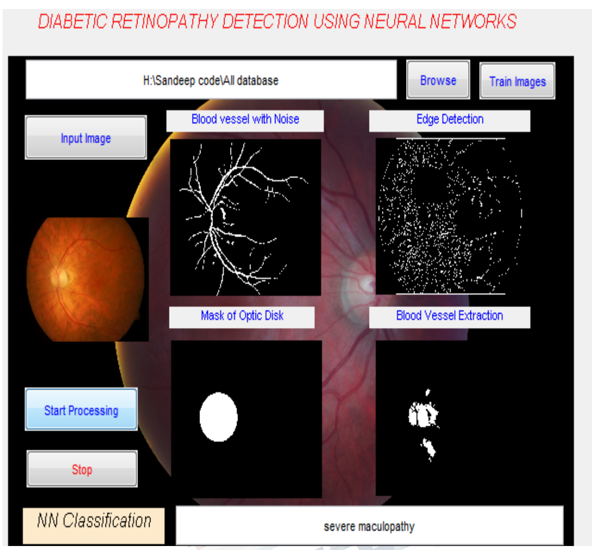


Fig:6

REFERENCES

1) G. Eason, B. Noble, and I.N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," *Phil. Trans. Roy. Soc. London*, vol. A247, pp.529-551, April 1955.

2) J. Clerk Maxwell, *A Treatise on Electricity and Magnetism*, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68-73.

3) I.S. Jacobs and C.P. Bean, "Fine particles, thin films and exchange anisotropy," in *Magnetism*, vol. III, G.T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp.271-350.

4) K. Elissa, "Title of paper if known," unpublished.

5) R. Nicole, "Title of paper with only first word capitalized," *J. Name Stand. Abbrev.*, in press.

6) Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopy studies on magneto-optical media and plastic substrate interface." *IEEE Transl. J. Magn. Japan*, vol. 2, pp.740-741, August 1987 [*Digests 9th Annual Conf. Magnetics Japan*, p.301, 1982].

7) M. Young, *The Technical Writer's Handbook.* Mill Valley, CA: University Science, 1989.

8) D. E. Singer, D. M. Nathan, H. A. Fogel, A. P. Schachat, "Screening for Diabetic Retinopathy," *Annals of Internal Medicine*, Vol. 116, No. 8, 1992, pp. 60-71. doi:10.7326/0003-4819-116-8-660..

9) M. J. Cree, J. A. Olson, K. C. McHardy, P. F. Sharp and J. V. Forrester, "The Preprocessing of Retinal Images for the Detection of Fluoresce in Leakage," *Physics in Medicine & Biology*, Vol. 44, No. 1, 1999, pp. 293-308. doi:10.1088/0031-9155/44/1/021

10) M. J. Cree, E. Gamble and D. Cornforth, "Colour Normalisation to Reduce Inter-Patient and Intra-Patient Variability in Micro Aneurysm Detection in Colour Retinal Images," *Proceedings of the APRS Workshop on Digital Image Computing, Brisbane*, 21 February 2005, pp. 163- 168.

11) M. Foracchia, M. Grisan and A. Ruggeri, "Luminosity and Contrast Normalization in Retinal Images," *Medical Image Analysis*, Vol. 9, No. 3, 2003, pp. 79-90.

12) A.Pinz, M. Prantl and P. Datlinger, "Mapping the Human Retina," *IEEE Transactions on Medical Imaging*, Vol. 17, No. 4, 1998, pp. 606-619. doi:10.1109/42.730405.

13) N. Patton, T. M. Aslam, T. MacGillivray, I. J. Deary, B. Dhillon, R. H. Eikelboom, et al., "Retinal Image Analysis: Concepts, Applications and Potential," *Progress in Retinal and Eye Research*, Vol. 25, No. 1, 2006, pp. 99-127. doi:10.1016/j.preteyeres.2005.07.001

14) S. Bjorvis, M. A. Johansen and K. Fossen, "An Economic Analysis of Screening for Diabetic Retinopathy," *Journal of Telemedicine and Telecare*, Vol. 8, No. 1, 2002, pp. 32-35.

15) S. S. Feman, T. C. Leonard-Martin and J. S. Andrews, "A Quantitative System to Evaluate Diabetic Retinopathy

from Fundus Photographs," *Investigative Ophthalmology & Visual Science*, Vol. 36, No. 1, 1995, pp. 174-181.

16) A.M. Aibinu, M. I. Iqbal, A. A. Shafie, M. J. E. Salami and M. Nilsson, "Vascular Intersection Detection in Retina Fundus Images Using a New Hybrid Approach," *Computers in Biology and Medicine*, Vol. 40, No. 1, 2010, pp. 81-89. doi:10.1016/j.compbiomed.2009.11.004

17) M. Aibinu, M. I. Iqbal, M. Nilsson and M. J. E. Salami, "A New Method of Correcting Uneven Illumination Problem in Fundus Images," International *Conference on Robotics, Vision, Information, and Signal Processing, Penang,* 28-30 November 2007, pp. 445-449.

18) G. G. Gardner, D. Keating, T. H. Williamson and A. T. Elliot, "Automatic Detection of Diabetic Retinopathy Using an Artificial Neural Network: A Screening Tool," *British Journal of Ophthalmology, Vol. 80*, No. 11, 1996, pp. 940-944. doi:10.1136/bjo.80.11.940.

19) Sinthanayothin, J. F. Boyce, H. L. Cook and T. H. Williamson, "Automated Localization of the Optic Disc Fovea and Retinal Blood Vessels from Digital Colour Fundus Images," *British Journal of Ophthalmology,* Vol. 83, No. 8, 1999, pp. 231-238. doi:10.1136/bjo.83.8.902

20) H. Wang, W. Hsu, K. G. Goh and M. L. Lee, "An Effecttive Approach to Detect Lesions in Color Retinal Images," *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Hilton Head Island,* 13-15 June 2000, pp. 181-186.

21) H. Li and O. Chutatape, "A Model-Based Approach for Automated Feature Extraction in Fundus Images," *International Conference on Computer Vision (ICCV), Nice,* 13-16 October 2003, pp. 394-399.

22) Usher, M. Dumskyj, M. Himaga, T. H. Williamson, S. Nussey and J. Boyce, "Automated Detection of Diabetic Retinopathy in Digital Retinal Images: A Tool for Diabetic Retinopathy Screening," *Diabetic Medicine*, Vol. 21, No. 1, 2004, pp. 84-90. doi:10.1046/j.1464-5491.2003.01085.x

23) K. G. Goh, W. Hsu, L. Lee and H. Wang, "ADRIS: An Automatic Diabetic Retinal Image Screening System," *In: J. C. Krzysztof, Ed., Medical Data Mining and Knowledge Discovery,* Physica-Verlag, Heidelberg, 2001, pp. 181-210.

24) B. M. Ege, O. K. Hejlese, O. V. Larsen, K. Moller, B. Jennings, D. Kerr and D. A. Cavan, "Screening for Diabetic Retinopathy Using Computer Based Image Analysis and Statistical Classification," *Computer Methods and Programs in Biomedicine*, Vol. 62, No. 3, 2000, pp. 165- 175. doi:10.1016/S0169-2607(00)00065-1

25) A. Osareh, M. Mirmehdi, B. Thomas and R. Markham, "Comparative Exudate Classification Using Support Vector Machines and Neural Networks," *In: T. Dohi and R. Kikinis, Eds., Medical Image Computing and Computer-Assisted Intervention, Springer,* Berlin, 2002, pp. 413-420.

26) L. Tang, M. Niemeijer and M. D. Abrilmoff, "Splat Feature Classification: Detection of the Presence of Large Retinal Hemorrhages," IEEE *International Symposium on Biomedical Imaging, Chicago*, 30 March 2011-2 April 2011, pp. 681-684.

27) J. J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever and B. van Ginneken, "Ridge Based Vessel Segmentation in Color Images of the Retina," *IEEE Transactions on Medical Imaging*, Vol. 23, No. 4, 2004, pp. 501- 509. doi:10.1109/TMI.2004.825627