RESEARCH ARTICLE OPEN ACCESS

Smart Supervised Method for Blood Vessel and Optic Disc Segmentation from Fundus Images

P.Anu [1], T.Jeyaselvi [2], J.Johncy Eunice[3], M.Magie Pushpa [4]

UG Scholars [1]

Department of Electronics and Communication Engineering

Jayaraj Annapackiam CSI College of Engineering

Nazareth - India

ABSTRACT

Glaucoma is a condition of increased pressure within the eyeball, causing a gradual loss of sight. Normal eye pressure ranges from 12 – 22 mm Hg. Vision loss from glaucoma occurs when the eye pressure is too high for the specific individual and damages the optic nerve. Any resultant damage cannot be reversed. Therefore early detection through regular screening and timely interven tion will be highly beneficial in effectively controlling the progress of the disease. Various aspects and stage of glaucoma are a nalyzed by examining the colored retinal images. The bright circular region from where the blood vessels emanate are called the optic disk. Glaucoma patients require frequent, at least, six monthly screening of a vast number of patients and automating the process will go a long way in relieving the burden on the specialist and reducing the most common cause of preventable blindness. The main objective of this paper is to detect and segment the blood vessels and optic disc from the retinal images. For that in blood vessel segmentation, using CLAHE, OGF and LET followed by in Optic disc detection, two algorithms is used for selecting which method among the two is best fitted. The two methods such as CHT and super pixel, the brightness based is used for locating the optic disc. Finally, generate a report by calculating the average blood vessel and optic disc pixels.

Keywords: - Fundus Image, Blood vessels, Glaucoma, Optimized Gabor Filtering, Local Entropy Thresholding.

I. INTRODUCTION

Glaucoma, chronic eye disease, which results in damage to the optic nerve and vision loss. A major risk factor of Glaucoma is increased pressure in the eye. Open – angle glaucoma is painless and does not have any attacks, thus, the lack of clear symptoms make screening via regular eye checkups important.

The process of automatic or semi – automatic detection of the boundaries within a 2-D or 3-D image is known as Medical Image Segmentation. Image Segmentation is the process of dividing a given image into meaningful regions with homogeneous properties.

In general, medical image segmentation is very time-consuming. Therefore, much more concentrate on the minimization of user interaction in order to keep things as simple as possible. To achieve this goal, we take advantage of latest developments in computer graphics hardware for noticeable performance speedups.

Glaucoma is an irreversible chronic eye disease and is predicted to affect around 80 million people by 2020[1]. In early stages, the visual symptoms of the disease are not easily noticeable as the disease is progress silently. About 50 – 90% of patients are unaware of the disease until it has reached the advanced stages [2] – [4]. Thus, the Glaucoma is also called the silent theft of sight. The screening of people at high risk of glaucoma for timely detection is very meaningful. Currently, the glaucoma assessment is often used in the air – puff intraocular pressure (IOP) measurement, visual field test, and optic nerve head (ONH) assessment. ONH assessment is more promising for glaucoma screening. Many image processing methods proposed for retinal vessels extraction [5], [6], [7], [8], [9], [10], [11].

This paper has been proposed a much robust and fast method of retinal optic disc and blood vessels extraction using optimized gabor filter with local entropy thresholding and superpixel method.

The flow chart of the proposed methodology is as follows:

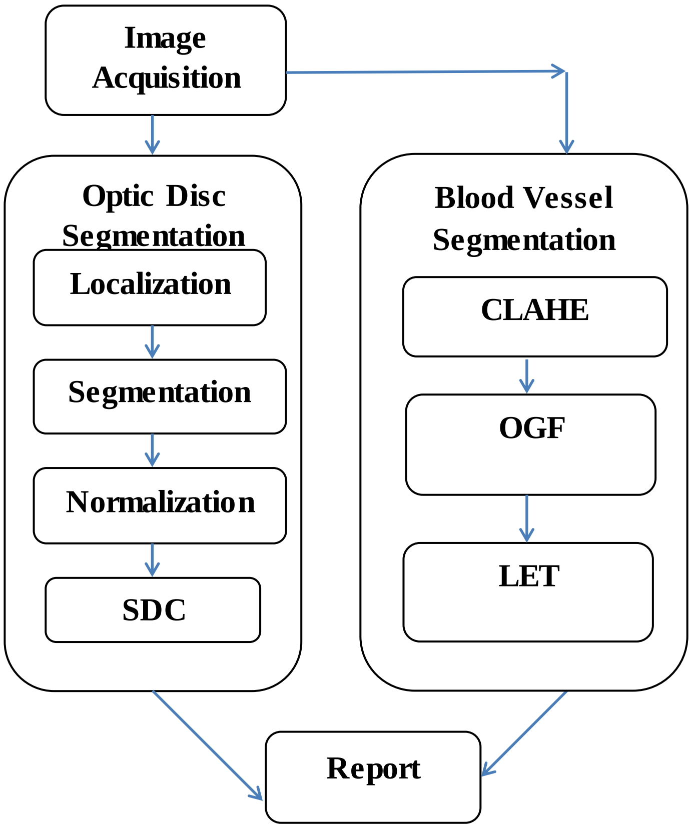


Fig. 1 Architecture Diagram of Blood Vessel Segmentation.

II. MATERIALS AND METHODS

For this analysis, here DRIVE database is used[13]. Here the images were captured at 584 * 565 pixels. As compare to background blood vessels usually have poor local contrast.

The following steps are used in our proposed method: (i) Green channel extraction, (ii) Adaptive Histogram Equalization, (iii) Optimized Gabor Filter, (iv) Local Entropy Thresholding, (v) Binary Conversion for blood vessel extraction and for optic disc detection (i) localization, (ii) segmentation, (iii) Normalization and (iv) SDC.

A) Image Acquisition

In this module, the image is first obtained from the dataset.

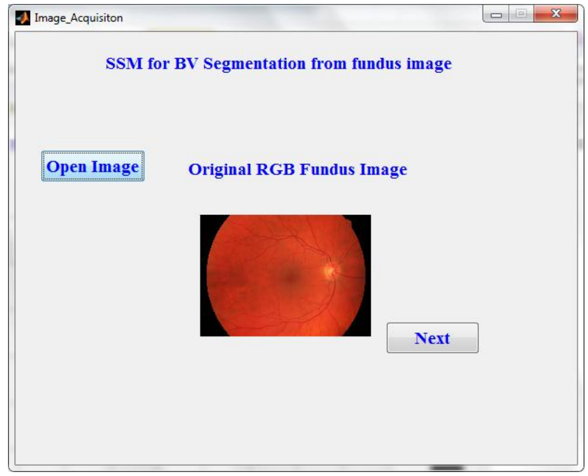


Fig. 2 Image Acquisition

B) Optic Disc Segmentation

1) Optic Disc Localization

In this paper, the optic disc is located by using the brightness based method [14]. Before that, the green channel from fundus image is extracted to find the optic disc localization. All disc images from right eyes are flipped horizontally in order to avoid the difference between eyes.

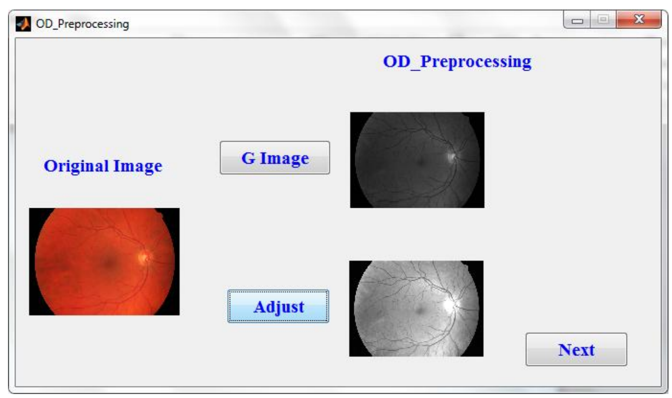


Fig 3 Optic Disc Preprocessing

The optic disc is localized as follows:

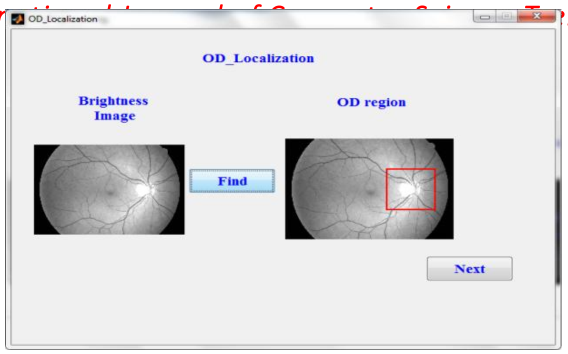


Fig 4 OD region Localized

2) Segmentation

The optic disc is segmented by two methods. First one is Circular Hough Transform (CHT). In this method, the optic disc boundary is not clearly visible.

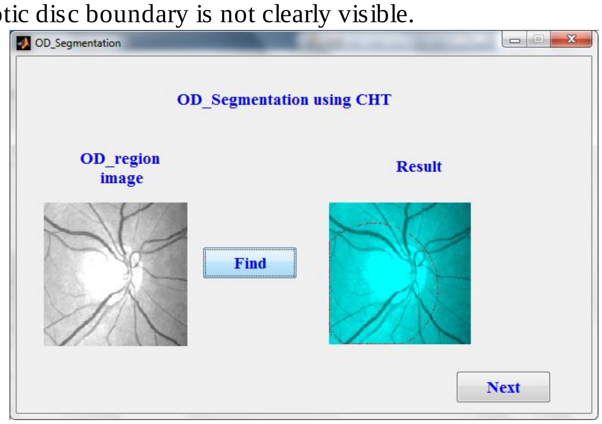


Fig 5 OD Segmetation using CHT

So in order to detect the optic disc region here using simple linear iterative superpixel based clustering (SLIC) algorithm is used. By using this algorithm we produce the output as:

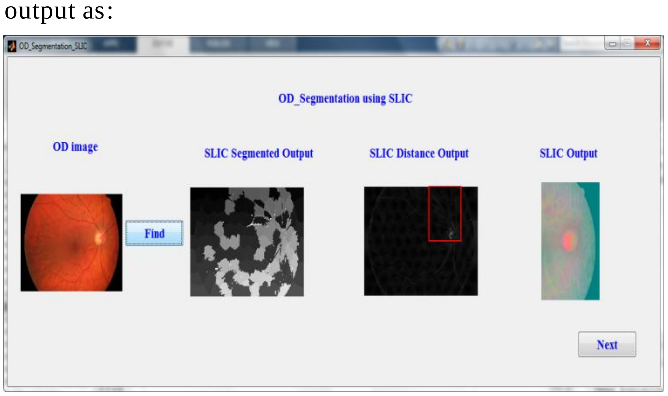


Fig 6 OD Segmentation using SLIC

3) Disc Normalization

In this module, blood vessel and uneven illumination corrections are removed. In order to disc reconstruction and dissimilarity computation it is important to remove blood vessel. In this paper, we use a morphological closing process is used with structuring element size of 5 to estimate the blood vessel.

$$BV(j,k) = \begin{cases} 1, if \ \left|x(j,k) - \widehat{x(j,k)}\right| > T \\ 0, \qquad Otherwise \end{cases}$$

where $\hat{x}$ =morph(x) denotes the image after applying a morphological closing process on x.

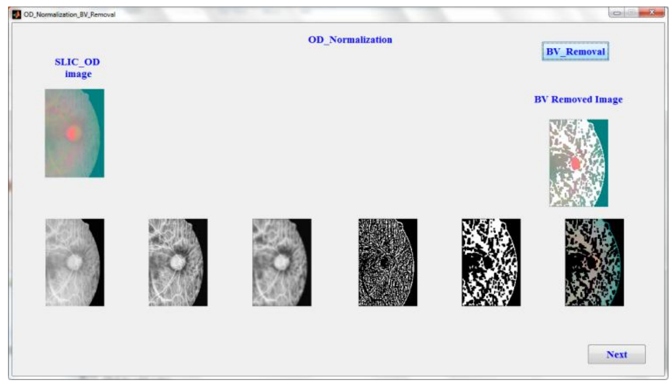


Fig 7 OD Normalization – BV Removal

The temporal side of the disc is brighter than the nasal side while the unbalance varies from one disc image to another. Here, we applying linear mapping to correct the unbalance, and the output as follows:

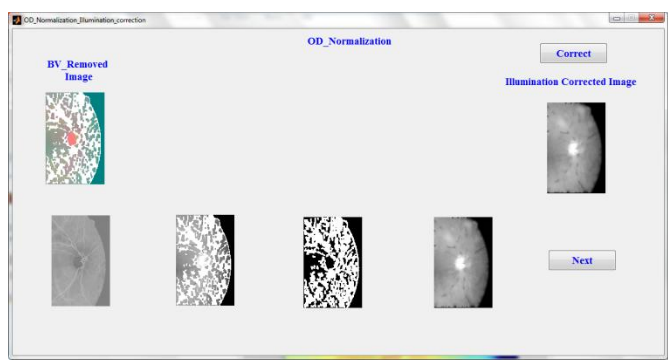
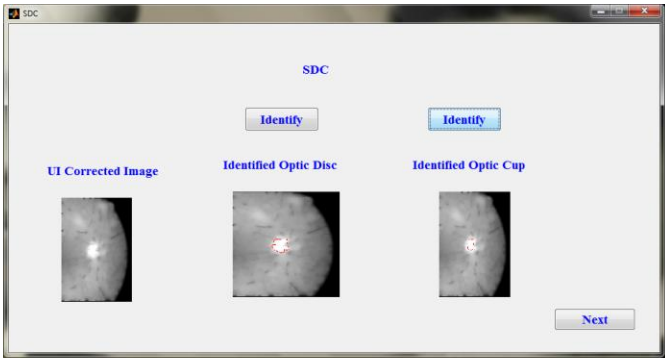


Fig 8 OD Normalization – Uneven Illumination Correction

4) Sparse Dissimilarity Constrained Coding (SDC)

In this section, apply the sparse dissimilarity constrained coding to detect the optic cup and optic disc. Here, the pixelwise distance between two disc images suffers from various noise including BV, disc alignment etc.,For that three process is there (i) Dissimilarity, (ii) Formulation of SDC, (iii)Solution and (iv) CDR Assessment



Fid 9 SDC

Finally, the CDR ratio report is computed as:

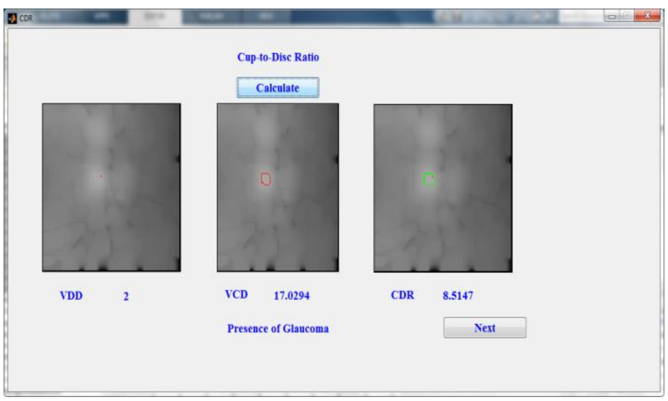


Fig 10 Cup to Disc Ratio

C) Blood Vessel Segmentation

Now we are extracting the blood vessel from the same image acquisition image by using modules as follows:

1) R, G, B Channel Splitting

Here, the input images are preprocessed by splitting into R, G, B channels. Retinal images have often low contrast that cause to hardly detect the blood vessels. The results are shown below:

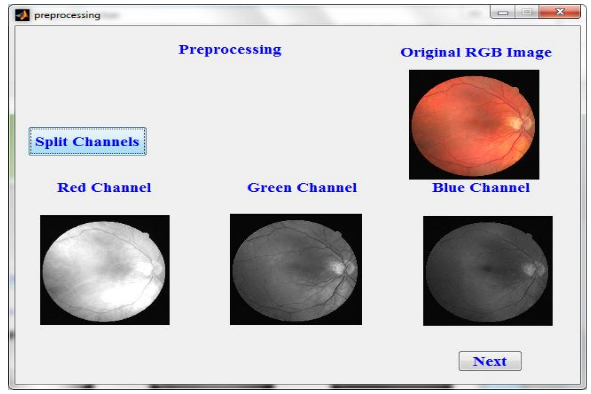


Fig 11 R,G,B, Channel Splitting

From the above result, the vessels are not clearly visible than green channel image due to contrast in red and blue channel image. The green channel of colored retinal image is used, because compare to other channels it has the highest contrast [5].

2) Contrast Limited Adaptive Histogram Equalization (CLAHE)

The next module used here as CLAHE. Contrast Limited adaptive histogram equalization is used for the analysis such as decreasing the contrast between the abnormalities and the retinal background. Therefore, CLAHE is used to enhancing the contrast of the green channel retinal image.

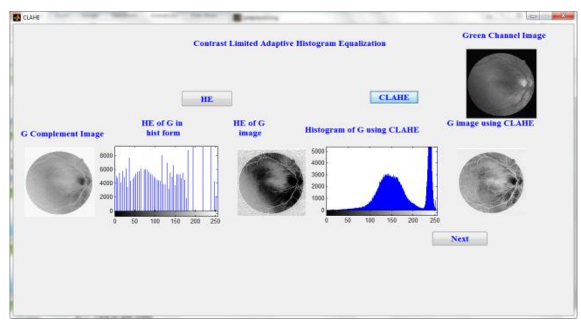


Fig 12 CLAHE

The above figure shows the comparison between the usage of histogram equalization and contrast limited adaptive histogram equalization.

3) Optimized Gabor Filter

Gabor filters have been widely used for multi – directional analysis in image processing. For detecting the blood vessel from the retinal images here using the algorithm as optimized gabor filter. The kernels are modulated sinusoid ally by optimized gabor filter [9].

$$\sigma_x = k \quad (1)$$

$$\sigma_y = \frac{\sigma_x}{\gamma} \quad (2)$$

$$x_\theta = x\cos\theta + y\sin\theta \quad (3)$$

$$y_\theta = -x\sin\theta + y\cos\theta \quad (4)$$

Optimized Gabor filter Kernel:

$$g_\theta(x,y) = \exp\left\{-\frac{1}{2}\left(\frac{x^2{}_\theta}{\sigma_x} + \frac{(\gamma y_\theta)^2}{\sigma_y}\right)\right\} cos\left(2\pi\,\frac{x_\theta}{\lambda} + \psi\right) \quad (5)$$

Where,

σ_x : Standard deviation of Gaussian in x direction along the filter that determine the bandwidth of the filter.

σ_y : Standard deviation of Gaussian filter that control the orientation selectivity of the filter.

θ : Orientation of the filter, an angle of zero gives a filter responds to vertical feature.

λ : Wavelength of the cosine factor of the Gabor Kernel i.e., preferred wavelength of this filter.

γ : Spatial aspect ratio, specifies the ellipticity of the support of the Gabor function.

ψ : Phase offset.

The width of the vessels is found to lie within a range of 2 – 14 pixels (40 – 200 micrometre). ψ always (2π) rotation phase in this method. The optimized parameters are to be derived by taking into account of size of the lines structure to be detected. The magnitude of each response if retained and combined to generate the result image. The optimized gabor filter is show below:

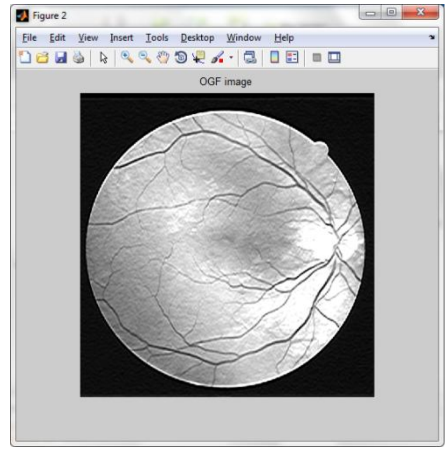


Fig 13 OGF Proposed Output

By using different parameters of gabor filter, didn't get the exact result like the below:

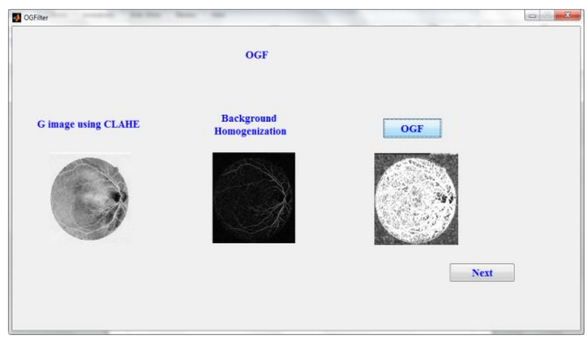


Fig 14 OGF Existing Output

For obtaining the exact gabor filter output, use the optimized sigma and other parameters.

4) Local Entropy Thresholding

In order to perform the proper extraction of the enhanced segments from the Gabor filter response images, an effective thresholding method is required.

One way to consider the grey-level co-occurrence matrix, which contains matrix developed by Haralick et al [12] is used to derive the Haralick texture feature chosen its entropy of the retinal image.

The transition of intensity between adjacent pixels, indicating spatial structural information of image. Depending upon the ways in which the gray level *i* follows gray level *j*, different definition of co-occurrence matrix are possible. The co-occurrence matrix asymmetric by considering the horizontally right and vertically lower transitions.

Let t be the value used to threshold an image. Assume that the pixels with grey levels above the threshold are assigned to foreground and those equal to or below the threshold are assigned to the background. The probabilities associated with each quarant are then given by

$$P_{ij} = \frac{t_{ij}}{\sum_i \sum_j t_{ij}} \qquad (6)$$

Obviously $0 \leq P_{ij} \leq 1$

$$P_{ij}^{(1)} = \frac{t_{ij}}{\sum_{i=0}^{s} \sum_{j=0}^{s} t_{ij}} \qquad (7)$$

$$P_{ij}^{(2)} = \frac{t_{ij}}{\sum_{i=s+1}^{L-1} \sum_{j=s+!}^{L-1} t_{ij}} \qquad (8)$$

The second order local entropy of the object can be defined as

$$H^{(A)}(S) = -\frac{1}{2}\sum_{i=0}^{s} \sum_{j=0}^{s} P_{ij}^{(1)} \log_2 P_{ij}^{(1)} \qquad (9)$$

Similarly the background written as

$$H^{(C)}(s) = -\frac{1}{2}\sum_{i=s+1}^{L-1} \sum_{j=s+1}^{L-1} P_{ij}^{(2)} \log_2 P_{ij}^{(2)} \qquad (10)$$

$$H_T(s) = H^{(A)}(s) + H^{(C)}(s) \qquad (11)$$

$$t^* = arg\{max H_T(s)\} \qquad (12)$$

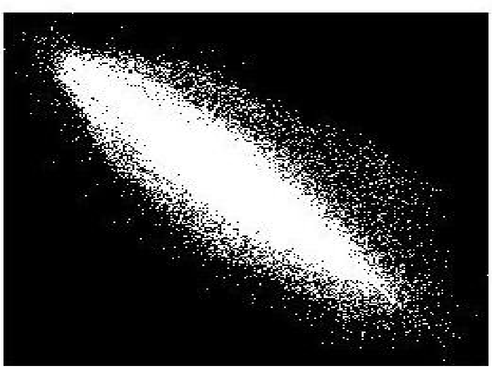


Fig. 15 Scatter plot obtained by plotting the local entropy of the optimized Gabor Filter retinal response image

The entropy threshold determines the optimal threshold t^* by maximum of the entropy curve. That threshold value is used for the segmentation of retinal images. This threshold find it automatically form the entropy-threshold curve.

The LET applied output as shown below:

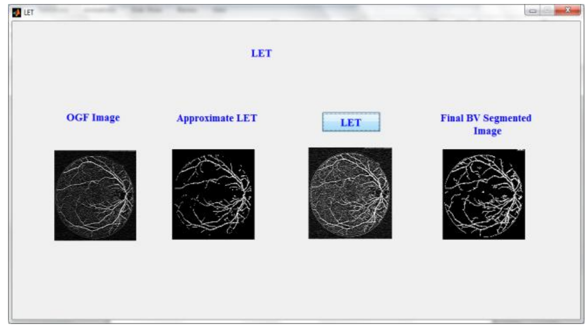


Fig 16 LET Output

Finally the binary image of LET is mapped to the original image.

The output as:

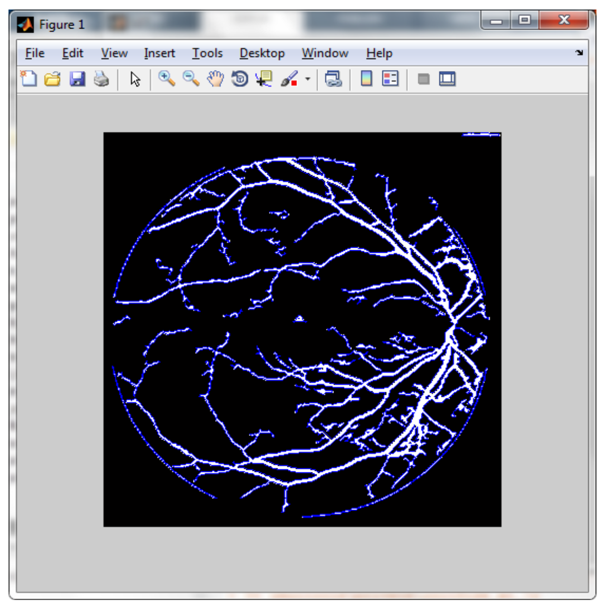


Fig 17 BV Detected Output

Finally producing the BV ratio as shown in Fig 18:

Fig 18 Blood Vessel Ratio

Then the CDR and BVR ratios are considered to detect whether the retinal fundus images have glaucoma or not and finally generate the output as follows with accuracy.

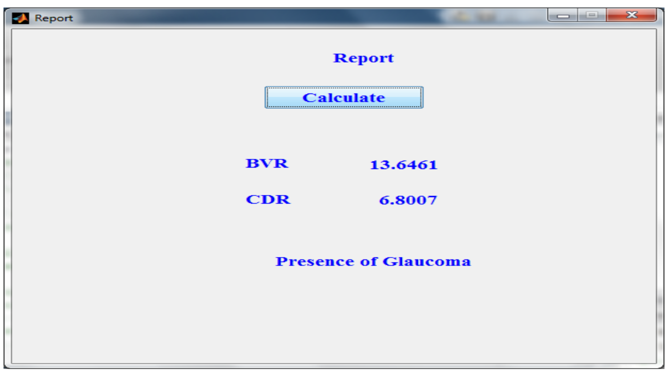


Fig 10Final Report

III. CONCLUSION

In this paper, presented a fully automatic SSM for optic disc and blood vessel segmentation from fundus images. The advantage is first introduce the CHT and SLIC for optic disc segmentation and SDC for better accuracy. Then the optimized gabor filter with local entropy Thresholding for vessel extraction. Haralick texture feature based entropy feature from the grey level co-occurrence matrix of the optimal gabor filter retinal image is one of the ways for segmentation of retinal images. The proposed method uses the DRIVE dataset [13]. Finally producing the report as whether the retinal image is affected by glaucoma or not with better accuracy result.

REFERENCES

[1] H. A. Quigley and A. T. Broman, "The number of people with glaucoma worldwide in 2010 and 2020," *Brit. J. Ophthalmol.*, vol. 90, no. 3, pp. 262–267, 2006.

[2] S. Y. Shen, "The prevalence and types of glaucoma in Malay people: The Singapore Malay eye study," *Investigative Ophthalmol. Vis. Sci.*, vol. 49, no. 9, pp. 3846–3851, 2008.

[3] P. J. Foster *et al.*, "The prevalence of glaucoma in Chinese residents of Singapore: A cross-sectional population survey of the Tanjong Pagar district," *Arch. Ophthalmol.*, vol. 118, no. 8, pp. 1105–1111, 2000.

[4] Centre for Eye Research Australia. (2008). Tunnel vision: The economic impact of primary open angle glaucoma. [Online]. Available: http://nla.gov.au/nla.arc-86954

[5] P.C. Siddalingaswamy, K. Gopalakrishna Prabhu, *"Automatic Segmentation of Blood Vessels in Colour Retinal Images using Spatial Gabor Filter and Multiscale Analysis,"* 13th International Conference on Biomedical Engineering, IFMBE Proceedings Volume 23, 2009, pp 274-276 Springer

[6] Wu, D.; Ming Zhang; Jyh-Charn Liu; Bauman, W., "On the adaptive detection of blood vessels in retinal images," *Biomedical Engineering, IEEE Transactions on* , vol.53, no.2, pp.341,343, Feb. 2006

[7] Fraz, M.M.; Remagnino, P.; Hoppe, A.; Velastin, S.; Uyyanonvara, B.; Barman, S.A., "A supervised method for retinal blood vessel segmentation using line strength, multiscale Gabor and morphological features," *Signal and Image Processing Applications (ICSIPA), 2011 IEEE International Conference on* , vol., no., pp.410,415, 16-18 Nov. 2011

[8] D. S. Fong, L. Aiello, T. W. Gardner, G. L. King, G. Blankenship, J. D. Cavallerano, F. L. Ferris, and R.

Klein, “Diabetic retinopathy,” *Diabetes Care*, vol. 26, pp. 226–229, 2003.

[9] S. J. Lee, C. A. McCarty, H. R. Taylor, and J. E. Keeffe, “Costs of mobile screening for diabetic retinopathy: A practical framework for rural populations,” *Aust. J. Rural Health*, vol. 8, pp. 186–192, 2001.

[10] American Academy of Ophthalmology Retina Panel, Preferred Practice Pattern Guidelines. Diabetic Retinopathy. San Francisco, CA, Am. Acad. Ophthalmo., 2008 [Online]. Available: http://www.aao.org/ppp.

[11] S. Chaudhauri, S. Chatterjee, N. Katz, M. Nelson and M. Goldbaum, "Detection of blood vessels in retinal images using two dimensional matched filters," *IEEE Trnas. Medical imaging*, vol. 8, no. 3, September 1989.

[12] R. M. Haralick, K. Shanmugan, I. Dinstein, “Textural Featues for Images Classification,” IEEE Trans. System, Man and Cybernetics.Vol. SMC-3, No - 6, Nov1973, 610-621.

[13] Research Section, Digital Retinal Image for Vessel Extraction (DRIVE) Database. Utrecht, The Netherlands, Univ. Med. Center Utrecht, Image Sci. Inst. [Online].

[14] Z. Zhang *et al.*, “Optic disc region of interest localization in fundus images for glaucoma detection in ARGALI,” in *Proc. Int. Conf. Ind. Electron. Appl.*, pp. 1686-1689.2010