

Retinal Blood Vessel and Optic Disc Segmentation



Alex David S, Mahesh C

Abstract: Diabetic Retinopathy (DR) is a main source of vision misfortune in diabetic patients. DR is a predominantly caused because of the harm caused in retinal veins of a diabetic patients. It is fundamental to recognize and fragment their tinal veins for DR identification and determination, which avoids prior vision misfortune in diabetic patients. The PC helped programmed discovery and division of veins through the end of optic location district in Retina. Optic Disc (OD) discovery is a principle step while creating computerized screening framework for diabetic retinopathy. This is a technique to naturally recognize the situation of the OD in advanced retinal fundus pictures. The strategy begins by normalizing glow and difference all through the picture utilizing brightening evening out and versatile histogram balance techniques individually. The OD recognition calculation depends on coordinating the normal directional example of the retinal veins. Henceforth, a straightforward coordinated channel is proposed to generally coordinate the headings of the vessels at the OD region. The retinal vessels are portioned utilizing a basic and standard 2-D Gaussian coordinated channel.

Index Terms: Data analytics, Diabetic Retinopathy(DR), Image Segmentation, Optic Disc (OD).

I. INTRODUCTION

Everywhere throughout the world there are a few wellbeing issues influencing individuals of any age. Ones of such most pervasive issue is Diabetes. Individuals with diabetes are inclined to be diabetic patients. DR, causes retinal anomalies as microaneurysms, haemorrhages, and exudates, which are the different sorts of scatters caused because of the harm of veins. The retinal veins begin from the focal point of OD and spreads over the district of the retina. The veins are in charge of providing the blood all through the whole locale of Retina. The retinal veins are harmed because of the maturing of the general population and different components. Microaneurysms, Haemorrhages and exudates sores are framed in retinal picture because of the harm in retinal veins. The retinal vein location and division are one of the pre-processing ventures for the recognition and determination of these unusual injuries.

Revised Manuscript Received on 30 July 2019.

* Correspondence Author

Alex David S*, Research Scholar and Associate Professor, Department of Computer Science and Engineering

Mahesh C, Associate Professor, Department of Information Technology

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an [open access](https://creativecommons.org/licenses/by-nc-nd/4.0/) article under the CC-BY-NC-ND license <http://creativecommons.org/licenses/by-nc-nd/4.0/>

Disregarding these sore manifestations prompts the loss of vision, as these indications are not uncovered effectively and require conclusion at a prior stage. It is fundamental for diabetic patients to have their eye checked frequently to stay away from DR. Early screening and finding of DR in diabetic patient lessen the danger of losing the visual perception by half.

Early recognition of DR can be screened by the investigation of veins inside the retina the programmed identification and division of retinal veins are significant for the programmed location of DR. A few PC helped programmed division of retinal veins exist whose division procedures are mostly founded on highlight calculation on pixel varieties these techniques utilized complex pre and post handling steps and bigger division time, there-by making the retinal vein identification process increasingly mind boggling. In existing methods, the vessel division has been refined without killing the optic plate. Since the optic circle is for merging purpose of the considerable number of vessels inside the retina end of OD limit makes some noticeable veins cross through it. Hence the limit of OD must be expelled before the vessels are fragmented as it might prompt misdetection of OD pixels of over lapping with the veins so as to keep away from such misdetections so we proposed a programmed division and end of OD limit and after that continue with the procedure of vessel division which further improves the exactness and in vessel discovery.

II. LITERATURE REVIEW

Diabetic Retinopathy is a genuine vascular turmoil that may prompt total visual deficiency. In this manner, the early location and the treatment are important to counteract significant vision misfortune. In spite of the fact that the manual screening strategies are accessible, they are tedious and wasteful on an enormous picture database of patients. In addition, it requests talented experts for the finding. Programmed Diabetic Retinopathy conclusion frameworks can supplant manual techniques as they can essentially diminish the difficult work associated with the screening procedure. Screening directed over a bigger populace can wind up proficient if the framework can isolate ordinary and anomalous cases, rather than the manual examination all things considered. In this manner, programmed retinopathy identification frameworks have pulled in huge notoriety in the ongoing occasions. Programmed retinopathy discovery frameworks utilize picture preparing and PC vision strategies to recognize various abnormalities related with retinopathy.

Retinal Blood Vessel and Optic Disc Segmentation

This audit has different techniques for diabetic retinopathy location and arrangement into various stages dependent on seriousness dimensions of different images [1]. S. R. Dhanushkodi performed research on Diagnosis System for diabetic retinopathy to avoid vision misfortune during 2013. According to his work, Diabetic Retinopathy [DR] is one of the serious issues in diabetic patients. The diabetic patients are not aware of manifestations that will be brought about by the diabetic retinopathy. This may prompt loss of vision in diabetic patients. This diabetic retinopathy results in retinal issue that incorporate Micro aneurysms (MA), soft variations from the norm. There are numerous strategies actualized for diminishing the diabetic retinopathy. They incorporate Soft Computing Neural Networks which will be utilized to identify this infection in beginning period before it impacts the whole retina[2]. Blood vessel of fundus pictures has acquired impressive significance amid the previous couple of years since it encourages the early discovery of eye illnesses. A technique dependent on high pass separating and morphological task is presented in the proposed strategy for vessel division. This technique can be used to distinguish infections affecting eyes like glaucoma and diabetic retinopathy. Glaucoma is recognized by highlight extraction and characterization. The nearby paired example of the optic plate is removed to order the pictures based on surface. Inadequate portrayal classifier is used to arrange the glaucomatous eye. Diabetic retinopathy is an ailment brought about by the intricacy of diabetes. It harms the little veins in the retina bringing about loss of vision. The vein division is a significant errand in Diabetic Retinopathy identification. Optic circle in the fundus picture is distinguished by Hough change. After the division the vessels and optic circle are expelled from the first picture. Diabetic Retinopathy is portrayed by the nearness of exudates. The exudates are distinguished by methods for imtool administrator in the matlab. The reproductions are performed on matlab 2011 and the information are gathered from DIARETDB1 and HRF databases[3]. The optic circle is a key anatomical structure in retinal pictures. The capacity to recognize optic circles in retinal pictures assumes a significant job in computerized screening frameworks. Enlivened by the way that people can discover optic plates in retinal pictures by watching some nearby highlights, we propose a neighborhood include range examination (LFSA) that dispenses with the impact brought about by the variable spatial places of nearby highlights. In LFSA, a lexicon of neighborhood highlights is utilized to recreate new optic circle applicant pictures, and the usage frequencies of each particle in the word reference are considered as a sort of "range" that can be utilized for order. We additionally utilize the inadequate word reference choice way to deal with develop a reduced and delegate lexicon. In contrast to past methodologies, LFSA does not require the division of vessels, and its technique for considering the differing data in the retinal pictures is both straightforward and powerful, making it appropriate for computerized screening frameworks. Test results on the biggest openly accessible dataset demonstrate the viability of our proposed approach [4].

III. PROPOSED SYSTEM

Optic disc detection, optic disc segmentation / elimination and blood vessel segmentation are included in proposed

method for retinal blood vessel segmentation. From the center of optic disc, the retinal blood vessel starts and distributed over the retina region. Because of the interference between OD and blood vessel it is important to detect and eliminate the OD.

Optical Disc Segmentation

Three channels were included in the retinal such as red green and blue. For the blood vessel detection, the red channel is over saturated and blue is illuminated. Due to the high contrast between blood vessel and background the green channel is used for detection of blood vessels. For better accuracy in blood vessel segmentation the optic disc must be eliminated from the retinal image. From the retinal image using green channel the anisotropic diffusion filter has been used for the detection and segmentation of optic disc.

OD segmentation by anisotropic filter

Segmenting the optic disc, the nonlinear anisotropic diffusion filter is used for segmenting the optic disc. For noise removal it makes use of four neighboring pixels. To detect the OD boundary from the DRIVE dataset this nonlinear filter has been used.

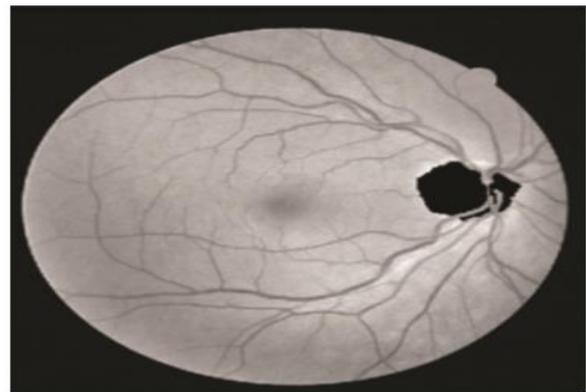


Fig 3.3 Optic Disc eliminated image

The equation of anisotropic nonlinear diffusion filter involves the calculation of the divergence of the Laplacian and gradient operators of the image. The discrete anisotropic filter equation is expressed as follows

$$\begin{aligned} I_{\text{aniso}+1} = & I_{\text{aniso}} \\ & + \psi (DN \cdot \nabla N [PN_i] + D S \cdot \nabla S [PS_i] \\ & + DE \cdot \nabla E [PE_i] + DW \cdot \nabla W [PW_i] \\ & + DNE \cdot \nabla NE [PNE_i] + DSE \cdot \nabla SE [PSE_i] \\ & + DSW \cdot \nabla SW [PSW_i] \\ & + DNW \cdot \nabla NW [PNW_i]) \end{aligned}$$

IV. IMPLEMENTATION

Using Multi scale morphological enhancement technique the authors achieved the accuracy of 96.33% in DRIVE dataset and in the STARE dataset the accuracy is 95.79%. To improve the accuracy Wilcoxon uses matched pairs testing algorithm.



For the segmentation of blood vessels, the feature extraction-based region growing algorithm was used by Palomera-Perez et al. 92.6% accuracy in DRIVE dataset and 92.5% accuracy in STARE data set. In the ensemble classifier the gradient vector field and Gabor transform and used as the feature and achieved 72.62% sensitivity, 97.64% specificity, and 95.11% accuracy in STARE data set and 74.06% sensitivity, 98.07% specificity, and 94.8% accuracy in DRIVE dataset. The DRIVE and STARE publicly available datasets has been used for testing the proposed method. Ground truth images are the images manually marked as blood vessel images. Results were analyzed against this ground truth images with segmented images obtained by proposed method and the mathematical computation is given below.

Sensitivity (Se) = TP / (TP + FN).

Specificity (Sp) = TN / (TN + FP).

Accuracy (Acc) = (TP + TN) / (TP + FN + TN + FP).

The following tables TABLE 3.1(a),(b) and TABLE 3.2 shows the data set and the performance of the STARE data set.

Table 3.1(A) Stare Data Set (Normal)

| Image sequence | STARE dataset (Normal) | | |
|----------------|-------------------------|-------|-------|
| | Se | Sp | Acc |
| 1 | 92.5 | 98.4 | 94.5 |
| 2 | 93.7 | 99.6 | 95.7 |
| 3 | 93.8 | 99.4 | 96 |
| 4 | 94.9 | 98.5 | 96 |
| 5 | 92.1 | 96.9 | 95.7 |
| 6 | 93.1 | 99.8 | 96.1 |
| 7 | 92 | 98.5 | 94.4 |
| 8 | 93.3 | 99.7 | 96.6 |
| 9 | 92.8 | 99.2 | 96.7 |
| 10 | 92.8 | 99.5 | 97.7 |
| Average | 93.1 | 98.95 | 95.94 |

Table 3.1(B) Stare Data Set (Abnormal)

| Image Sequence | STARE dataset (Abnormal) | | |
|----------------|---------------------------|-------|-------|
| | Se | Sp | Acc |
| 1 | 93.8 | 98.6 | 94.9 |
| 2 | 94.4 | 99.4 | 95.3 |
| 3 | 95.1 | 99.6 | 96.4 |
| 4 | 95.6 | 98.3 | 95.6 |
| 5 | 93.4 | 96.8 | 96.1 |
| 6 | 93.8 | 99.9 | 95.7 |
| 7 | 93.3 | 98.8 | 94.8 |
| 8 | 94 | 99.4 | 96.2 |
| 9 | 94.1 | 99.3 | 97.1 |
| 10 | 93.5 | 99.7 | 97.3 |
| Average | 94.1 | 98.98 | 95.94 |

TABLE 3.2 Performance comparison of STARE dataset

| Algorithm | Sensitivity (%) | Specificity (%) | Accuracy (%) |
|--------------------|-----------------|-----------------|--------------|
| Proposed Method | 93.60 | 98.96 | 95.94 |
| Fraz et al (2012) | 72.62 | 97.64 | 95.11 |
| Xiao et al (2013) | 71.47 | 97.35 | 94.76 |
| Manoj et al (2013) | 93.14 | 98.84 | 95.83 |
| Budai et al (2013) | 58.00 | 98.19 | 93.86 |

The tables TABLE 3.3(a),(b) and TABLE 3.4 shows the data set and the performance of the DRIVE data set.

Table 3.3(A) Drive Data Set(Normal)

| Image Sequence | STARE dataset (Abnormal) | | |
|----------------|---------------------------|-------|-------|
| | Se | Sp | Acc |
| 1 | 96.2 | 99.1 | 98.9 |
| 2 | 95 | 99 | 98.3 |
| 3 | 94.6 | 99.1 | 98.2 |
| 4 | 92.8 | 97.9 | 96.2 |
| 5 | 95.6 | 99.5 | 97.7 |
| 6 | 95 | 98.9 | 99.1 |
| 7 | 94.1 | 98.4 | 98.7 |
| 8 | 94 | 96.1 | 96.6 |
| 9 | 93.4 | 99.9 | 99.1 |
| 10 | 92.8 | 98.2 | 98.6 |
| 11 | 96.5 | 99.5 | 99.4 |
| 12 | 94.7 | 98.6 | 98.8 |
| 13 | 94.9 | 99.5 | 98.7 |
| 14 | 93.4 | 97.9 | 99.7 |
| 15 | 92.6 | 98.7 | 98.1 |
| 16 | 94.1 | 98.6 | 97.1 |
| 17 | 93.8 | 98.9 | 97.8 |
| 18 | 91.1 | 99.2 | 96.5 |
| 19 | 90 | 96.1 | 98.2 |
| 20 | 91.4 | 98.7 | 97.9 |
| 21 | 92.6 | 97.8 | 98.5 |
| 22 | 93.4 | 98.1 | 98.1 |
| 23 | 94 | 97.3 | 97.2 |
| 24 | 91.1 | 98.1 | 98.7 |
| 25 | 90.1 | 96.2 | 98.1 |
| 26 | 92.1 | 97.8 | 98.9 |
| 27 | 95.2 | 98.4 | 98.5 |
| 28 | 96.1 | 98.2 | 98.4 |
| 29 | 95.1 | 97.9 | 99.2 |
| 30 | 96.2 | 97.9 | 98.5 |
| 31 | 98.1 | 97.6 | 96.1 |
| 32 | 96.6 | 97.1 | 97.4 |
| 33 | 98.1 | 99.1 | 96.2 |
| Average | 94.08 | 98.28 | 98.10 |

Table 3.3(B) Drive Data Set (ABNORMAL)

| Image Sequence | STARE dataset (Abnormal) | | |
|----------------|---------------------------|------|------|
| | Se | Sp | Acc |
| 1 | 93.1 | 98.3 | 96.7 |
| 2 | 95.3 | 99.1 | 97.2 |
| 3 | 94.7 | 99.3 | 99.6 |

Retinal Blood Vessel and Optic Disc Segmentation

| | | | |
|---------|-------|-------|-------|
| 4 | 93.8 | 98 | 98.2 |
| 5 | 94.3 | 96.5 | 97.1 |
| 6 | 93.1 | 99.6 | 98.6 |
| 7 | 93.1 | 98.5 | 99.1 |
| Average | 93.91 | 98.47 | 98.07 |

TABLE 3.4 Performance comparison of DRIVE dataset

| Algorithm | Sensitivity (%) | Specificity (%) | Accuracy (%) |
|--------------------|-----------------|-----------------|--------------|
| Proposed Method | 93.99 | 98.37 | 98.08 |
| Fraz et al (2012) | 74.06 | 98.07 | 94.8 |
| Xiao et al (2013) | 75.13 | 97.92 | 95.29 |
| Manoj et al (2013) | 94.29 | 98.75 | 96.23 |
| Budai et al (2013) | 64.40 | 98.70 | 95.72 |



Fig. 3.1 (a) represents the Retinal image from STARE dataset.



Fig 3.1 (b) Represents ground truth image.



Fig 3.1 (c) Represents vessel segmented image by the proposed method.



Fig 3.2 (a) Represents the Retinal image from DRIVE dataset.

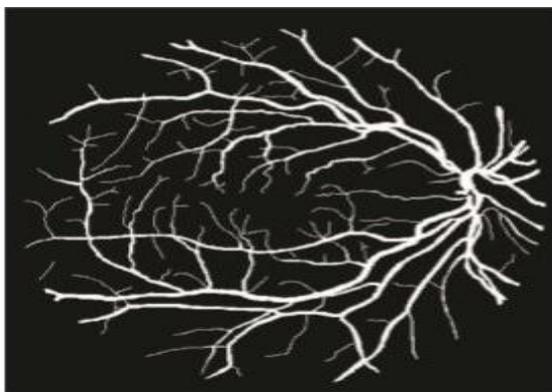


Fig 3.2 (b) Represents the ground truth image.



Fig 3.2 (c) represents vessel segmented image by the proposed method.

V. RESULT AND DISCUSSION

Investigate the efficiency and suitability of different input representations for blood vessel segmentation. Two types of input representations are distinguished here. They are non-affected fundus image and affected fundus image. Further we performed segmentation algorithm to detect DR is affected or not.

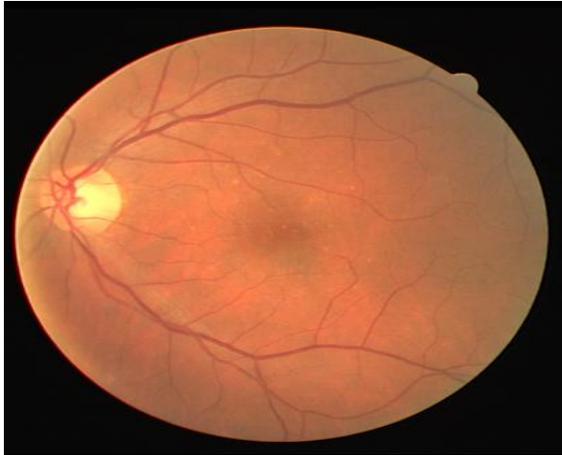


Fig 5.1 Non-Affected Fundus Image



Fig 5.2 Affected Fundus Image

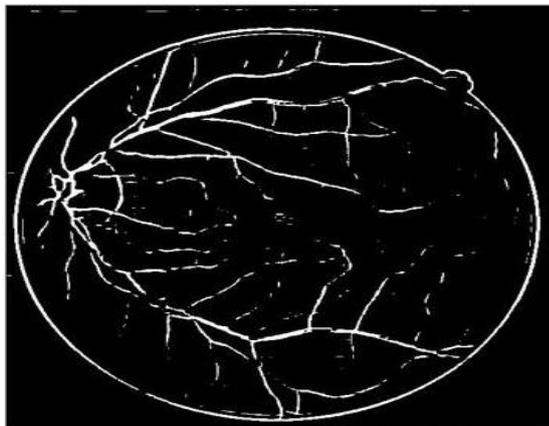


Fig 5.3 Non-Affected Segmented Image

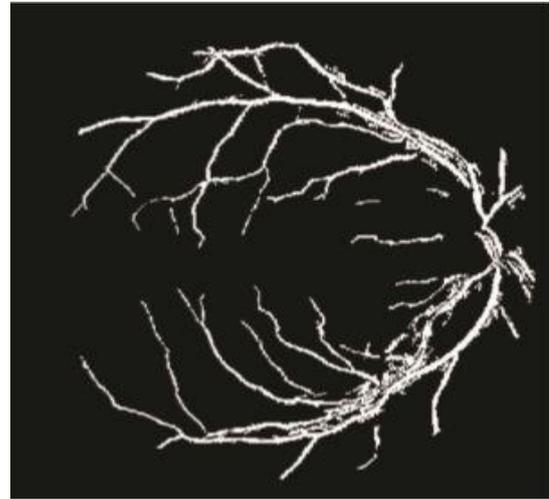


Fig 5.4 Affected Segmented Image

In Existing system, the segmentation will be through the removal of optic disc. It makes the blood vessels to see clearly. This removal is done by using the mathematical computations. In this segmentation complexity of finding the effected region will take long time. Hence the time complexity will be high. Whereas in the case of Proposed system the segmentation will be done through the filtering technique. In this filtering technique, we can implement segmentation without removing the optic disc. Here in this technique, we will be using MATLAB R2011 version for detecting the affected area in short period of time. Hence in this the time complexity of time will be low and efficiency of this technique will be high.

VI. CONCLUSION

Automatic blood vessel detection for retinal blood vessel has been proposed in the paper. For the classification severity of the DR and diagnosis the blood vessel segmentation is important. The retinal blood vessel has been automatically detect and segment by eliminating the OD region from the retina image which increases the accuracy level of segmentation of the blood vessel. The proposed methods performance was analyzed with respect to the fundus images.

REFERENCES

1. S. Bortolin Jr. and D. Welfer, "Automatic detection of microaneurysms and haemorrhages in colour eye fundus images," International Journal of Computer Science & Information Technology, vol.5 ,no.5,pp. 21–37,2013.
2. S.S.R. Dhanush kodi & V. Manivannan, "Diagnosis system for diabetic retinopathy to prevent vision loss," Applied Medical Informatics, vol.33, no.3, pp. 1–11,2013.
3. M. A. Palomera-Perez, M. E.Martinez-Perez, H. Ben ´itezP´erez, & J. L. Ortega-Arjona, "Parallel multiscale feature extraction and region growing: application in retinal blood vessel detection," IEEE Transactionson Information Technology in Biomedicine, vol.14, no.2, pp.500–506, 2010.
4. Qasem A. Al-Radaideh, Adel Abu Assaf, Eman Alnagi, "Predicting Stock Prices Using Data Mining Techniques" The International Arab Conference on Information Technology (ACIT'2013).
5. D.Jeyashree, G. Sharmilaand K. Ramasamy, "Combined Approach on Analysis of Retinal Blood Vessel Segmentation for Diabetic Retinopathy and Glaucoma Diagnosis", International Journal of Scientific & Engineering Research, Volume 5, Issue 5, May-2014.

AUTHORS PROFILE



Alex David S, M.E., CSE, currently working as an Associate Professor and a Research Scholar in Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology



Mahesh C, M.E., PhD IT, currently working as an Associate Professor in Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology.