International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 06 | June - 2022 Impact Factor: 7.185 ISSN: 2582-3930

A REVIEW ON ADAPTIVE THRESHOLD APPROACH FOR GLAUCOMA DETECTION USING FUNDUS IMAGES

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Abstract: A group of diseases of the eye called Glaucoma damage the optic nerve permanently. Glaucoma gradually leads to a loss of sight. If diagnosed and treated early, Glaucoma can be cured before fatigue sets in. If blindness is to be avoided, early detection of glaucoma is highly desirable, as it lacks symptoms while developing and is irreversible once severe vision loss is detected. Several methods have been used to predict glaucoma from other retinal images, such as using structural and non-structural features. This paper proposes the methodology to detect Glaucoma automatically by using fundus images. A database from IIIT Hyderabad, Drishti-GS1, is used in this research.

Keywords: Glaucoma Detection, eye disease, image processing, segmentation, fundus images, research paper.

I. INTRODUCTION

Glaucoma is one of the leading cause of eye blindness . But blindness from glaucoma can be prevented at early stage with proper treatment and medication. Our eye constantly makes aqueous humor fluid. As new aqueous fluid flows into our eye, the same amount should drain out of eye. The aqueous fluid drains out through an drainage angle. This process creates pressure in eye (called as intraocular pressure) stable. But ,If the drainage is not working properly,the fluid builds up. The Pressure inside eye rises and damage our optic nerve.

The optic nerve consists more than million tiny nerve fibers. It's like electric cable which made up of so many small wires. If these nerve fibers dies, it will lead to develop blind spots in your eye vision. You may not notice,these spots until

most of our optic nerve fiber have died. If all the optic fibers die, you will become blind.

People with the "normal tension glaucoma" ,have pressure in eye within normal range, but shows signs of glaucoma infection, such as blind spots in their vision and optic nerve damage.

Glaucomous eye tests are the group of tests that helps in diagnose of glaucoma, Glaucoma infection happens when fluids in eye builds up in front part of your eye. The eye pressure increases because of extra fluid. Increased eye pressure damages the optic nerve. The optic nerve contains information from eye to brain. It can lead to serious vision issues,if optic nerve is damage.

II. AIM & OBJECTIVES

To design and implement the software which can detect the eye disease called glaucoma at its very early stage.

Objectives are as follows:-

- Collect fundus images of eye by using fundus imager or using any appropriate image capturing machines or from image databases.
- Detect Glaucoma by using the images(eye) by calculating CDR using Machine learning

III. RELATED WORK

In related work, we discussed the work from history employed for detection and classification of glaucoma from fundus sample images. The methods which are used for glaucomlous eye recognition are classified in ML-based approaches or DL-based approaches. We recreated and worked on ML-Based approaches in our project.

Shoba et al. [1] introduced ML-based methods for glaucomatous eye region detection. After performing preprocessing steps, the Canny Edge Detection approach was applied ,to perform blood vessel segmentation. After that the morphological operations was performed for segmentation of blood vessels from all the suspected samples. In the next step, the Finite Element Modeling analysis was conducted for final computation. The computed features were used for support vector machine training to perform the classification tasks. The work [2] is robust to noisy images. however, the model needs to be evaluated on a challenging datasets.

In [3] a method named the Glowworm Swarm Optimization algorithm was introduced for automatic identification of optic cups/disks from retinal fundus images. The framework [4] is robust to glaucomous eye detection, however, unable to calculate cup-to-disc ratio. Kirar et al. [5] presented an technique for glaucoma detection employing second stage quasi bivariate variation mode decomposition based fine sub-band image from suspected images. The computed features from the stage quasi bivariate variation framework used to train the least-square SVM classifiers. The work [6] performs very well for glaucomous eye detection, however the classification accuracy needs improvement. Qureshi et al. [7] presents a framework which can recognize glaucomatous lesions. After performing the image sample preprocessing tasks, the Optic Disk and Optic Cup segmented by employing using the pixel based threshold and watershed transformation techniques. Finally, the CDR was calculated by distributing the number of optic cup pixels by the number of optic disc pixels. The work [8] performs well for the glaucomatous eye region recognition, however, it may not performed well for the scale and rotation variations in the suspected sample images. In [9] ML-based automated framework was presented for calculation of the vertical cup-to-disk ratio (VCDR) to identify the glaucomatous eye areas from the fundus sample images. Initially, the vasculature and disk selective filters were employed for Optic Disk localizations. After this, an generalized matrix learning vector quantization classifier utilized for classifying Optic Disk and Optic Cup regions. This work shows better glaucoma detection accuracy.however, not robust for noisy samples.

IV. IMPLEMENTATON APPROCH

A. Adaptive Threshold Algorithm

Adaptive thresholding is one of the method ,where the threshold value is calculated for the smaller regions,in this method there will be different threshold values for the different regions.We can perform Adaptive threshold operation on an image using the method adaptiveThreshold() of the imgproc class in OpenCV.

Thresholding is method which is used for segmentation of an image by setting all the pixels whose intensity values are above a threshold to a foreground value & all remaining pixels values to a background value.Whereas the conventional threshold operators uses global threshold for all the pixels, adaptive thresholding method changes the threshold value dynamically over the images. This is more sophisticated version of thresholding and can accommodate changing in lighting conditions in image, *e.g.* occurring as result of the strong illumination gradient or its shadows

B. IMPLEMENTITION FLOW

In this glaucoma detection using fundus image system we had used an Machin Learning approach to develop the system.we had used image processing techniques, image segmentation techniques and image processing algorithms as well as some filters for more details and clarification. Algorithm we had used is adaptivethreshold algorithm which we had explained earlier in this paper. The filter we had used is gaussion filter which is used to blur images and remove noise and detail.

The Gaussian function is used in numerous research areas: – It defines probability distribution for the noise or the data. – It is also called as smoothing operator. – It is also used in mathematics Gaussian filtering for used to remove the noise. It's not particularly effective at removing salt and pepper noises. Gaussian filtering is more effective at smoothing the images. It found that in the human visual perception system.

Then we used image segmentation technique calculated threshold and indentify the cup and disk after that convert this to the channels ,color channels of blue green and red color then convert this into the histograms to get more clarification about the cup and disk. Then calculate the cdr and depend upon the cdr our model will predict whether the patients eye is glaucomous or not if yes then whether it is heaviy glaucomous or moderately glaucomous.

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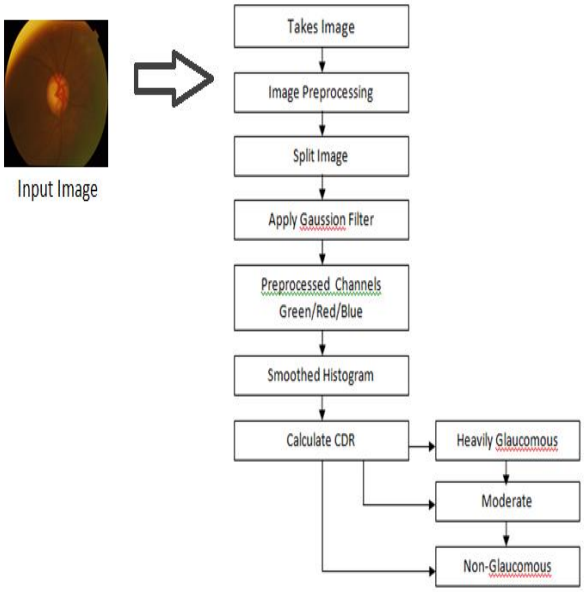
C. SYSTEM ARCHITECTURE



IV. CONCLUSION

The recognition of the glaucoma manually from the fundus images require trained human experts who can accurately identifies the tiny visible details as well as categorize the images. However, because of the complex structure of the glaucomatous eye regions and the unreachability of domains experts, there is need of a fully automated detection system. In our introduced technique, we have presented a ML-based approach named Glaucoma Detection Using Fundus images .We have tested our approach over the drishti-gs1 database which is challenging in terms of variations of glaucoma
lesions sizes, colors, positions, and shapes.For the drishti-gs1 database, we obtain the average accuracy values of 98.2%. Both the visual & numeric comparison confirms that the used framework is more robust to glaucoma classification as compared to other latest approaches and can certainly identify the lesion of variables masses from the sample images with the several image distortions. Therefore, this work can play a vital role in the automated recognition of the glaucomatous eye.

V. REFERENCES

[1] 1. Moreno, M.V.; Houriet, C.; Grounauer, P.A. Ocular Phantom-Based Feasibility Study of an Early Diagnosis Device for Glaucoma. Sensors 2021, 21, 579. [CrossRef] [PubMed]

[2] 2. Syed, H.H.; Tariq, U.; Armghan, A.; Alenezi, F.; Khan, J.A.; Rho, S.; Kadry, S.; Rajinikanth, V. A Rapid Artificial Intelligence-Based Computer-Aided Diagnosis System for COVID-19 Classification from CT Images. Behav. Neurol. 2021, 2021, 2560388. [CrossRef] [PubMed]

[3] 3. Khan, T.M.; Khan, M.A.; Rehman, N.U.; Naveed, K.; Afridi, I.U.; Naqvi, S.S.; Raazak, I. Width-wise vessel bifurcation for improved retinal vessel segmentation. Biomed. Signal Process. Control 2022, 71, 103169. [CrossRef]

[4] 4. Tan, M.; Pang, R.; Le, Q.V. Efficientdet: Scalable and efficient object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, 13–19 June 2020; pp. 10781–10790.

[5] 5. Shoba, S.G.; Therese, A.B. Detection of glaucoma disease in fundus images based on morphological operation and finite element method. Biomed. Signal Process. Control. 2020, 62, 101986. [CrossRef]

[6] 6. Pruthi, J.; Khanna, K.; Arora, S. Optic Cup segmentation from retinal fundus images using Glowworm Swarm Optimization for glaucoma detection. Biomed. Signal Process. Control 2020, 60, 102004. [CrossRef]

[7] 7. Kirar, B.S.; Reddy, G.R.S.; Agrawal, D.K. Glaucoma Detection Using SS-QB-VMD-Based Fine Sub-Band Images from Fundus Images. IETE J. Res. 2021, 1–12. [CrossRef]

[8] 8. Qureshi, I.; Khan, M.A.; Sharif, M.; Saba, T.; Ma, J. Detection of glaucoma based on cup-to-disc ratio using fundus images. Int. J. Intell. Syst. Technol. Appl. 2020, 19, 1–16. [CrossRef]

[9] 9. Guo, J.; Azzopardi, G.; Shi, C.; Jansonius, N.M.; Petkov, N. Automatic Determination of Vertical Cup-to-Disc Ratio in Retinal Fundus Images for Glaucoma Screening. IEEE Access 2019, 7, 8527–8541. [CrossRef]