

GLAUCOMA DETECTION SYSTEM USING FUNDUS IMAGES

Prof N. R. Hatwar^{*1}, Neha Meshram^{*2}, Amit Adhikari^{*3}, Sarita Mohankar^{*4},
Mayank Gajbhiye^{*5}, Achal Maddalwar^{*6}

^{*1}Guide, Department of Information Technology, Priyadarshini College of Engineering,
Nagpur, India.

^{*2,3,4,5,6}UG Student, Department of Information Technology, Priyadarshini College of Engineering,
Nagpur, India.

ABSTRACT

Glaucoma is a group of eye diseases that permanently damage optic nerve and gradually result in loss of vision. However, with early diagnosis and treatment Glaucoma can be recovered before getting fatigue. As it lacks symptoms in its developing stages, and concurrent irreversibility once heavy vision loss is detected, early detection of glaucoma is highly desirable if blindness is to be avoided. While there has been work done on predicting glaucoma from other retinal image such as using structural and non-structural features. This paper proposes the methodology to detect Glaucoma automatically by using fundus images. The database used in this research is Drishti-GS1 Dataset by IIIT Hyderabad.

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

I. INTRODUCTION

Eyes plays a vital role when it comes to human body functioning and are the most delicate yet complex organ of the human body. Glaucoma refers to an eye disease that results into vision loss by permanently damaging the optic nerve. Eduard Jaeger (1854) described glaucoma as the silent thief of vision which is a specific optic nerve disease with the progressive break down of nerve fiber. Vision loss is usually caused by changes in intraocular eye pressure (IOE) caused by obstructions that restrict the passage of aqueous fluid in the eye or by issues with the optic nerves themselves (blood supply, structure of nerve, etc.). IOE gets increased due to the blockage of normal flow and this leads to the damage optic nerve. This is one of the situation, but there may have some additional factors to cause glaucoma too. Early detection of glaucoma is particularly important if blindness is to be prevented, due to its absence of symptoms in its early stages and the simultaneous irreversibility of one's substantial vision loss. The main sign is usually a loss of lateral or peripheral vision. Glaucoma can be classified into two types:

- Open-angle glaucoma: This is the most common type of Glaucoma also known as wide-angle glaucoma. The drainage structure of the eye which is called the trabecular meshwork looks good, but the liquid is not drained as it should.
- Acute angle-closure glaucoma: It is also called acute or chronic angle-closure glaucoma or angle-closure glaucoma. This is more common in Asia. The drainage space between the iris and the cornea is too narrow for the eyes to drain properly. This can cause a sudden buildup of eye pressure which leads to Glaucoma.

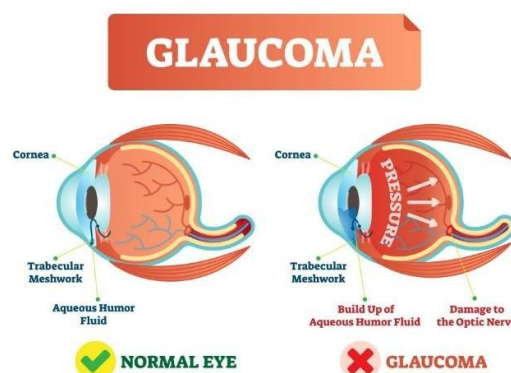


Fig. 1 Glaucoma Eye Representation

The first and foremost variation due to glaucoma is in the intraocular pressure of eye. In fact glaucoma is said to be a disease due to elevation in eye pressure. The usual value of intraocular pressure ranges between 10 to 20 mmHg. But in patients with glaucoma it may increase. Due to this pressure increase the nerve fibres begin to die. When these fibres die the light that falls on these regions will not induce any sense of vision. Thus the spot becomes blind (also known as cup). Due to glaucoma the disc area reduces correspondingly the cup area may increase. It is a slow process that it may

take years for a small change. As a result of these changes the side vision of the patient reduces gradually.

II. LITERATURE SURVEY

Several studies on the detection of optic nerve and the detection and classification of glaucoma have been reported in the literature.

Baidaa Al-Bander et al., "Automated glaucoma diagnosis using deep learning approach" [1]. Using a deep learning method, this research investigates the potential of building an automatic feature learning technique for detecting glaucoma in coloured retinal fundus images. For diagnostic purposes, a completely automated approach based on convolutional neural networks (CNN) is being developed to discern between normal and glaucomatous patterns. Unlike traditional approaches, in which the optic disc features are constructed, CNN extracts the features automatically from the raw images and feeds them to the SVM classifier, which then classifies the images as normal or abnormal. This method achieved 88.2% accuracy, 90.8% specificity, and 85% sensitivity, respectively, which compare favorably to the state-of-the-art but at a significantly lower computing cost. The preliminary results show that the suggested deep learning method is promising in terms of automatic glaucoma detection.

Shwetali M. Nikam et al., "Glaucoma detection from fundus images using MATLAB GUI" [2]. Glaucoma is usually recognized when the aqueous fluid increases. As this aqueous fluid increases, so does the pressure on the eyes. Accordingly, the size of the OD and OC is increased as a result diameter also increased. The ratio of the cup and disc diameter is known as a cup-to-disc ratio (CDR). Threshold type segmentation method is employed during this system for localizing the blind spot and eyecup. Another edge detection and ellipse fitting algorithm can also be used. The proposed system for localizing optical discs and optical cups and calculating CDR is the MATLAB GUI software.

F. Ajesh, et al., "Hybrid features and optimization- driven recurrent neural network for glaucoma detection" [3]. The proposed methodology Jaya Chicken Swarm optimization (JayaCSO) was used to train a recurrent neural network (RNN) for the detection of glaucoma. This method uses optic disc, statistical, and blood vessel features for the determination of the glaucomatous area. The features provided from the Optic Disc, blood vessels, and the fundus image is formulated as a feature vector. This results in glaucoma classification using RNN using feature vector. This method achieved maximal accuracy, specificity, and sensitivity of 0.97.

Guangzhou An et al., "Glaucoma Diagnosis with Machine Learning Based on Optical Coherence Tomography and Color Fundus Images" [4]. In this methodology, the main purpose is to develop a machine learning-based algorithm for glaucoma diagnosis in patients with open-angle glaucoma, based on three-dimensional optical coherence tomography (OCT) data and color fundus images. This technique uses the transfer learning of convolutional neural network (CNN) with the images as inputs with different types such as (1) fundus image of the optic disc in grayscale format, (2) disc retinal nerve fiber layer (RNFL) thickness map, (3) macular ganglion cell complex (GCC) thickness map, (4) disc RNFL deviation map, and (5) macular GCC deviation map. In this train CNN augmentation and dropout were performed. For combining the results from each CNN model, a random forest (RF) was trained to classify the disc fundus images of healthy and glaucomatous eyes using the feature vector representation of each input image, removing the second fully connected layer. The area under the receiver operating characteristic curve (AUC) of a 10-fold cross validation (CV) was used to evaluate the models. The 10-fold CV AUCs of the CNNs were 0.940 for color fundus images, 0.942 for RNFL thickness maps, 0.944 for macular GCC thickness maps, 0.949 for disc RNFL deviation maps, and 0.952 for macular GCC deviation maps. The RF combining the five separate CNN models improved the 10-fold CV AUC to 0.963. Therefore, the machine learning system described here can accurately differentiate between healthy and glaucomatous subjects based on their extracted images from OCT data and color fundus images.

With a deep feed-forward neural network, the visual field of patients with preperimetric glaucoma can be distinguished from the visual field of healthy subjects with very high accuracy (AUC: 0.926). Furthermore, there have been reports that the accuracy reaches 0.98 when age, IOP, central corneal thickness, cpRNFLT, and the visual field are all considered. Thus, the accuracy of diagnosis was higher with various kinds of measuring data.

Fink et al., (2008) use independent component analysis (ICA) for feature extraction from color fundus images and k-nearest neighbour classifier (KNN) for glaucoma classification [5]. ICA finds

the basis images which represent the independent feature characteristic of the observed retina images of the papilla. The corresponding coefficients of basis images have been learned from a training data set. Then classification is done by the KNN classifier. Here, the L2 norm is used for deciding the corresponding class. The technique was applied to 250 images of size 256×256 pixels. By this methodology 90.8% images are correctly classified.

Wong et al., (2009) developed an automatic cup to disc ratio measurement system ARGALI for glaucoma detection and analysis [6]. This ARGALI technique used different segmentation method such as color histogram analysis, level

set method etc., to detect cup and disc from the color fundus images. CDR is calculated by different methods for different images due to their variability. The obtained CDR by different methods is merged by adaptive neural network. This method was tested on the color fundus images of size: 3072×2048 pixels taken from Singapore Eye Research Institute.

Hatanaka et al., (2011) measures the cup to disc ratio based on line profile analysis in retinal images for early detection of glaucoma [7]. Here blue channel of the color fundus image is used as it has higher contrast between the cup and rim regions. Zero crossing method is used to find the cup edge. Authors found CDR by measuring the ratio of cup diameter to disc diameter after segmenting the blood vessels erased OD from the color fundus images. This method was tested on 45 retinal images (33 glaucoma images) taken by retinal fundus camera (Kowa VX-10i) with the photographic angle of 27°. They have noted an average CDR of 0.74 and 0.59 for abnormal and normal cases respectively. In this method concordance and accuracy were found to be 85% and 94.7% respectively.

Dey, Abhishek, and Samir K. Bandyopadhyay. "Automated glaucoma detection using support vector machine classification method" [8]. In this method image is first pre-processed. Then Principal Component analysis (PCA) method is used for extracting features from pre-processed images. After PCA, the modified images are fed into a Support Vector Machine (SVM) classifier for training purpose. The performance of the classifier is tested by cross validation approach. Now, the classifier can distinguish between a normal eye fundus and a glaucoma affected eye fundus up to a certain level of accuracy. This method after cross validation trained SVM classifier has accuracy rate 96%, sensitivity 100%, specificity 92%, positive predictive accuracy 92.59% and negative predictive accuracy 100%. After training, this method has tested the performance of the trained classifier on 50 eye fundus images (20 normal and 30 glaucoma affected) which were not in the trained set of input images. The SVM classifier can successfully classify this test set with accuracy rate 86%, sensitivity 100%, specificity 65%, positive predictive accuracy 81.08% and negative predictive accuracy 100%.

Huang, Mei-Ling, Hsin-Yi Chen, and Jian-Jun Huang. "Glaucoma detection using adaptive neuro-fuzzy inference system." Expert Systems with Applications 32.2 (2007): 458-468. [9] This method uses adaptive neuro-fuzzy inference system (ANFIS). This research takes normal and glaucomatous eyes from the quantitative assessment of summary data reports of the Stratus optical coherence tomography (OCT) in Taiwan Chinese population. Method of detecting glaucoma starts with measurement of glaucoma variables were obtained by stratus OCT. Decision making was performed in two stages: feature extraction using the orthogonal array and the selected variables were treated as the feeder to adaptive neuro-fuzzy inference system (ANFIS), which was trained with the back-propagation gradient descent method in combination with the least squares method. With the Stratus OCT parameters used as input, receiver operative characteristic (ROC) curves were generated by ANFIS to classify eyes as either glaucomatous or normal.

III. MATERIAL AND METHODS

A. PROPOSED METHOD

The block diagram of the proposed system for the detection of glaucoma is shown in Fig. 1. The various steps in our proposed method i.e image pre-processing, segmentation and image classification are described below:

1. **Image Pre-processing:** Retinal images are captured using a digital fundus Camera that captures reflected light from the surface of the retina. Pre-processing is the prior step to the major image processing task. It eliminates disease independent variations from the input image. At first, some pre-processing tasks are required to be done on the input images such as normalizing the images, colour conversion from RGB to grayscale, resizing the images, noise removal from the images and contrast adjustment for improving image quality. In our method, instead of preprocessing some particular regions of images, entire images are preprocessed before feature extraction and classification.

$$\text{Cup to disk ratio} = \frac{\text{Diameter of the cup}}{\text{Diameter of the disc}}$$

2. **Segmentation:**

- **Optic Disc Segmentation :** The interweaving of blood vessels is one of the major obstacles for accurate OD segmentation. The fundus image obtained contains the least information about the blood vessels. In such cases, an artificial image that is created by arithmetic operations on the green and blue components is used. In order to determine the best image to process, we define the image contrast ratio. Optic disc is a bright circular region in fundus image, thus Laplacian of Gaussian (LoG) is applied on the preprocessed padded image for its application in blob detection.

- **Optic Cup Segmentation :** The glaucoma detection is carried out by analyzing the optic cup. The optic cup will be enlarged under glaucoma condition. The optic cup size is varies from patient to patient depending on the progression of glaucoma, its diameter lies between 30 and 50 pixels in 256X256 size images. The fundus retinal image is first filtered and watershed transformation is applied to locate the optic cup boundaries. In green channel, the optic cup appears as the brightest part and its contours looks most continuous and most contrasted against background. To locate the optic cup, find out the maximum intensity in the fundus retinal image. The optic cup localization is done by a shade correction operator to eliminate slow background variations, which reduces the contrast of exudates and drusen.
- 3. **Image Classification:** The CDR is calculated by counting total number of pixels in the segmented optic cup and disc regions. The CDR is obtained by dividing the number of pixels in the optic cup and number of pixels in the optic disc. The calculated OCCR is 0.3 then the retinal image is said to be normal eye images. If CDR exceeds more than 0.3, the retinal image said to be under glaucoma condition. The severity of the progression of glaucoma is found on the CDR value. If higher the CDR value, the progression of the glaucoma is severe and vice-verse

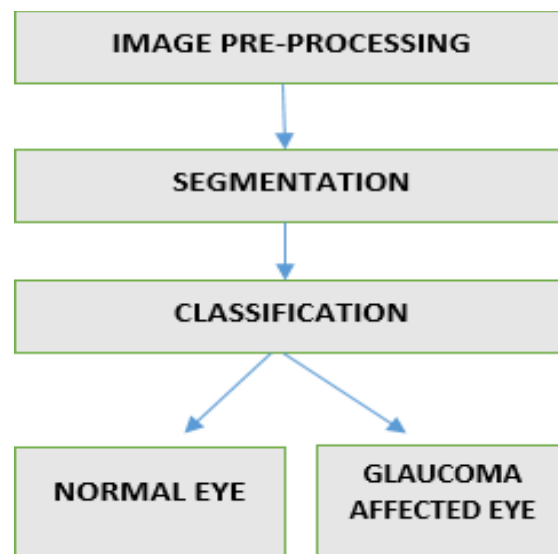


Fig 2. Proposed design for detection of Glaucoma

B. DATASET USED:

We have used the Drishti-GS database in our methodology. Drishti-GS is a database intended for verification of OD separation, cup, and notching detection. Images from the Drishti-GS database were collected and interpreted by Aravind Eye Hospital, Madurai, India. This database belongs to a single population as all subjects whose visual images are part of this database are Indians. The Drishti Dataset contains 101 fundus images of which 50 are training sets and 51 images for test sets.

IV. CONCLUSION

As a result of this study, we have developed an accurate, effective, and purposeful way to automatically divide digital fundus images into standard or glaucomatous forms for the convenience of eye doctors. For this reason, we have developed an affordable system that will detect glaucoma in the human eye and show the message whether the eye has it or not.

V. REFERENCES

- [1] Baidaa Al-Bander, "Automatic glaucoma diagnosis using an in-depth study method", Morocco, 28-31 March 2017.
- [2] Shwetali M. Nikam, "Diagnosis of Glaucoma in fundus images using MATLAB GUI", Dehradun, India, 15-16 Sept. 2017.
- [3] Mei-Ling Huang, "Diagnosis of glaucoma using a neuro-fuzzy flexible identification system", Volume 33, Issue 1, July 2007, Pages 263.
- [4] F. Ajesh, R. Ravi, "Hybrid features and a well-functioning neural network operated to detect glaucoma", Volume 30, Release 4 p. 1143-1161, 30 May 2020.
- [5] Glaucoma Classification by Combining Classification and Image Based Factors. Ch Chakravarty A and Sivaswamy J, ISBI 2016.

[6] A complete set of image data for a complete set of Glaucoma Tests from Optic Headache Analysis. Sivaswamy J,

-
- S. R. Krishnadas, Arunava Chakravarty, Gopal Dutt Joshi, Ujjwal and Tabish Abbas Syed, JSM Biomedical Imaging Data Papers, 2 (1): 1004, 2015.
- [7] Optic Disk and Cup Segmentation from Monocular Color Retinal Images for Glaucoma Assessment. Joshi GD, Sivaswamy J and Krishnadas SR, IEEE Transactions on Medical Imaging, 30 (1) pp.1192-1205, June-20
- [8] Optic Disk and Cup Separation from Monocular Color Retinal Images For Glaucoma Diagnosis. Joshi GD, Sivaswamy J and Krishnadas SR, IEEE Transactions on Medical Imaging, 30 (1) pp.1192-1205, June-20
- [9] Kako NA, Abdulazeez AM, "Peripapillary Atrophy Segmentation and Classification Methodologies for Glaucoma Image Detection: A Review", 08 Mar 2022.
- [10] L Divya, Jaison Jacob, "Performance Analysis of Glaucoma Recognition Methods from Fundus Images", Volume 143, 2018, Pages 544-551, 8th International Conference on Computer and Communication Development (ICACC-2018).
- [11] Georg Michelson, "Glaucoma Risk Indication: Automatic Detection of Glaucoma in Color Fundus Factors", Medical Photo Analysis, Volume 14, Issue 3, June 2010, Pages 471-481.
- [12] Juan J. Gómez-Valverde, "Automatic glaucoma classification using color fundus images based on convolutional neural networks and transmission learning", Biomedical Optics Express Vol. 10, Issued 2, pages 892-913 (2019)