Method for detecting cup to disk ratio for the prediction of glaucoma disease – A review

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Abstract

Glaucoma is the world's second most prominent blindness condition. This is caused by intraocular pressure and damage to the optic nerve which prevents information from being transmitted from the eye to the brain. In this paper we addressed various methodologies and algorithms using different modalities for the optical disk and cup ratio detection. In addition, output metrics of various methods are discussed and also compared in terms of precision, specificity sensitivity of the model, with various state of the art techniques. As contrasted with various conventional techniques, the machine learning algorithm was a state-of-the-art standard. The random forest method proves a better predictive algorithm for glaucoma.

Keywords –*Optic disc &optic cup segmentation, Cup to Disc Ratio(CDR),classifiers, Modality.*

1. Introduction

In India, glaucoma affects more than 11.2 million people older than 40. More than 50 percent of Australia's people who have had glaucoma are unidentified. More than 3 million Americans have glaucoma but It has estimated that about half of those who know they have it. Glaucoma is the leading cause of blindness after cataract for African-Americans. Fig. suggests that in 2020, more than 100 million people will be affected by glaucoma due to pressure within the eye that causes damage to the internal optic nerve and optic disc(OD). The eye's intraocular pressure (IOP) rises due to the discharge of aqueous humor and damage to the optic nerve, which prohibits information from the eye to the brain from passing through. The severity rates of the loss of vision with glaucoma are shown in fig.2. The two forms of glaucoma are open-angle and angle-closure. Open-angle glaucoma is the most common type of glaucoma caused by drainage canal blockage and induces increased pressure in the eyes. Angle Closing is caused by the blockage of drainage channels owing to a dramatic increase in intraocular pressure in the eye. Other forms of glaucoma include secondary, pigmentary, pseudoexfoliative, traumatic, neurovascular, and uveitis. The pressure inside your eye is determined by tonometry. Ophthalmoscopy is the diagnostic test that lets the doctor look for glaucoma damage in your optic nerve. The visual field is measured in a systematic way using perimetry. Pressure within the eye is maintained by constant fluid development and drainage. The damage to the drainage system results in intraocular pressure, assessed by gonioscopy. Corneal thickness affects the pressure of the eye, and it is detected by pachymetry. The only way to avoid glaucoma is early intervention, because there are no signs. The glaucoma disorder is treated using a camera image from a fundoscopy. Fig.1 spotts the difference between affected healthy eye and glaucoma. The ratio of OD and optic cup regions is important for the detection of glaucoma. OD to cup ratio is addressed in several articles.

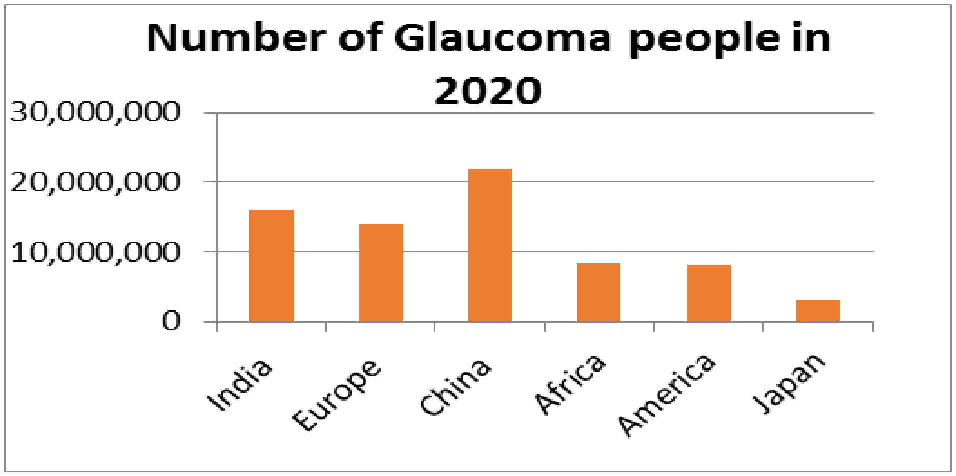


Figure 1: Statistics of glaucoma affected people.

Figure 2: Various stages of glaucoma vision.

Figure 3: Healthy and glaucoma fundus image.

The remainder of the paper is structured according to this. Section II describes different methods of OD segmentation. Section III describes experimental findings of current methods. Discussing the successful approach for glaucoma diagnosis is given in section IV. The ending part is discussed in section V.

2. Materials

The evaluation of glaucoma is diagnosed using datasets of the fundus camera. The detection and evaluation techniques are done using publically available datasets [1][2] is shown below. The datasets are partition into testing and training datasets. The some of the datasets are

1. DRIVE
2. STARE
3. MESSIDOR
4. KAGGLE

3. Methodology

Retinal imaging techniques are used in numerous applications in the medical industry, such as ocular fundus procedures, detecting early stage glaucoma. An automatic diagnosis of OD detection is very necessary for avoiding the blindness caused by glaucoma. With the automated method, the work of ophthalmologists can be that, and the cost also reduced. The fundus camera helps to diagnose glaucoma and treatment. The images obtained perform preprocessing, segmentation, feature extraction, and classification is based on a cup to disc ratio(CDR). The widespread glaucoma detection workflow is shown in fig 4.

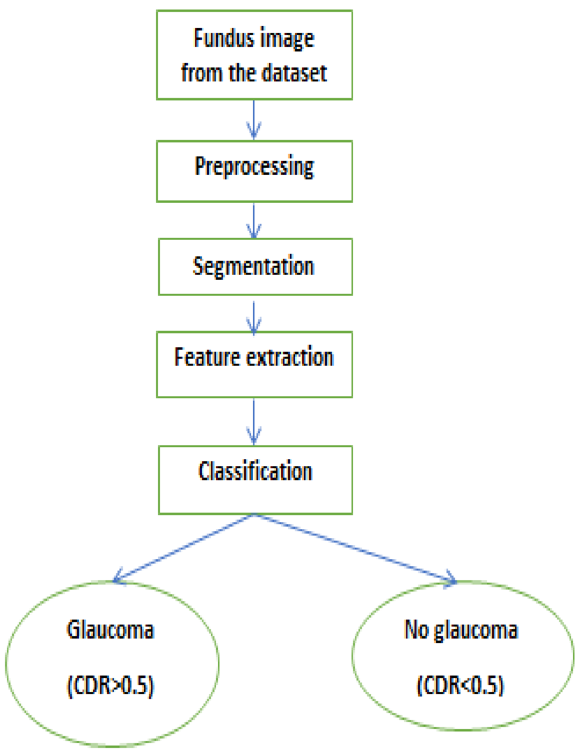


Figure 4: The workflow of glaucoma detection.

3.1. Preprocessing

The eye's fundus image is captured by means of optical image capture tools. Preprocessing main aim is to eliminate unnecessary artifacts and improve the image quality. Several preprocessing techniques are applied, and their forms are listed below, in the fundus images. During preprocessing of images, there might be artifacts in the images that need to be corrected before measuring and analyzing the feature.

3.2 Segmentation

Segmentation is the process whereby the pixels of an image are divided according to semantic content. The main objective of segmentation is to identify boundaries between regions and to exclude undesirable regions. OD segmentation is the most basic and fundamental approach for glaucoma detection. On the other hand, segmentation of the optic cup is a challenging task because of the presence of blood vessels. Many techniques have been suggested for the segmentation of disks, such as template based methods, pixel labeling, deformable based, circular hough transform method[5].

3.3 Feature Extraction

More relevant are the features for more accurate classification of the data. Numerous features such as colour, location, appearance, gist, and texture are extracted using different extraction methods of features. Features are important to distinguish the area of the optic discs and non-optic regions.

3.4 Classification

Pixel classification based on the cup-to-disc ratio (CDR) is critical in confirming the advanced stage of glaucoma. Classification performance depends on how the features are chosen correctly and optimally. A number of Classifiers are discussed with precision below.

4. Overview

Table 1 consolidates the overall methodologies, and therefore one may evaluate the correct method for their implementation. The traditional chan vese model was adapted by Gopal Dutt[1] to strengthen the OD segmentation regions, and robust to the disturbances found closer to the OD limits. To extract the optic cup regions a new r-bend-based optic cup segmentation method is implemented.Arturo Aquino[9] proposed the new template-based methodology for optic disc segmentation, which is a voting type algorithm. This model is compared with elliptical and deformable models, where the proposed method shows good performance, success rate, quality, and efficiency. Rajendra Acharya[presents a combination of texture and high order spectra method for the detection of glaucoma. He used a modalities have classification results than other classifiers. Tehmina [9] proposed a novel combination of hybrid structural features (HSF) and hybrid textural features (HTF).HSF module classifies the input images using SVM. HTF module analyses various texture and intensity-based features. This model achieves precision of 100% and sensitivity of 94 percent.

In his research Jun cheng[6] suggests superpixel classification for optical disks and optic cup segmentation. The proposed work provides an average 9.5 % overlap error and achieves an region in the two datasets under curve 0.80 and 0.82. The key problems in this approach are certain morphological regions and poor change of colour. Sumeet dua[13] performs on wavelet transformation, where it extracts and ranks the features. Based on the energy level, the graded coefficients are obtained which can differentiate between normal and glaucoma images. The energy levels are extremely intolerant, with 93 % accuracy. The downside is more time consuming. Enrique[3] developed the algorithm that combines the power cepstrum with the mean zero structured cross-correlation techniques to abstract the depth information in a stereo pair. This system, however, does away with subjective uncertainty, cost reduction and time. Acharya[12] suggested a decision-support method for glaucoma diagnosis using Gabor transformation. Use an SVM classifier, the t-test rating system demonstrates high output in precision, sensitivity, and specificity. This new approach is used to validate the risk indexing system for glaucoma. A huge storage space is required to keep the system effective.

Table 1: Different state of art literature review depends on Dataset, modality, OD and cup methods, Metrics, advantages and drawbacks

Author	Dataset	Modality	OD and cup methods		Metrics	Advantages	Drawbacks
			Image processing steps	**Algorithms/ Model**			
Gopal Datt joshi[1]	33 normal and 105 glaucoma	Color fundus imaging	1.localized and vector-valued. 2.OD localization &contour initialization. 3.segmentation. 4. Medical axis detection. 5.multi-stage selection of r-band. 6.2-D spline interpolation.	1.Chan-Vese active counter model. 2.circular Hough transform 3.3.r-bend information scheme	1.CDR vertical diameter ratio 2.CDR area ratio	1.High sensitivity 2.More accuracy 3.computationally intensive	1.loss of depth information. 2.estimation error in cup regions
Jun Cheng[10]	1.Simes 2.Singapore Chinese Eye Study (SCES)	A 2D retinal fundus camera	1. Self-assessed disc segmentation. 2.disc normalization 3.CDR assessment	Sparse dissimilarity-constrained coding	1.CDR error rate 2.Pearson correlation 3.The area under the curve	1.Low cost 2.Time-consuming 3.greater potential for using in a large population	1. Not capture local cup deformation.
Arturo, Aquino[9]	MESSIDOR	Topcon trc nw6 fundus camera	1.Optic disc location 2.Optic disc boundary segmentation 3.Final optic disk boundary segmentation	Template Based Methodology	1.overlapping rate	1.100% of the overlapping areas are achieved. 2.reliable 3.robust solution	1.more sensitive 2.low boundary contrast.
Jiang Liu[6]	MESSIDOR SiMES SCES	Fundus camera	1.Generation of superpixels 2.Extracting features 3.Initialization & deformation 4.Self-assessment score. 5.Superpixel Optical Cup Estimation Ratio 6.CDR	Superpixel classification	1.Mean CDR error 2.Area Under Curve (AUC) 3. Mean overlapping error.	1. High classification accuracy. 2. Good enough for screening. 3. Identify difficult regions.	1. Training of cup segmentation is difficult. 2. May not cover some morphological regions due to sudden changes.

Erique corona[3]	Stereo fundus images	Fundus camera	1.Preprocessing and identification of stereo-pair. 2.Extracting the features 3.Depth of the stereo and cubic B-spline Interpolation	Standardized cross-correlation of the power cepstrum and zero mean .	1.cup to dis area ration correlation 2.cup to disc volume ratio correlation 3.Vertical and horizontal cup disc ratio.	1.Time-consuming. 2.Good correlation 3. More efficient evaluation.	1.Repeatable outcomes in the use of proper constraints and optimisation.
Siamak yousefi[2]	African Descent and Glaucoma Evaluation Study	OCT	1.Data acquisition 2.Feature sets for Machine learning classifiers(MLC) 3.MLC 4.Feature selection	MLC	1.Sensitivity 2. F-measure. 3.AUROC 4.ARC	1.High diagnostic accuracy, sensitivity &specificity in random forest classifier.	1. Bayesian net classifier performs not well.
Sumeet dua[13]	Kasturba medical college, Manipal.	Fundus camera	1.DWT based features. 2. Preprocessing of Features. 3.Normalization of features. 4.Feature ranking	2D Discrete Wavelet transform	1.Accuracy 2.Sensitivity 3.Specificity	1.High accuracy. 2.SMO classifier performs well in DWT.	1. Time is taken more.
Koen A. Vermeer[14]	Laser diagnostic technologies images	SLP	1.Analysis 2.Synthesis	1.t-test 2.aniostrophic filtering 3.morphological operations	1.Mean 2.standard deviation 3.Sensitivity	1.Time-consuming 2. Improved specificity.	1.occlusion 2.preventing direct calculation

Xiaoyun Yang[15]	10 sets of HRT images.	HRT	1.Placement of initial curve 2.Region-based 3. Extracting the optic disk using the boundary-based Model 5.Coarse-to-fine multi-scale extension	Multi-scale region and boundary hybrid snake method to extract the optic disk.	1.overlap ratio	1.Accurate segmentation	1. It does not find the exact boundary when compared to the gold standard. 2. low contrast 3.large distractor
Tehmina, khali[8]	Glaucoma database	OCT and fundus camera.	1.Image scaling 2.OD segmentation 3.Image enhancement 4.HSF &HTF Module 5.SVM[20][8]	Hybrid structural and textural features	1.Sensitivity 2. Accuracy 3.Sensitivity	1.maximum accuracy 2.best performance	1. Illumination noise is present in the red and blue channels. 2. The fundus image does not provide a depth analysis of the optic nerve.

Many treatment approaches for detecting glaucoma are listed from the table 2 below. It is necessary to evaluate the effectiveness and accuracy of device dataset. Using fundus camera and OCT modalities, datasets are mostly selected. Different image processing methods are used to segment and detect the OD and optic cup. In the table, we conclude that the enhanced chan-vese[1]active contour model gives better accuracy, sensitivity for segmentation of the OD boundary, and r-bend scheme for segmentation of optic cups. The key goal in glaucoma diagnosis is to use these current methods to find the CDR limit. The explanation for glaucoma calculation is extremely high cup size due to pressure shown in Figure 5.

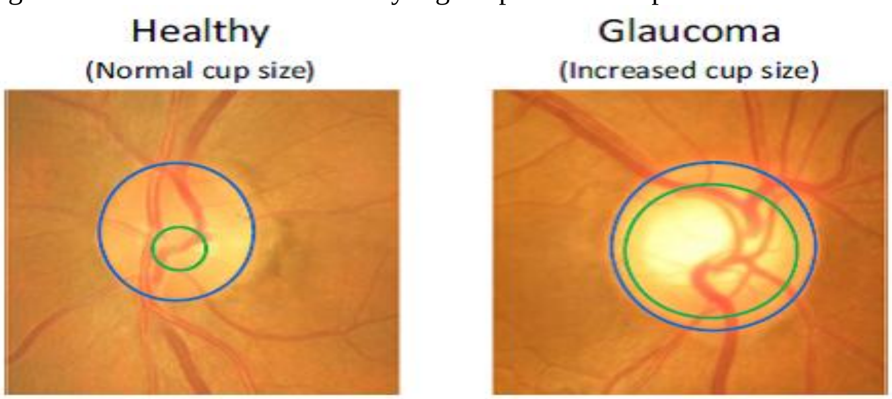
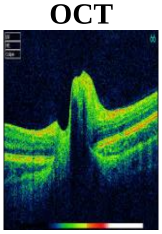
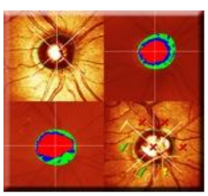
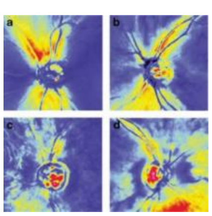


Figure 6: Difference between normal & glaucoma cup size.

Existing work output is evaluated using different metrics such as CDR, precision, sensitivity, specificity, mean, F-measure, Area under Convergence Region (AUROC), AREA under PRC, and overlap ratio of different resolution, portability, access time, and accuracy level. It is shown from the overall study that the fundus camera image offers better information to accurately detect the cup disk ratio for prediction of glaucoma

Table 4: Depicts the different modalities for the identification of glaucoma.

Medical imaging modality	Principles	Focused region	Advantages	Drawbacks
Fundus camera 	monocular indirect ophthalmoscopy	Interior region of the eye (optic disc, retina, macular)	1.2D; 2.slightly wider regions of the fundus can then be seen with handheld ophthalmoscopes at one time[21]	1. It does not detect abnormalities that are outside of the field viewer. 2. Does not detect Artifact from under- and over-exposure 3.less detail information
OCT 	Interferometry	Cornea thickness, retinal nerve fiber	1.3D imaging 2. high-resolution cross-sectional imaging 3.very accurate measurements easier and faster 4.portable[17]	1.OCT has a limited penetration power 2.expensive 3.the transverse resolution needs to be similar to axial resolution
HRTs 	confocal scanning laser ophthalmoscope	Retina	1.Improved image quality 2.less bright light, 3.3D imaging capability 4. video capability	1.difficulty in projecting a curved surface on 2D image 2. determine whether retinal surface area can be precisely measured in square millimeters.
GDx 	Scanning laser polarimetry	The thickness of the membrane of nerve fibres.	1.High resolution 2.cross-sectional imaging 3.Easy to operate 4.Good reproducibility 5. Doesn't require any reference plan	1. Need a large number of databases. 2.Affected by anterior and posterior segment pathology. 3.Difficult in small pupil and media opacities
Fundus autofluorescence	Autofluorescence	Para papillary	1.Image quality	Nil

			and contrast are enhanced 2.high resolution 3.A better understanding of disease	

4. Conclusion

In this review article, the different segments of glaucoma prediction are discussed from the dataset source to performance metrics. The information content of publicly available datasets was discussed in the material section. Glaucoma can diagnose using a cup to disk ratio using traditional image processing techniques. Due to the advancements in algorithm development, machine learning techniques have provided better accuracy, sensitivity, and selectivity when compared to earlier image processing techniques. The random forest machine learning algorithms provide better performance metrics when compared to naïve.

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