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ANALYSIS OF RETINAL IMAGES FOR DETECTION OF GLAUCOMA USING IMAGE PROCESSING TECHNIQUES

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Abstract

Medical image processing is a tool and technique for creating a visual image of inside of the body. The rapid advancement of digital imaging and computer vision has broadened the potential for the use of imaging technology in medicine. Image processing is especially useful in diagnostic medical systems. Reliable glaucoma detection in digital fundus images remains an open problem in biomedical image processing. Detection of glaucoma in the retinal fundus image is necessary to avoid loss of vision. Glaucoma is an irretrievable chronic eye condition that causes blindness due to damage to the optic nerves. The time of diagnosis of glaucoma is very critical for slowing down the adverse effect, since glaucoma can not be cured. Several studies have shown that glaucoma is detected or screened in a 2D retinal fundus image. This paper discusses the various methods of segmentation and classification techniques used to diagnose retinal glaucoma based on the Cup to Disk Ratio (CDR) assessment of the pre-processed image. This survey paper proposes an image processing technique for the segmentation of the optic disc and cup as well as the diagnosis of glaucoma using the features obtained from the image based on the study of the adaptive thresholding technique and the classification technique compared to the remaining or present algorithms.

Keywords: Fundus Image, Optic Disc, Biomedical image processing; Optic Disc detection; SVM classification; Glaucoma detection; Cup to Disc Ratio (CDR).

1. INTRODUCTION

The retina, which is a layered tissue, lines inside of the eye to enable the incoming light to be converted to a neural signal that is processed further in the visual cortex of the brain. The process of imaging in the retina and developing techniques to analyze the produced images becomes an interest of research in medical field (Abràmoff et al 2010). The main function of the retina is to capture the outside world and the concerned ocular structures within the eye have to be optically transparent in the image formation process. Various systemic diseases affecting the retina of the human include diabetic retinopathy (DR) and glaucoma, which are the most common cause of blindness in developed countries. The retina is affected by systemic and organ-specific diseases; also imaging the human retina affects its normal operation. The complications of diabetes, hypertension and other cardiovascular diseases in the retina, can be detected, diagnosed and properly treated [1].

A patient whose fasting plasma glucose is over 7.0mmol/l is considered to suffer with Diabetes mellitus, according to the current definition from the World Health Organization (WHO report 2007, WHO report 2010)[2]. It directly affects the functions of kidneys, heart, brain and human eyes. Diabetic retinopathy is the most common retinal disorder in the type 2 diabetic patients. DR is one of the complications of diabetes mellitus, causing blindness and partial visual loss in the working age people. Glaucoma is the second most retinal disorder in the diabetic patients. It is principally a neuropathy, not a retinopathy, since it damages the ganglion cells and their axons, thereby damaging the retina. It is the prime cause of blindness due to diabetes or hyper tension, characterized by gradual damage to the optic nerve in the retina, and its detection is essential to prevent visual loss in type 2 diabetic patients. It is a complication of the human eye which leads to blurred/ reduced capacity of vision in diabetic or hypertension patients.

World Health Organization (WHO) predicted that the number of persons with diabetes will increase to 366 million in 2030 worldwide (WHO report, 2010). Quigley & Broman stated that 60 million people were affected by glaucoma in the year 2010 and will increase to 80 million by 2020. Diabetic retinopathy and glaucoma are the two irreversible disorders related with retina of the human[3].

Generally, the retinal image consists of blood vessels, Optic disc (OD), Optic cup (OC) and macula region as shown in Figure 1. The blood vessels start from center of the OD and spread over the entire region of the retina,which supply the blood to the entire region of the retina.

The retinal blood vessels get damaged in diabetic patients due to high pressure which lead to the formation of abnormal lesions exudates in and around the macula region. The formation of exudates in the retina leads to the development. The optic nerves also get damaged due to the high pressure in diabetic patients, which forms the glaucoma in diabetic

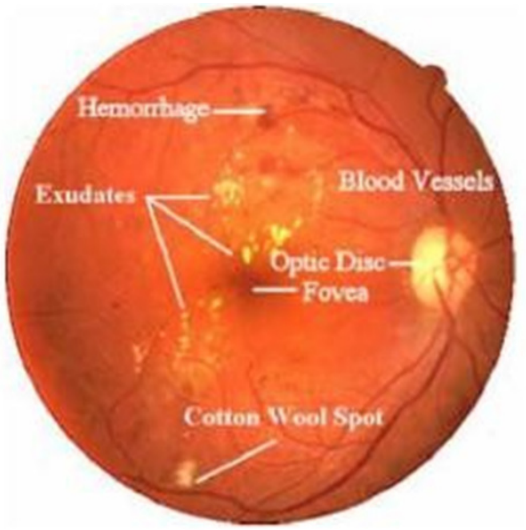


Figure 1: Retinal Imageshowing various lesions

patients. Once glaucoma is developed in diabeticpatients, it cannot be cured. Both DR and glaucoma are irreversible retinal disorders which lead to vision loss in diabetic patients[5].

2. ABNORMAL LESIONS IN RETINA:

The blood vessels are responsible for the supply of blood to the entire retina region. Retinal blood vessels are weakened due to human ageing and other factors such as blood pressure (WHO Study 2010)[2]. Hemorrhoids and exudate lesions are produced in the retinal picture due to damage to retinal blood vessels. Ignoring these lesion signs leads to vision loss, since these signs are not readily exposed and require early diagnosis. Diabetic patients also need to have their eyes tested to prevent DR. Early screening and diagnosis of DR in diabetes patients decreases the chance of vision loss by 50% (WHO Study 2010)[2].

The abnormal lesions are formed in the retinal image due to blood or protein leakage from the retinal blood vessels as listed below and depicted in Figure 1.

- Exudates
- Hemorrhages
- Microaneurysms (MAs)
- Cotton woolspots

The analysis of shape and structure of the blood vessels, abnormal lesions and macula in retina are essential for the detection and severity classification of DR in diabetic patients. Therefore, computer aided automatic screening and diagnosis system for DR provides a solution for this problem in diabetic patients using their retinal images alone.

3. DISEASES RELATED WITH RETINA

3.1 Diabetic Retinopathy:It directly affects the kidneys, heart, brain and human eyes. Diabetic retinopathy is most common retinal disorder in the type 2 diabetic patients. It is a complication of diabetes mellitus and the second most common cause of blindness and visual loss in the U.S., and the most important cause in the working age population. The primary cause for DR is the formation of retinal abnormal lesions such as exudates, hemorrhages and microaneurysms in the retinal images due to the damage of retinal blood vessels.

3.2 Glaucoma:It is the second most retinal disorders in the diabetic patients due to the structural changes in neuro retinal rim region between OD and OC in retinal images of the diabetic patients. It is typically treated with ocular pressure lowering drops, and in refractory cases through surgery.

3.3Age Related Macular Degeneration:In the U.S., one of the most emerging diseases causing visual loss is Age related macular degeneration (AMD) (Cheng et al 2012)[6]. AMD can be further classified based on its activity, namely wet AMD and dry AMD. Wet AMD, also called choroidal neo-vascularization (CNV), is considered to be the most dangerous form, which comprises an in growth of a choroidal vascular structure within the macula characterized by an increase in vascular permeability. Whereas, a gradual loss of visual acuity is observed in dry AMD[6].

3.4Cardio-vascular Diseases:This disease affects the retina in various ways. The ratio of the diameter of retinal arteries to veins (A/V ratio) is mostly varied due to atherosclerosis and Hypertension. As the A/V ratio reduces, i.e., thinning of the arteries and widening of the veins occurs, a high risk of myocardial infarction and stroke may be anticipated (Tien Yin Wong et al 2002, Wong et al 2012)[7][8].

4. LITERATURE SURVEY

Segmentation is an extremely important operation in a number of applications, especially in the field of medical imaging and computer vision, as it is the very first step in the low-level processing of medical imaging to divide the image into regions that meet specific constraints. This chapter summarises the previous work on the segmentation of retinal blood vessels, exudates, haemorrhages, glaucoma identification and segmentation, and also discusses the disadvantages of conventional techniques.

The component analysis system used by Goldbaum et al (2005) to define the cup region more precisely compared to the manual threshold analysis method. The Bayesian Version Independent Component Analysis Model partitioned the regular automated

perimeter (SAP) fields to the most insightful number of clusters. At the same time, the model has learned an optimum number of overall independent axes for each[9].

Mendonca&Campilho (2006) proposed a vessel segmentation algorithm using a vessel centre line followed by a vessel filtering process. Multi-scale morphological enhancement technique has been used to improve the contrast of the blood vessels. The authors achieved 96.33 percent accuracy in the DRIVE data set and 95.79 percent accuracy in the STARE data set. The Wilcoxon paired test algorithm was used to demonstrate the consistency of the results[10].

Palomera-Perez et al (2010) used the regional extraction feature of an increasing blood vessel segmentation algorithm. The parallelism of the partitioning of the domain was used to group the vessels together. The authors achieved 92.5 percent accuracy in the DRIVE data set and 92.6 percent accuracy in the STARE data set[4].

Rajendra et al (2011) used higher-order texture and spectra features to detect and diagnose glaucoma in diabetic patients. Help vector machine, sequential minimal optimization, native Bayesian and random forest classifiers were used as a supervised classifier.

In addition, Bayesian and random forest classifiers were used in this work to distinguish between regular and glaucoma retinal images. The authors obtained 91 percent accuracy in the classification for the diagnosis of glaucoma[3].

Fraz et al (2012) used an ensemble classifier for the segment of the vessel. The gradient vector field and the Gabor transform have been constructed and used as an ensemble classifier function. The authors achieved 72.62 percent sensitivity, 97.64 percent specificity and 95.11 percent accuracy of the STARE dataset, and 74.06 percent sensitivity, 98.07 percent specificity, and 94.8 percent accuracy of the DRIVE datasets. The key drawback of the Gabor transformation is that its outputs are not mutually orthogonal, which can contribute to a substantial relationship between the texture features[11].

Bansal&Dutta (2013) has developed a fuzzy algorithm for the segmentation of vessels. The Bloc wise fuzzy rules for classifying vessels and non-vessels have been created. The sensitivity of 86.53%, the accuracy of 98.33% and the accuracy of 97.28% of the DRIVE data set were achieved in this work[12].

The extended version of the Frangi algorithm has been used for the segmentation of the retinal blood vessel tree (Budai et al 2013). The methodology used in this study resulted in a vessel detection time of 1.31 seconds for images in the STARE dataset and of 1.04 seconds for images in the DRIVE dataset. The transformed 2D-Gabor wavelet and the supervised classifier have been used for the detection and segmentation of blood vessels in retinal images (Soares et al 2006). The total time for this work was approximately 180 seconds for both STARE and DRIVE dataset images. The method proposed in this study reduced the mean time-based segmentation of the retinal blood vessels and improved mean sensitivity , specificity and accuracy[13].

Yousefi et al (2014) proposed machine learning classifiers for the classification of glaucomate progression using a longitudinal collection of structural data. The longitudinal vector function was developed using the longitudinal data collected. The extracted longitudinal features were educated and graded using a machine learning classifier as either advanced or non-progressed retina. Classifiers of Bayesian, Lazy, Meta and Tree were added as classifiers individually to the retinal picture for the classification of glaucoma. Table 2 demonstrates the literature analysis of Glaucoma detection strategies[14].

Kaur et al (2014) observed glaucoma in diabetic patients by disk ratio of their retinal images. In this work, the basic evaluating the cup-to- mathematical morphological operations were used to detect the optical disc and the optical cup from the retinal images. The key contribution of this work was to assess the degree of seriousness of glaucoma. The authors found that the CDR value for extreme glaucoma was approximately 0.3 and above.helped this method achieve superior sensitivity results of 0.8043 and 0.7974 for the DRIVE and CHASE_DB1 datasets while maintaining decent specificity and accuracy scores. The potential future research directions of this work includes the exploration of combining the directional filters with contrast enhancement and noise cancellation techniques to optimize the performance and reduce the classification inaccuracies during the segmentation process[15].

li et al. (2017) proposed retinal blood vessel segmentation method based on the reinforcement local description. For each pixel, line sets based feature was firstly developed for representing the shape of the blood vessel. The proposed line set feature was extracted by employing the length prior of vessels, which is more robust to intensity variety. And then, line sets based feature, local intensity feature, and morphology gradient feature are combined for obtaining more effective reinforcement local descriptions. The descriptions contained the rich local information of the shape and gray and enhanced edge, which is more robust. After feature extraction, SVM has been trained for vessel segmentation. Finally, postprocessing was proposed for further obtaining more accurate segmentation result. The experiment resulted on DRIVE database and STARE database demonstrate the effectiveness of the proposed method[16].

Khawaja et al. (2019) used directional multi-scale line detectors for segmenting directional vessel images extracted from DFB. The evaluation of this technique on three publicly available datasets suggested that this technique not only yielded balanced and robust performance parameters under difficult testing environments, but also competed with supervised learning techniques which are much more computationally intensive[17]. This computational flexibility also gave this technique great leverage while working on considerably large databases with retinal disorders and abnormalities. The intricate geometry of retinal vessels meant that special methods be adopted to successfully segment troublesome areas such as parallel vessels and vessel crossings. The use of an array of directional images acted upon by a directional detector and binarization [17].

Islam et al. (2020) proposed a deep-learning-based approach to segment vessels involving the simultaneous use of three OCT en-face images as input. A human expert vessel tracing combining information from OCT en-face images of the retinal pigment epithelium (RPE), inner retina, and total retina as well as a registered fundus image served as the reference standard. The deep neural network was trained from the imaging data from 18 patients with optic disc swelling to output a vessel probability map from three OCT en-face input images. The vessels from the OCT en-face images were also manually traced in three separate stages to compare with the performance of the proposed approach. On an independent volume-matched test set of 18 patients, the proposed deep-learning-based approach outperformed the three OCT-based manual tracing stages. The manual tracing based on three OCT en-face images also outperformed the manual tracing using only the traditional RPE en-face image. In cases of optic disc swelling, use of multiple en-face images enables better vessel segmentation when compared with the traditional use of a single en-face image. Improved vessel segmentation approaches in cases of optic disc swelling can be used as features for an improved assessment of the severity and cause of the swelling. Table 2 provides a literature analysis of retinal vessel segmentation techniques[18].

Table 1: Literature survey on Glaucoma Detection

Reference	Method	Advantages	Disadvantages
Foracchia et al (2004)	Simulated annealing optimization technique	High classification accuracy (98%) High computational time	Foracchia et al (2004)[43]
Rajendra et al (2011)	Bayesian random classifiers	and forest High segmentation accuracy	OD
Palomera et al (2013)	Support Machine classifier Vector (SVM)	Low computational time	Low classification accuracy (88%)
Cheng et al (2013)	Statistics features	OD and OC boundaries were clearly segmented	High average overlapping error of 9.5%
Stefano et al (2014)	Bayesian classifier High segmentation accuracy	OD Low Sensitivity (85%)	
Carrillo et al. (2019)	CDR (Cup to Disk ratio)	Low execution time	Low accuracy rate (88.5 %)

Table 2: Glaucoma Detection Accuracy

S. No	Technique	Dataset	Image Size	Accuracy% (classifier)	Sensitivity %	Overall Accuracy	Specificity %
1	Detection of RNFL Gabor Filtering [19]	52 images	768 x 576 pixels	Not mentioned	Not mentioned	71 %	71 %
2	Texture Analysis of Nerve Fiber Layer [20]	28 images	3504 x 2336 pixels	2.85 % 0.55 % 10.88 %	Not mentioned	Not mentioned	Not mentioned
3	Markov Random Fields Texture Modelling [21]	28 images	3504 x 2336 pixels	0.55 % 3.05 % 11.7 % 9.88 %	Not mentioned	Not mentioned	Not mentioned
4	Retinal Optic Cup Detection[22]	71 images	Not mentioned	Not mentioned	97.2 %	97.2 %	97.2 %
5	Close Angle Glaucoma Detection in RetCam Images [23]	186 6 images	Not mentioned	Not mentioned	86.7 % 97.8 %	Not mentioned	83.3 % 92.6 %
6	Enhancement of Optic cup to Disc Ratio Detection [24]	Few images	Not mentioned	Not mentioned	Not mentioned	97.5 %	Not mentioned
7	Diagnosis System for Early Glaucoma Screening [25]	128 images	Not mentioned	Not mentioned	96.2 %	Not mentioned	96. 6 %
8	Diagnosis of Glaucoma Using Texture and Spectra Features [26]	60 images	560 x 720 pixels	91 %	Not mentioned	91 %	91 %
9	Diagnosiso f Glaucoma[27]	61 images	560 x 720 pixels	Not mentioned	100 %	Not mentioned	80 %
10	Convex Hull Based Neuro Retinal Optic Cup Ellipse Optimization [28]	70 images	Not mentioned	Not mentioned	43 %	43 %	43 %
11	SVM, Statistical Technique Method [29]	144 images	Not mentioned	Not mentioned	Not mentioned	98.24% 96.49%	Not mentioned

5. WORK DONE

In this section, we discussed our work on retinal image analysis for glaucoma detection. We have developed a scheme for automated processing and classification of the acquired images based on the usual practice in the clinic. The Fig. 2 shows our proposed System which follows a standard 3-step image analysis pipeline consisting of (i) preprocessing; (ii) segmentation of preprocessed image and (iii) classification based on evaluation of CDR. The techniques i.e. multi thresholding is applied for the segmentation of pre- processed fundus image in order to detect the disease by computing CDR.

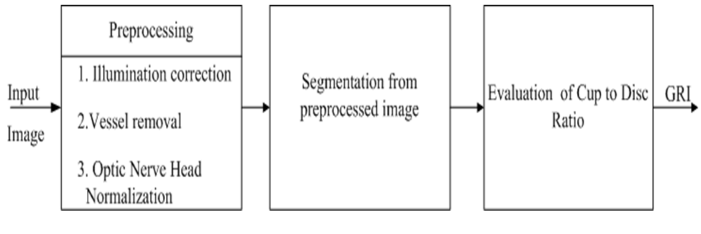
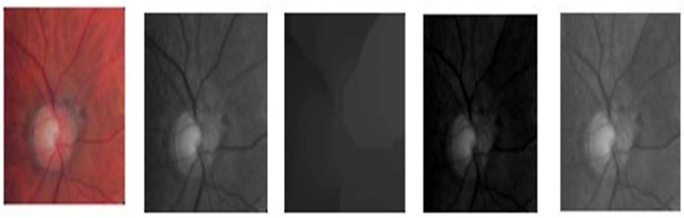


Fig. 2.Processing pipeline in detail: glaucoma risk calculation comprises of steps: (i) Preprocessing of input images for eliminating disease independent variations, (ii) Segmentation of preprocessed image and (iii) Classification based on CDR for generating GlaucomaRisk Index (GRI)

The variations not related to the glaucoma disease are excluded from the images in a preprocessing step for emphasizing the desired characteristics. This includes variations due to image acquisition, such as inhomogeneous illumination and the blood vessels which are not directly linked to glaucoma. The main objective of preprocessing is to attenuate image variation by normalizing the original retinal image against a reference model or data set for subsequent viewing, processing or analysis [30]. The preprocessing retinal images may be classified in terms of the correction for non-uniform illumination, contrast enhancement and color normalization.

5.1 Illumination Correction

The peripheral part of the retina often appears darker than the central region because of the curved retinal surface and the geometrical configuration of the light source and camera. These interferences affect the illumination of the ONH and would have an influence to the subsequent statistical analysis, though they are not originated through glaucoma [3]. Homogeneously illuminated fundus image is obtained by subtracting the estimated retinal background from the original image. Various techniques for illumination correction like morphological operations, homomorphic filtering and median filtering have been published in the literature [31]. We implemented a correction method based on morphological operations as it has certain advantages over other techniques. The benefits of this technique over linear approaches include direct geometric interpretation, simplicity and efficiency in hardware implementation. Uniformly illuminated image is obtained by subtracting the estimated background image from original image. Morphological opening is used to estimate the background illumination. Fig.3 shows the different steps needed to obtain an illumination corrected image.

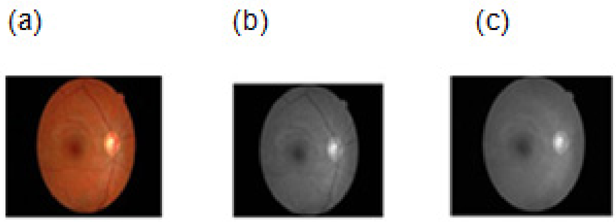


Original fundus image (i) is first converted into grey image(ii)andthenbackgroundisestimated(iii).Imageobtainedfromsubtractingfrom (ii) is added with fixed dc level to get the final illumination corrected image shown in(v).

Fig. 3. Result of illumination correction using morphological operations

5.2 Blood Vessels Removal

Blood vessels are minimally affected by glaucoma disease; hence blood vessels need to be removed from the fundus images. Blood vessel removal consists of two steps: (i) extraction of blood vessels and after that (ii) inpainting of extracted blood vessels. Image inpainting is the technique of filling in a region of an image based on the information outside the region [32]. The major blood vessel branches rising from the ONH hide large portions of the rim and their existence makes analysis of the visible parts of the ONH more difficult. This can hinder the accurate segmentation of OD. Therefore, inpainting technique is applied to remove these blood vessel structures after the extraction blood vessels before further processing. The extracted blood vessels act as a mask and the region covered by the mask is inpainted. In this implementation, the vessel regions are filled iteratively layer by layer from outside inwards while the missing pixels get a weighted average of the already known neighboring values. Morphological operations are also used for removal of blood vessels from fundus image. Morphological closing consisting of dilation followed by erosion is applied to remove the blood vessels. Fig.4 shows the result of morphological operations for blood vessels removal.



a) Fundus Image b)Illumination Corrected c) Blood Vessels Removed

Fig. 4. Result of morphological operations for blood vessels removal

5.3 Normalization of the ONH Region

Papilla (ONH) is the most important structure for observing changes in order to detect glaucoma. It appears as an extremely bright, mostly circular region in fundus images. The image obtained after blood vessels removal is normalized for better analysis.

5.4 Segmentation from the Preprocessed Image

The preprocessed images are used for the segmentation of optic disc and cup which helps in classification of glaucoma. In this subsection, the three different techniques for glaucoma detection are discussed.

5.5 Multi-thresholding Technique

Multi-thresholding technique is one of the simplest methods and natural way to segment cup and disc of preprocessed fundus image. The preprocessed image containing the optic disc is converted to binary image and than multi-thresholding technique is applied. This technique allows the detection of cup, the brighter region of the optic disc with higher threshold value and the whole disc with lower threshold value. Fig.6 shows the detection of optic disc and cup from preprocessed image for glaucoma classification

Fig5. Result of multi-thresholding for disc and cup detection

It has shown correct segmentation for 19 images out of 25 set of images. The accurate segmentation was not possible for rest of 6 images as the optic disc and some portions of background image have similar illumination level. The quality of original images was also one of the reasons for improper segmentation. The major demerit of the method is the manual thresholding based on the pixel intensity values. Hence other techniques like active counter method based on adaptive thresholding and region growing segmentation methods are applied for cup and disc segmentations from the preprocessed fundus image for glaucomaclassification.

The processed image obtained as discussed earlier is used to determine the CDR by finding the number of ones present in the cup region to that of number of ones in disc region of binary image. CDR of 25 fundus images downloaded from www.opticdisc.org (7 normal and 18 abnormal images) is determined in order to detect glaucoma. Efficiency of the proposed method in identifying true positive and true negative is shown the column-I of the table-1. The performance measure of this method with sensitivity (classify abnormal fundus images as abnormal) of 80% and specificity (classify normal fundus image as normal) of 60 % is summarized in column-I oftable-2.

5.6 Glaucoma Detection Based on Region Growing Segmentation Technique

Region growing segmentation technique is applied to estimate radius of cup and disc from the pre processed fundus image as discussed in subsection 2.2.3. Like the other two methods, CDR evaluation was the criteria for the classification of the disease. The results obtained by this third proposed method are better compared to other two mentioned techniques as it is based on clustering of homogeneous regions. It is able to classify all eighteen abnormal images as abnormal but two images were misclassified out of seven normal images. Efficiency of this method in identifying true positiveand true negative is shown the column-III of the table. The performance measure of this method with sensitivity and specificity of 94.73% and 100% respectively is summarized in column-III of table-II

Table 3. Shows the comparative results of Multi-thresholding;

Sr. No.	Performance parameter	Efficiency (percentage)	
		Multi-thresholding Segmentation	Region Growing Thresholding
1	True Positive	88.89	100
2	True Negative	42.85	85.71
3	False Positive	11.11	0
4	False Negative	57.17	14.29

Sr. No.	Accuracy parameter	Efficiency (percentage)	
		Multi-thresholding Segmentation	Region Growing Thresholding
1	Sensitivity	80	94.73
2	Specificity	60	100

Table 4: Shows the comparative accuracy of Multi-thresholding

6. Conclusion:

This study paper provides a variety of strategies for early detection of glaucoma affecting eye vision. A variety of automated approaches to the diagnosis of glaucoma have been proposed. Several medical devices have been used to detect and diagnose glaucoma, but their use is very costly. This severe eye condition has affected a large number of people around the world. The paper is also making a slight attempt to diagnose glaucoma. A systematic literature review has shown that while a number of methods to diagnosing glaucoma have been developed, there is still a need and potential for a computer-aided device that not only helps diagnose glaucoma but can also help track the progression of the disease so that it can be monitored if it does not stop progressing. Similarly, optical cup segmentation approaches can be improved by the use of vessel observation, and the use of machine learning approaches in painting can also be used to distinguish meaningful statements in a variety of patterns, such as threshold level setting and edge detection. Some of the existing approaches were also evaluated in a small range of datasets, such as DRIVE and STARE. These datasets do not contain a number of different features of the images. Advanced cameras capable of collecting high-resolution, high-resolution retinal images can be used for glaucoma screening. In order to achieve good results for images captured by different systems, robust and fast segmentation methods are required. Most retinal images used to test segmentation approaches have been taken from adults

The CDR, an important glaucoma parameter of fundus images publically available from messidor and optic data bases were evaluated using three different methods namely morphological operations based on multi-thresholding techniques and region growing segmentation techniques. As a comparative study to these methods for glaucoma classification, we observed that region growing segmentation technique gives better result in comparisons to other method. The proposed methods are simple and easy to implement. The results obtained can be used as an initial investigation step in the automated diagnosis of glaucoma especially in the screening programs. These proposed methods may further be combined with some other techniques for achieving better results with large databases.

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