Cognitive Science and Technology

Vinit Kumar Gunjan
Sabrina Senatore
Amit Kumar *Editors*

# Cybernetics, Human Cognition, and Machine Learning in Communicative Applications

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# Cognitive Science and Technology

This series aims to publish work at the intersection of Computational Intelligence and Cognitive Science that is truly interdisciplinary and meets the standards and conventions of each of the component disciplines, whilst having the flexibility to explore new methodologies and paradigms. Artificial Intelligence was originally founded by Computer Scientists and Psychologists, and tends to have stagnated with a symbolic focus. Computational Intelligence broke away from AI to explore controversial metaphors ranging from neural models and fuzzy models, to evolutionary models and physical models, but tends to stay at the level of metaphor. Cognitive Science formed as the ability to model theories with Computers provided a unifying mechanism for the formalisation and testing of theories from linguistics, psychology and philosophy, but the disciplinary backgrounds of single discipline Cognitive Scientists tends to keep this mechanism at the level of a loose metaphor. User Centric Systems and Human Factors similarly should inform the development of physical or information systems, but too often remain in the focal domains of sociology and psychology, with the engineers and technologists lacking the human factors skills, and the social scientists lacking the technological skills. The key feature is that volumes must conform to the standards of both hard (Computing & Engineering) and social/health sciences (Linguistics, Psychology, Neurology, Philosophy, etc.). All volumes will be reviewed by experts with formal qualifications on both sides of this divide (and an understanding of and history of collaboration across the interdisciplinary nexus).

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# Convolutional Neural Network Assessment to Identify Glaucoma in Eyes Using Retinal Fundus Images

**S. Kirubakaran, Aelgani Vivekanand, G. Ravi Kumar, Jonnadula Narasimharao, Banothu Ramji, and Shaik Sharif**

**Abstract** In order to identify glaucoma, this study suggests an image processing technique using a computer tool. Glaucoma has been identified as one of the major factors that contribute to visual impairment, although early study on the condition was challenging. It is one of the causes of permanent visual impairment in people older than 40 years old. Because it balances convey ability, size, and cost, fundus imaging is a very popular screening method for glaucoma expose. We discuss improvements to disc segmentation alongside other studies in the literature. These upgrades include a novel technique for dividing the container at the threshold and a new comparison between the cup's and the disk's sizes. Results were obtained from a number of fundus photographs.

**Keywords** Cup-to-disc ratio · Cup segmentation · Disc segmentation · Fundus image · Glaucoma · Glaucoma detection · Image processing · Veins segmentation

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# 1 Introduction

Since glaucoma affects the eye's optic nerve, it is the main cause of irreversible vision loss. In the majority of individuals, vision loss symptoms don't become apparent until advanced stages.

Glaucoma frequently results in an unavoidable loss of vision that happens slowly and without warning. It is a major cause of eyesight loss all around the world. According to estimates, a significant proportion of individuals diagnosed with glaucoma in wealthy nations remain asymptomatic, indicating that the condition must be far worse in developing countries. Over 11.1 million people will have essential glaucoma-related visual impairment by 2020, according to an analysis of the prevalence of glaucoma from widely disseminated data. Additionally, it was shown that the expense of treatment for glaucoma in its advanced stages was rising. Glaucoma is 2.6% prevalent in Southern India, and 90% of these instances have never been examined, compared to roughly 50% previously unknown when comparable tests are performed in Europe.

Loss of vision is caused by a confluence of diseases that contaminate the optic nerve and the cells that make up the optic nerve.

The excessive production of aqueous humour or the obstruction of its sewerage system results in increased pressure in the eye, which damages the optic nerve. Additionally, there is proof that the disease's emergence may be influenced by a person's genetic family history. A patient with suspected glaucoma may undergo a number of procedures, including tonometry to measure eye pressure, gonioscopy to verify whether the angle of vision is closed or open, optical coherence tomography (OCT), and funduscopy or fundus imaging to view the retina and the optic nerve as given in Fig. 1.

The thickness of the retinal nerve fiber layer (RNFL) is measured using the retinal fundus image to analyze glaucoma. This is one of the minimally invasive methods that ophthalmologists frequently use. Its key advantage is that it can be used to take photographs of both healthy and unhealthy retinas. It is also portable and easy to employ for any medical professional, which makes it ideal for screening campaigns among populations without access to healthcare.

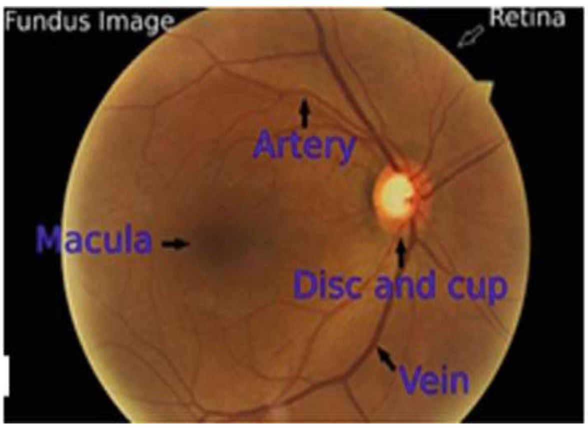


**Fig. 1** Fundus picture and significant parts of the eye

The proportion between the dimensions of the optic nerve (commonly known as the disc) and the dimensions of the cavity formed inside the optic nerve as a result of rising eye pressure (referred to as the cup) is worn to conclude the thickness of the RNFL. The Cup-to-Disc ratio (CDR) is named to this characteristic. The fundamental challenge in automatically detecting glaucoma using colour fundus images has been to offer an precision calculation of the CDR. The present study proposes a method for segmenting discs through the utilization of edge recognition techniques is proposed by Anusorn et al. [9]. If the eye has per papillary atrophy, a condition that causes the disc's edges to alternate, this procedure will not work. The distance that exists among the disc pixels and the cup pixels is occasionally equal, that made it challenging to segment photos collected from different people. The threshold used for cup segmentation is one third of the highest grayscale intensity. Finding the cup edges in the initial phases of the disease when they begin to expand is another issue.

The author of this article describes a computational approach for automatically detecting glaucoma from eye fundus images. The remainder of the chapter is functioned as given: a literature review will be covered in the next chapter, then methodologies, results, a summary, and references.

## 2 Literature Review

Mohammadi et al. [1] Preventive interventions are essentially divided into four categories: primary, secondary, tertiary, and primal.

The aforementioned groups of conventional ophthalmic instances encompass various interventions aimed at addressing specific eye conditions. These actions involve improved sanitation and environmental hygiene measures to reduce the prevalence of Chlamydia trachomatis-infected insects, which are integral to trachoma prevention efforts. Additionally, strict management of blood sugar levels in individuals with diabetes is crucial in preventing the development of retinopathy. Ensuring availability to and the successful implementation of cataract surgery is another important intervention. Lastly, the supply of black pupil contact lenses serves as a means of addressing the aesthetic concerns for those with visually impaired and disfigured eyes. Furthermore, it is important to acknowledge as these categories are subjective and may vary based on the perceived basic health condition.

Maya et al. [2] Glaucoma, which exaggerated 60.5 million people globally in 2010 and is predicted to influence 79.6 million people by 2020, is the most common cause of irreversible vision impairment in the globe. In order to stop the disease from progressing and causing vision loss, glaucoma screening is critical to identifying, diagnosing, and treating sufferers at the earliest possible stages. Stereoscopic digital imaging is used in teleglaucoma to capture images of the eyes that are then electronically sent to an eye doctor. The goal is to compile research to assess Teleglaucoma's cost-effectiveness, diagnosis accuracy, and advantages to the healthcare system.

Methods: For the purpose of locating both published and unpublished studies, a thorough search was carried out. Included were studies that looked at teleglaucoma as a tool for glaucoma screening. Results of accuracy of diagnosis, diagnostic odds ratio, and the proportion of glaucoma patients discovered were obtained by a meta-analysis. The enhancements to cost and quality data for healthcare services were evaluated. 45 studies out of the 11,237 assessed were included. Based on the results obtained from this investigation, it has been shown that teleglaucoma exhibits lower sensitivity and higher specificity compared to personally assessment. The specificity and sensitivity values were calculated to be 0.790 (95% confidence interval [CI] 0.668, 0.876) and 0.832 (95% CI 0.770, 0.881) accordingly. The likelihood of obtaining a favourable screening outcome is 18.7 times greater in individuals who have glaucoma compared to patients without glaucoma. Additionally, the average cost of glaucoma detection was $1098.67 US per case, and the average cost of teleglaucoma screening was $922.77 US per patient. In conclusion, teleglaucoma has a higher likelihood of producing positive instances than screen test results. In comparison to an in-person examination, it finds more glaucoma patients. Early detection, shorter waits and travel periods, higher referral rates for specialists, and cost savings benefit patients as well as healthcare systems. For remote and underserved communities, teleglaucoma is an efficient glaucoma screening technique.

Rohit et al. [3] to compile data on the economic costs of glaucoma, its epidemiology, and its personal toll. Analysis and synthesis of particular works of literature from 1991 until December 2010. Currently, glaucoma affects an estimated 3% of people over 40 in the world, the majority of whom are undiagnosed. Even during the initial phases of the disease, glaucoma-related vision loss has a major negative impact on good life in terms of health. As glaucomatous injure and vision loss worsen, the overall load rises. Glaucoma has a major financial impact that gets worse as the condition progresses. A person's loss of their health-related quality of life as well as the financial burdens on themselves and society are likely to be lessened by early diagnosis and treatment of glaucoma patients along with people with ocular hypertension at a significant risk of developing sight loss.

Broman et al. [4] to determine how many people will have angle closure glaucoma (ACG) and open angle glaucoma (OAG) in 2010 and 2020, respectively. A review of available information using prevalence models: Data across population-based studies on age-specific prevalence of OAG and ACG that fulfilled standard definitions were used to develop prevalence modelling for OAG and ACG by age, sex, and ethnicity, including data weighting according to sample size for every research. Models and UN forecasts of the world's population throughout 2010 and 2020 have been combined to estimate the approximate number of persons suffering glaucoma. 79.6 million people are expected to have OAG and ACG by 2020, having 74% of these individuals having OAG. In 2010, here is going to be 60.5 million people having OAG and ACG. Women will have 55% of OAG, 70% of ACG, and 59% of all glaucoma cases in 2010. 87% of those diagnosed without ACG and 47% of these without glaucoma will be Asian, correspondingly. By 2020, 5.9 million people with OAG and 5.3 million via ACG, accordingly, would have bilateral blindness, up from 4.5 million in 2010 and

3.9 million in 2010. The second largest cause of blindness in the world, glaucoma disproportionately affects Asians and women.

De La Fuente-Arriaga [5] the methodology employed in this work involves the utilization of blood vessel changes inside an optic disc (vascular bundle) in retinal images of patients for the purpose of glaucoma detection. The methodology involves the segmentation of the vascular bundle area inside an optic disc to determine an appropriate point for comparison on the spatial edge of the cup of vision. This is followed by the identification of the centroids of the segmented zones corresponding to the excellent, inferior, as well as nasal vascular bundles across the divided area. Finally, the deviation from the usual location is calculated via the chessboard distance metric. Among a total of 67 photographs, the method correctly identified 62 of them, yielding a pre-diagnosis efficiency rate of 91.34%. The sensitivity and specificity of the technique were determined to be 92.02 and 91.66%, respectively.

Dash [6] Due to its ability to extract a wealth of information related to various eye illnesses, retinal imaging has emerged as the most important instrument among all forms of medical imaging technology. Therefore, it is essential to accurately remove blood vessels in order to aid ophthalmologists and eye care professionals in early illness detection. We have suggested a computational method for haul out blood vessels as of fundus images in this work.

Nikam [7] Glaucoma, which results in permanent vision loss, is a severe condition that damages the optic nerve of the eye. If treatment for glaucoma is delayed, the patient may go blind. Glaucoma is typically identified when there's an increase in the amount of liquid in the front of the eye. Your eye's pressure rises as the amount of additional fluid does as well. As a consequence, the diameter has also amplified, the dimension of the two the optic disc and optic cup is being augmented. The cup-to-disc ratio (CDR) represents the proportional relationship among the lengths of the cup and disc. The localization of the optic disc and optic cup in this structure is achieved through the utilization of a method of segmentation of the threshold kind. Additionally, there exists an alternative approach for edge identification and ellipse fitting.

Nawaldgi et al. [8] glaucoma, a condition that affects the eyes is frequently called the quiet thief of sight. Glaucoma causes harm that is unrepairable. The only treatment for glaucoma is early detection and treatment. Numerous efforts have been made until date to automatically detect glaucoma using optical coherence tomography (OCT) and colour fundus imaging (CFI) pictures by extracting structural elements. Optic nerve head (ONH) study in the case of CFI and retinal layers (RL) study in OCT scans for glaucoma assessment can both be used to extract structural information. But regrettably, in this area, the works completed thus far fall short of expectations. This paper presents an overview of automated glaucoma detection methods. The research also analyzes several structural characteristics that are pertinent to automated glaucoma detection in CFI and OCT pictures, respectively. The study's findings support the idea that structural information from CFI and OCT images might be combined to produce a more precise glaucoma assessment.

Anusorn et al. [9] the second largest general reason of lifelong blindness in the world is glaucoma. Glaucoma's ability to progress can be slowed down with early identification. The cup-to-disc ratio (CDR), also known as the proportion of the size of the optic cup to the size of the optic disc, is one of the key clinical indications of glaucoma. However, it is presently measured automatically by skilled ophthalmologists, which limits its potential for mass screening for early identification. The authors of this work suggest a method for repeatedly manipulative the CDR using non-stereographic retinal fundus images collected by a non-mydriatic auto fundus camera, the NIDEK AFC-230. Two approaches using edge detection and variational level-set algorithms are suggested in the research for automatically obtaining the disc. The threshold level-set method and colour component analysis are assessed for the cup. Ellipse fitting is used to reshape the disc and cup border that was produced using our approaches [10]. In order to assess the effectiveness of the established CDR in comparison to the medical CDR, a dataset consisting of 44 retinal pictures obtained from Mettapracharak Clinic in Nakhon Pathom, Thailand, was utilized. The proposed method has been found to yield a precision level of 89% in determining the CDR.

This paper focuses on CDR-based automated glaucoma identification using fundus pictures. In order to identify the optic cup (OC) as well as optic disc (OD), the region of interest (ROI) is recovered by the utilization of the intensity weighted centroid strategy, preprocessing techniques, and iterative application of k-means clustering delineation. For OC and OD border smoothing, ellipse fitting is assumed [11]. A total of 100 fundus pictures, obtained from a local source, be utilized to evaluate the efficacy of the projected method. The projected method demonstrates an efficiency of 92% in detecting glaucoma, with a mean square error of 0.002 for the cup-to-disc ratio (CDR) [12].

## 3 Methodology

In reality, clinicians use the fundus images of the patient's two eyes to visually estimate the CDR in order to assess whether or not a patient has glaucoma. This procedure, the process of doing a diagnosis, that is inherently subjective, may require a highly skilled specialist to invest approximately a minute to three minutes. Moreover, the implementation of this method in screened initiatives, when every expert is required to review a substantial number of images, may potentially result in significant mental and physical strain. The CDR is intended as given

$$CDR = \frac{area\,Cup}{area\,Disc}$$

if the CDR $\geq 0.6$ it is glaucomatous, or else it is not. Based on this and what is learned from the literature analysis, the disc and cup must be segmented so as to perform automatic glaucoma recognition as shown in Fig. 2.

The subsequent subsections outline the methodologies employed to get multiple divisions and blood vessel information.

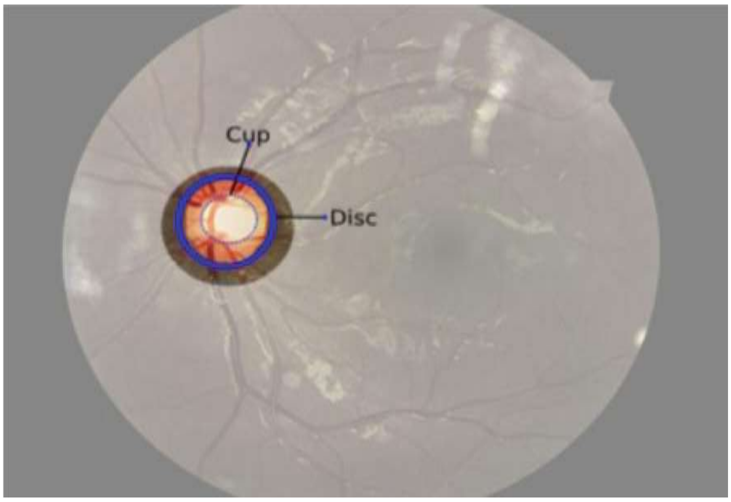


**Fig. 2** Disc and cup location

## *3.1 Disc Segmentation*

We utilized the channel of red to achieve the separation of the disc due to the retina's predominately orange background in the fundus image. The primary stage is to section the disc; the red channel provides the greatest results for this, thus a method to fix the starting point was required so as to identify the disc within the retina. According to the research in, the following parameter is determined to determine the typical number of pixels required to be considered a disc: [10],

$$Pavg = \frac{\pi * D^{2/2}}{7.33 * 8}$$

Here the D is the diameter of the retina in pixels. For the purpose of determining the segmentation threshold, this value is used as a guide. If the number of pixels along with two successive grayscale tones is greater than Pavg, it determines the ratio of pixels among the two tones and chooses the greatest tone as the limit if this proportion is greater than 10% from the graphic histogram, which starting from 255 down to 0. We suggest an enhancement to the procedure in this work because the disc segmentation isn't always accurate with that threshold. The disc-containing blob's height to width ratio must be roughly elliptical, it must be located in the image, and there must be fewer pixels inside the blob than the Pavg threshold. These three requirements are what we use to measure the segmentation's accuracy. Up until the three criteria are satisfied, the program continuously calculates the exact value of the greatest threshold. A matrix filtering was devised to meet the spatial criteria, as depicted in the following Fig. 3. This filter consists of ones within the space encompassing the disc, while the rest of the regions are assigned zeros [13].

Two white blobs are present in the filter to accommodate for the possibility that the image is coming from either one's right or left side of the eye. The exact center of the real blob's coordinates must line up with the left eye's overall image's 31%

**Fig. 3** The calculated filter

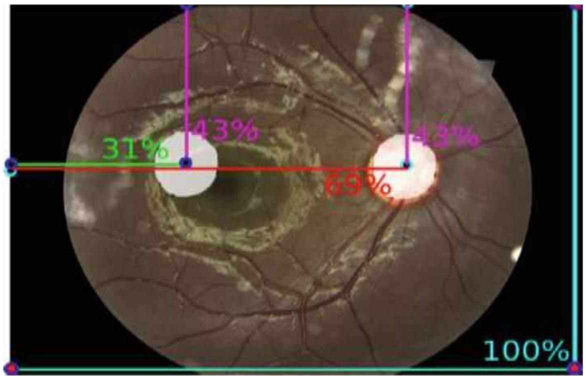


**Fig. 4** The filter that has been specifically designed for ocular modification

height and 43% width and the right eye's overall image's 69% height and 43% width as given in Fig. 4.

## *3.2 Eye Vessels Segmentation*

Prior to segmenting the cup, the blood vessels emerging as of the disc must first be segmented because their curvature makes it easier to see the cup's edge in the nasal (N), superior (S), and inferior (I) quadrants of the disc, in accordance with the ISNT division worn by ophthalmologists and depicted in Fig. 5. It is crucial to note that, in accordance with expert experience, digging forces veins to migrate in the direction of the nose, which is an important fact to take into consideration in order to find the cup's nasal edge.

In this phase, the utilization of the greenish section of the fundus photo is observed (see Fig. 5). The macula is an important feature that requires removal, and to accomplish this, the Dash and Bhoi method is employed. This method involves convolving the initial photo in the channel of green with a mean filter to effectively obscure the boundaries of the vessels. The macula becomes erased through the subtraction of the original picture from the blurry view. Subsequently, the blood vessels are separated by the utilization of a novel threshold which is derived from this point onward [14].

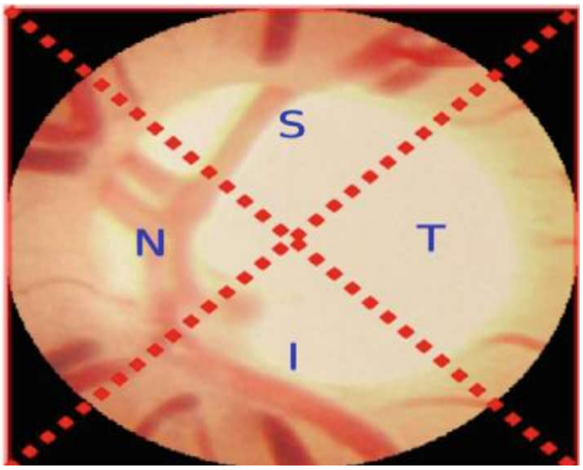


**Fig. 5** Disc quadrants

## 3.3 Cup Segmentation

The blue stream is employed for segmenting the cup due to the higher intensity of pixels exhibited by the cup in comparison to the substrate. The visual screen is partitioned into four distinct regions according to the ISNT rule, namely inferior, better, nasal, and posterior. The initial three components are employed to establish the limits of the veins within the cup, and the centroid of each component is computed utilizing the recommended approach. The transitory fragment is employed for the purpose of identifying the outer boundary of the cup. We present a formula exclusively applicable to the transitory quadrant for the purpose of determining an optimal boundary. The system generates a variety of pixel sizes, denoted as m, with each pixel having a size of 1 n. Here, n represents the quantity of pixels from the middle to the edge of the surface, while m corresponds to the amount of pixels located on the curved section of the plate. Notably, the system ensures that pixels within the vessels are excluded from this process. The equivalent is completed using the basic dim force. For each cluster, it determines the circumstance of its highest level of dark power and logs the typical dim estimate of their neighbouring pixels. With this, it produces a range of typical maximums and a range of typical necessities. Iteratively, the elements greater than a single standard deviation from each of these exhibits are eliminated, leaving each cluster with only the characteristics just outside of the standard deviation. These qualities are found the middle value of and this limit in Fig. 6.

## 3.4 Cup-To-Disc Ratio Measurement

We can now measure the Cup-to-Disc Ratio after properly segmenting the disc and the cup. We used two techniques, as indicated in Fig. 7, whose accuracy was compared to the expert's diagnosis. The initial method involves establishing an area of interest in the middle of the optic disc and thereafter measuring the lengths among that location and the outermost portion of the segmented cup (referred to as Rc), in addition to

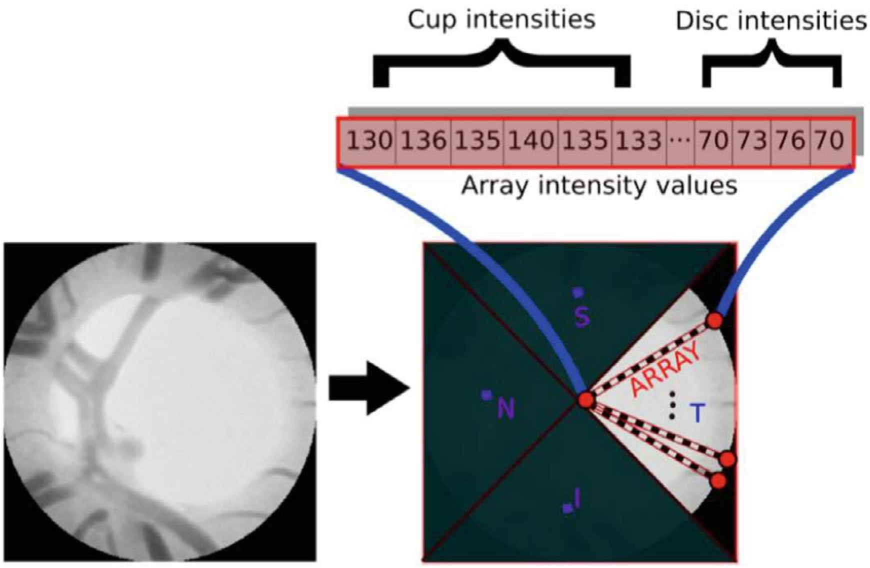


**Fig. 6** The acquisition of temporal disc arrays

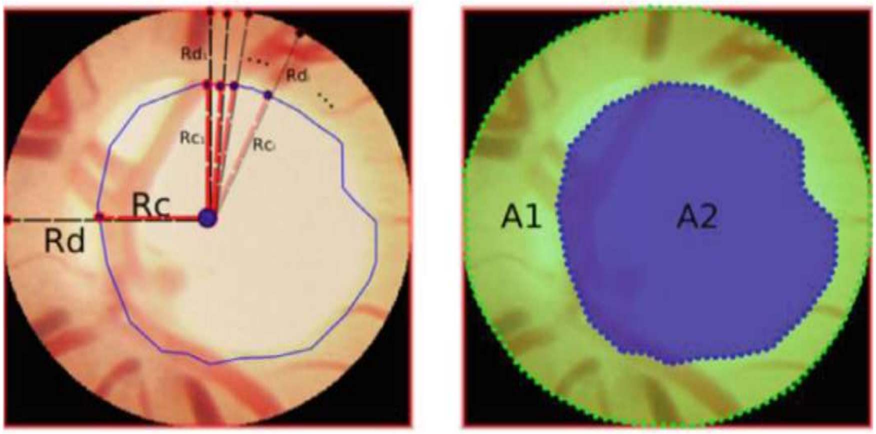


**Fig. 7** Techniques employed for the measuring of Cup-to-Disc ratio

the length among middle and the borders of the optic disc. The mean radius, a value between 0 and 1, is then calculated using a geometric mean. If this value is more than 0.6, the eye is considered to be glaucoma-suspicious, and the individual should be seen for additional therapy.

## 4 Results and Analysis

As a way to accurately segment the disc's blob using the filter stated, it was imperative to calculate the mean spot of the disc's the middle. The mean spot was calculated as the ratio of the disc center contrasted to the surrounding area of the image. This average spot served as a reference point for properly placing the filter. The data

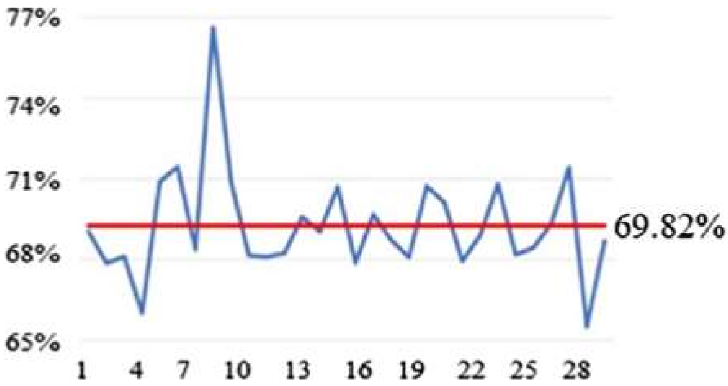


**Fig. 8** The horizontal positioning of the disc for a total of 30 eyes


**Fig. 9** The vertical positioning of the disc for a total of 30 eyes

are visually exposed in the subsequent plots, whereby the red line denotes the mean position of the 30 photographs. A total of 30 photos were utilized in order to ascertain the average region. Figure 8 illustrates the X-axis value as being 69.82%, and the Y-axis value as being 43.45% as seen the Fig. 9.

### *4.1 Disc Segmentation Results*

A total of 16 fundus pictures were used in the tests. With our enhanced technique, we were able to overcome the issues caused by noise, macular production, or instrument acquisition and achieve an exactness of 95% for the disc segmentation compared to 92% for the algorithm presented by [10]. Results for segmentations made using both methods are displayed in Fig. 10 for fundus pictures as of two separate patients.

### *4.2 Glaucoma Detection Results*

The opthalmologists gave us with their predicted CDR for each of the 26 fundus photos, which included both healthy and unhealthy eyes. As shown in Fig. 11, which contrasts the doctor's assessment with the output of the procedure of ratio of proportions and the output of the method of proportion of regions, consequences from our

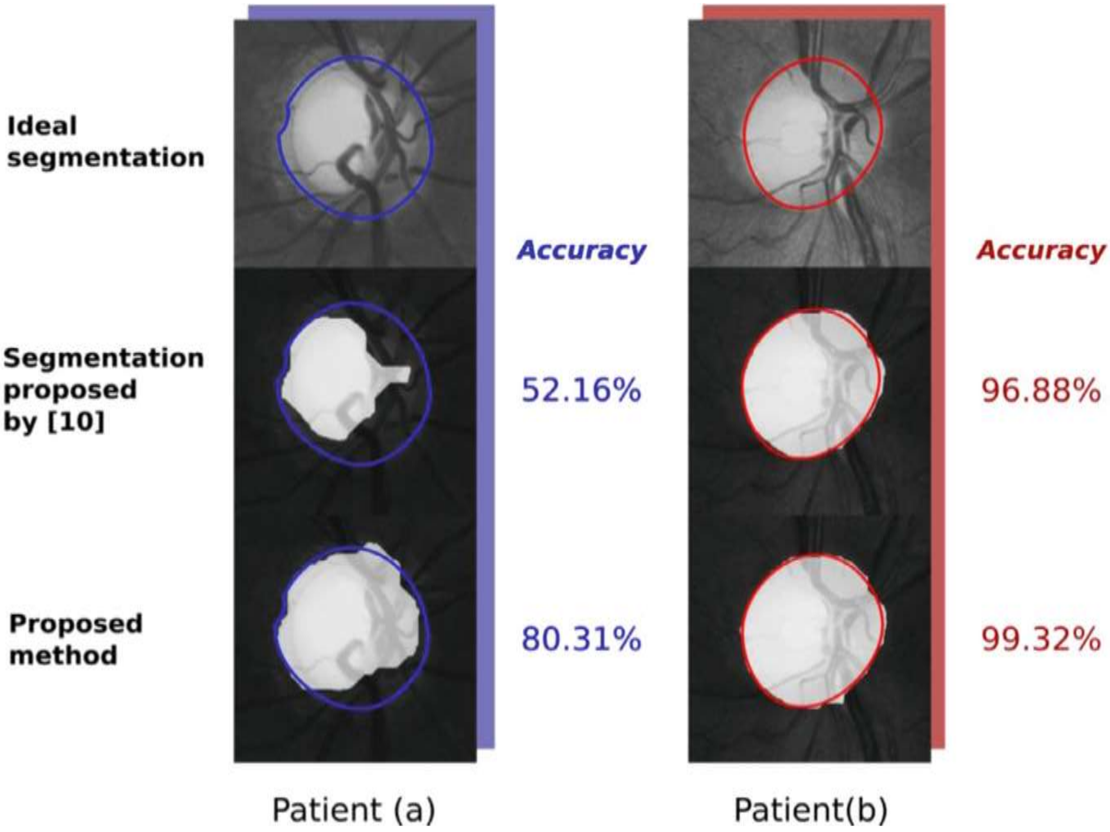


**Fig. 10** Disc segmentation analysis

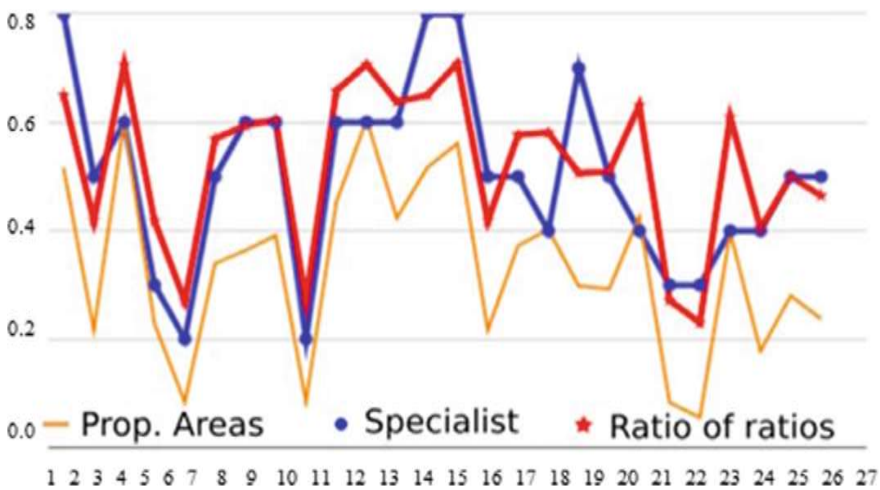


**Fig. 11** Compare the performance of an algorithm with an assessment provided by an expert

method have been compared to these reference estimations. 8.6% in terms of absolute inaccuracy and 19.2% in terms of relative error. The detection of cases of glaucoma was successful in 88.5% of the cases.

### 4.3 Algorithm

$Pseudo\ code\ for\ CNN$:

```
for(l = 0; l < L; l++){
for(m = 0; m < M; m++){
for(n = 0; n < N; n++){
sum = bias[l];
for(k = 0; k < K; k++){
for(s1 = 0; s1 < S1; s1++){
for(s2 = 0; s2 < S2; s2++){
sum+= weight[k][l][s1][s2] * input[k][m + s1][n + s2];
}}}
output [l][m][n] = activation_func(sum);
}}}
```

### 4.4 CNN Steps

1. Data Acquisition
2. Data Preprocessing
3. CNN Classification.

As shown the Fig. 12 represented the demographics percentage levels for male, female, age and MD it has three levels normal glaucoma and P.

As shown the Fig. 13 has average values of distance for clusters its having 5 levels described it represented the various conditions like normal, glaucoma, total number and weight average distance.

## 5 Conclusion

The approach to diagnose glaucoma was described here by correctly recognizing the location of the cup. This study discusses the strategies utilized for automated glaucoma detection, which includes applying the idea that the cup's existence in the disc is a significant predictor of the disease. Segmenting discs was accomplished using thresholding, segmenting vessels was accomplished utilizing detection of edges, and segmenting cups was accomplished by using vessel and cup intensities.

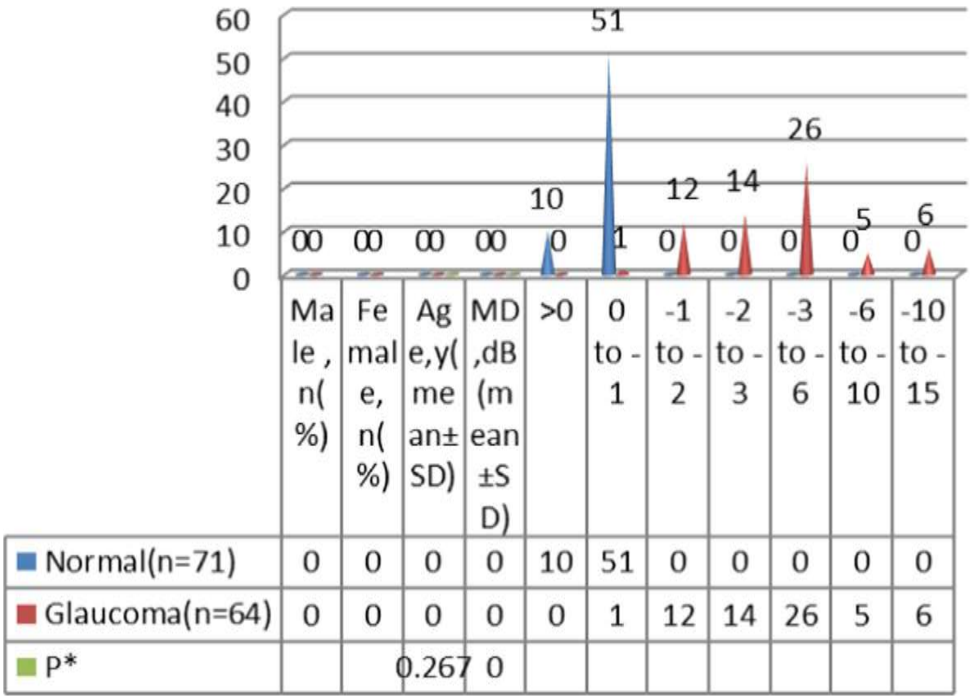


**Fig. 12** Subject demographics

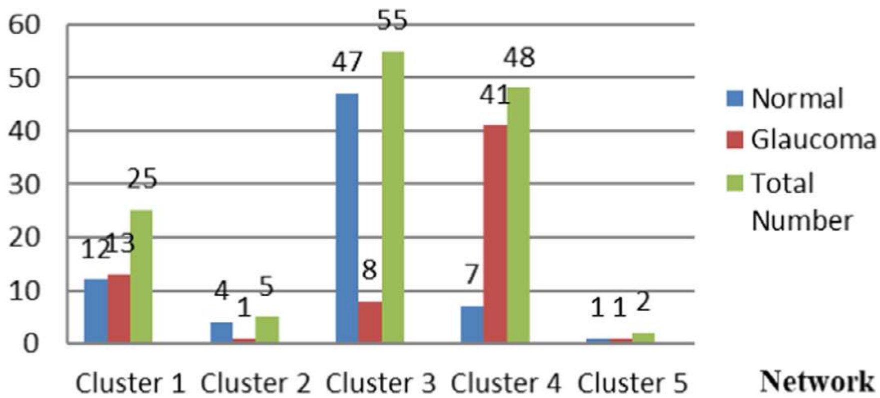


**Fig. 13** Mean distance for clusters

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