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Diagnosing Glaucoma Using Fundus Images

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Abstract: This paper presents a novel approach for the diagnosis of glaucoma, a leading cause of blindness, through the analysis of fundus images. Glaucoma is often marked by an insidious onset, with symptoms such as ocular redness, rainbow-colored halos, and gradual vision loss emerging as the disease progresses, ultimately leading to optic nerve damage. Given the subtlety of its early manifestations—earning it the mark "silent thief of sight"—early detection is critical. This research leverages advanced image processing techniques, including 2D Gabor filtering and Circular Hough transform, to enhance the features within retinal images that are indicative of glaucomatous changes. By integrating image segmentation through thresholding and match filtering, the proposed system effectively identifies the optic disc, a pivotal step in assessing the disease's presence. The methodology outlined herein demonstrates significant improvements in precision over existing diagnostic methods. This study lays the groundwork for future advancements, with the ultimate goal of augmenting the precision and ease of glaucoma detection for early intervention, thereby preserving the vision and quality of life for patients at risk.

Keywords: segmentation; Glaucoma; classification; SVM; convolutional neural network.

1. Introduction

Glaucoma, an ocular disease characterized by elevated intraocular pressure (IOP), poses a significant threat to vision integrity due to damage to the optic nerve. This damage disrupts the transmission of visual information from the eye to the brain, resulting in gradual vision loss [1]. Understanding the etiology and clinical manifestations of glaucoma is crucial for its early detection and effective management.

Glaucoma primarily arises from heightened IOP, which exerts pressure on the optic nerve, leading to its impairment [2] .The ensuing symptoms, including redness, pain, rainbow-colored rings, vomiting, and narrowed vision, often manifest insidiously, contributing to its epithet as the "silent thief of sight." Furthermore, the retina bears the brunt of glaucoma's effects, exhibiting redness, pain, and peripheral vision loss. Halos around the field of vision and the formation of blind spots on the optic disk further emphasize the progressive nature of glaucoma-induced vision impairment.

The visual process, integral to understanding glaucoma, begins with the entry of light rays through the cornea, regulated by the iris surrounding the pupil [3]. According to the anatomy of the eye, presented in figure 1, vision starts when light rays enter the eye through cornea. The cornea bends the light rays which pass through the pupil [3]. The colored portion of the eye surrounding the pupil regulates the amount of light that passes through the cornea.

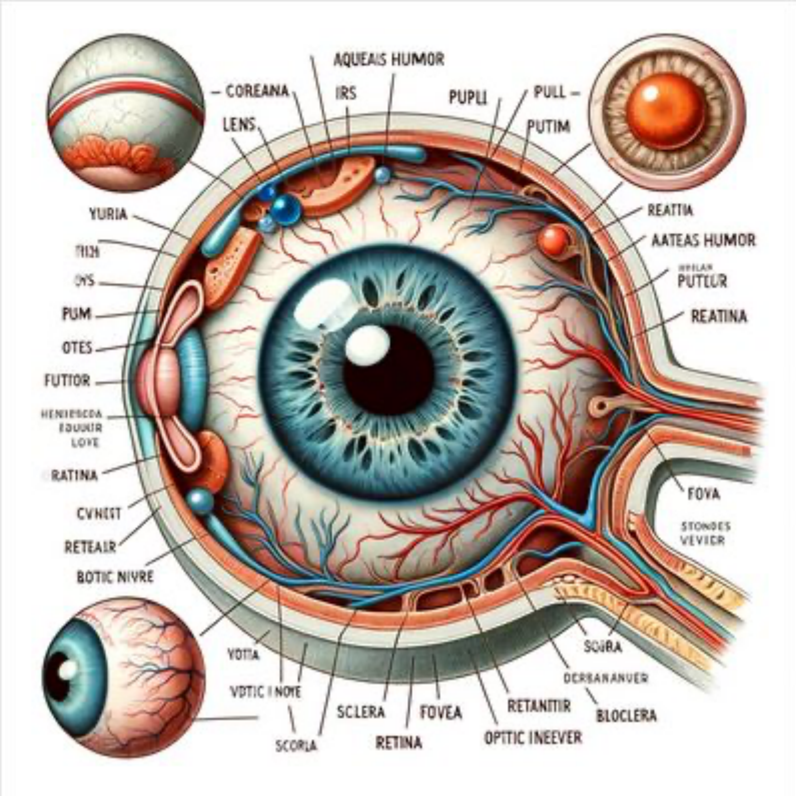

Figure 1. Image of a human eye

Given the significant impact of glaucoma on visual health and the challenges associated with its early detection, extensive research projects have been undertaken. This paper seeks to contribute to the existing body of knowledge by providing insights and resources aimed at facilitating the diagnosis and management of glaucoma by healthcare professionals.

2. Related Work

The method used in the early days for detecting glaucoma in retinal images is not much efficient. However a lot of work is going on to make it more and more efficient. Some of the work done previously is describe below.

Preeti et al. [4] uses the feature extraction to diagnose glaucoma. The researchers first segmented the optic disk and then enhanced the image. After enhancing, they applied the feature extraction to classify the image. Their findings revealed that when the cup to disk ratio is calculated and classification of image is done, then detection of glaucoma becomes easy whether the eye is normal or glaucomatous.

Likewise, Kevin Noronha et al. [5] detected the abnormalities of eye through fundus images that determined the brightest part of the fundus image using Hough transforms. The optic disk, blood vessels, fovea are the main features of fundus image through which detection of the disease becomes easy. The blood vessels are determined by using the hat transforms. All these features when combined were revealed useful for detection of the eye which is affected by glaucoma.

Another study [6] segmented the color fundus image and after segmentation calculated the segmented optic disk and cup by using gabor wavelet transform. After segmenting, their technique detects optical disk. The segmented optic disk and cup can be estimated by several methods cup-to-disk ratio, compactness etc. As the optical disk was detected by using CDR then it applies the feature extraction to determine the glaucomatic eye. This process is presented in figure 2.

Preventing the advancement of glaucoma requires prompt diagnosis of the condition. Emerging research proposed a technique to calculate Cup-to-Disk ratio (CDR), for which it first detects the edges in fundus image using edge detection technique and variation level set method & applies the threshold level set method to calculate CDR [7].

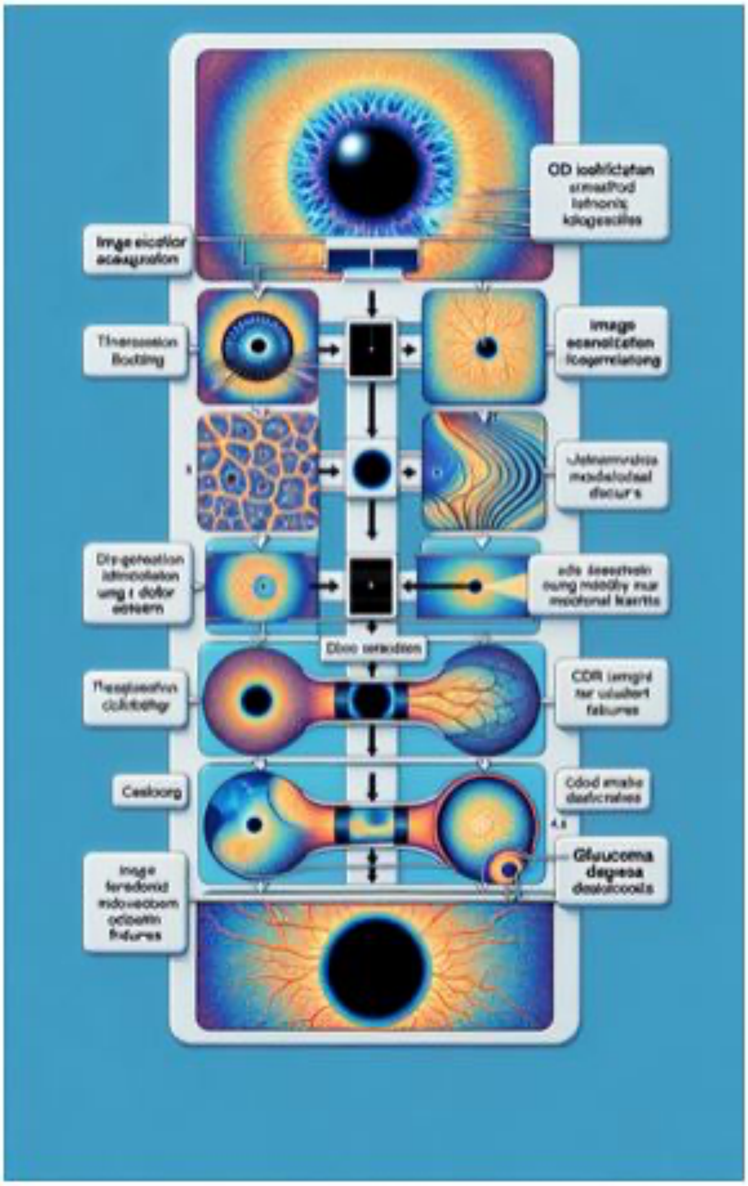

Figure 2. Graphical representation of the process starting from fundus image to glaucoma detection

The cup-to-disc ratio (CDR), which indicates the ratio of the size of the optic cup to the optic disc, is an important clinical sign in this context. Currently, CDR determination is based on the subjective evaluation of skilled ophthalmologists, which limits its applicability in early detection screening on a large scale. In an effort to overcome this constraint, the NIDEK AFC-230, a non-mydriatic auto fundus camera, is used to provide an automated approach for CDR calculation with non-stereographic retinal fundus pictures. The automated extraction of the disc and cup areas from retinal pictures is the main goal of the authors' methodology. Disc extraction is addressed from two different perspectives: variational level-set methods and edge detection techniques. The authors assess the effectiveness of threshold level-set techniques and color component analysis for cup extraction in a similar manner.

In a study, to enhance the boundaries derived from their extraction methods, the authors use elliptical fitting in addition to drawing boundaries between the disc and cup regions [7]. The performance of the suggested automated CDR determination is assessed using a dataset made up of 44 retinal pictures from the Mettapracharak Hospital in Nakhon Pathom, Thailand. The suggested method reaches an accuracy around 89% in CDR determination when compared to clinically determined CDR values. Hence it can be said that this work provides a robust approach for CDR calculation from retinal fundus pictures, which adds to the rapidly developing field of automated glaucoma identification. The remarkable precision exhibited when compared to clinically established CDR values highlights the possibility of automated methods to improve the effectiveness and efficiency of glaucoma screening initiatives.

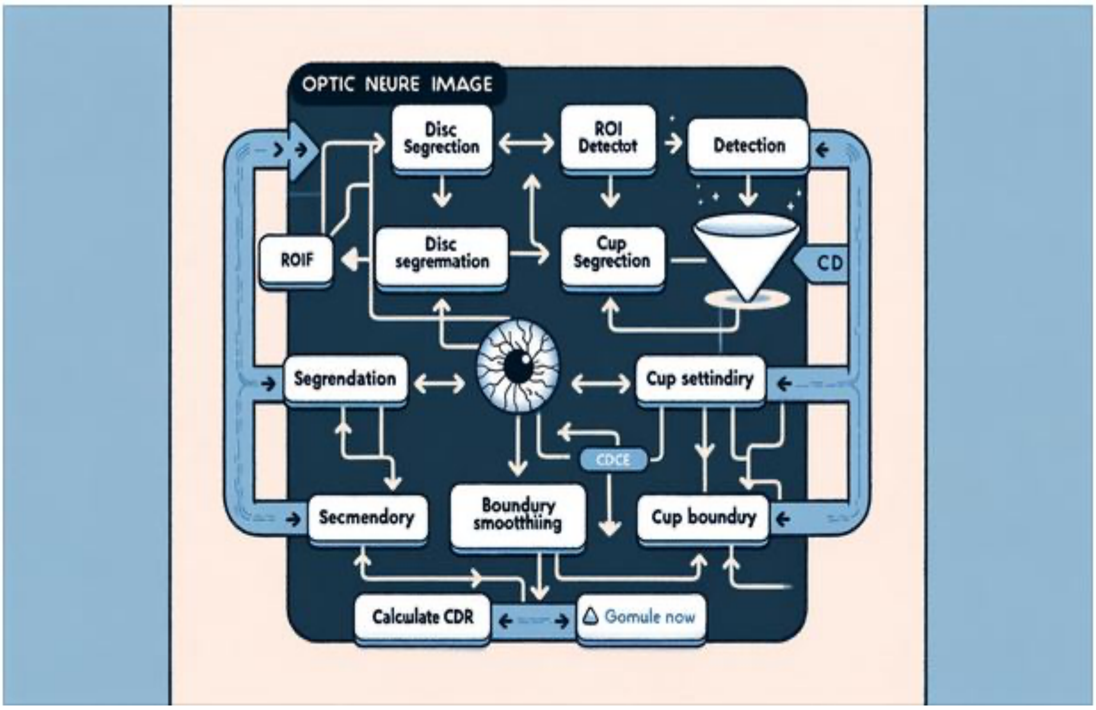

Figure 3. Cup to Disk Ratio

The fundus camera directly observes the layer of nerve fibers in the retina, a crucial component of the human visual system. In a previous study [8], a texture and fractal description-based technique for glaucomatous retina detection is described. A support vector machine classifier is then used for classification. The area of retinal nerve fibers is evaluated using color fundus imaging. The association between texture and fractal dimensions is demonstrated, and the linear correlation coefficient values for healthy retinal nerve fiber layers (RNFL), mild loss, and severe loss of RNFL, respectively, are estimated to be 0.35, 0.57, and 0.87. The characteristics are measured from 24 glaucomatous and 50 non-glaucomatous retinal fundus pictures at 303 RNFL regions retinal sites in the peri-papillary area. Glaucoma was detected by using fractal dimension where it first converted the input image into grayscale, and then it converted the grayscale image into binary image [8]. Once determined the binary image it became easy to determine fractal dimension. This method of inputting the color image, converting it into grayscale image, and then converting it into binary image is presented in following figure.

Similarly, another research [9] detected the glaucoma by using the automatic retina image analysis method. All the work has been done automatically not manually; first of all they took a colored fundus image as an input and then corrected the non-uniform illumination for reading the image easier. Then the blood vessel removal was the second part of the process. The Glaucoma Risk Index (GRI) obtained from the system gives 86% success rate. GRI detects the glaucoma by taking the fundus image automatically.

A study by Thorat et al. [10] indicated that after taking the fundus image the preprocessing is done on the image which includes image filtration and enhancement and segmentation. For detecting the glaucoma by using the super pixel classification optic disk and cup segmentation on the fundus image, the clustering algorithms have been used for classifying the super pixel optic disk and cup segmentation. Other techniques like Gabor filter and thresholding have also been used for optic cup segmentation. The segmented optic disk and cup were used for CDR that revealed the cup to disk ratio as one of the best way to check the glaucoma in a patient.

Detecting, diagnosing, and treating eye conditions early on can assist to avoid vision loss. Likewise another research [11] used a novel method for early detection of glaucoma, which is a combination of magnitude and phase features taken from the fundus images. The feature set extraction is carried out using Daugman's method and local binary patterns (LBP). Both the phase and the magnitude components of the histogram are computed. To forecast glaucoma, the Euclidean distance between the feature vectors is examined. The disparity between the two locations used to identify glaucoma in the input image is known as the Euclidean distance. The performance of the proposed method is compared with the properties of the higher order spectra (HOS) in terms of specificity, sensitivity, accuracy in classification, and time required for execution. Daugman's methods and local binary patterns (LBP) were employed for feature set extraction. The phase and magnitude components were computed using a histogram approach. The histogram method gives better results by using the LBP and daugman's algorithms. Hence, 95.45% of the output for sensitivity, specificity, and classification are produced by the suggested system. Moreover, their proposed method operates more quickly than the existing alternatives that rely on HOS features. Consequently, the proposed glaucoma feature prediction method is more reliable, accurate, and resilient than the current approaches.

In a similar vein, another study [12] segmented the medical image and utilized image processing techniques to clean it up before determining the damaged area. To enhance the quality of the fundus image and identify the afflicted area of the eye, a sequence of procedures must be taken during the image processing process. Basic filtration method was used for improving the image features so to find out the disease recognition.

Furthermore, Jayanthi et al. [13] uses the LDA and medical axis on the image and then find out the optic disk in the retinal image. They were able to determine the optic cup from the retinal image by employing the threshold level set technique. Similarly, to enhance the picture borders and the area of the optic disk and cup, Shruti et al. [14] employed the Hough circle approach. To bring attention to the image's border walls and to gain results this Hough circle approach is utilized. The optic disk and cup detection performance is enhanced through the use of gray level processing and morphology in conjunction with the Hough circle approach. To find out the exact optic disk and cup boundaries are a difficult way but this system is an automated technique for detecting cup and disk from the fundus image. This technique is additionally employed to reduce noise and apply various filters to enhance the image quality.

Prior literature also highlighted the use of an automated classification system to find out the glaucoma, that includes a method free from segmentation [15]. A data driven approach is used for detecting glaucoma from the fundas images. A retina database driven is used to process the image and then analyze the image by using feature extraction and then classification. A data driven approach is applicable on a huge amount of examinations and give accurate results.

Likewise, another study indicated the use of feature extraction methods to diagnose the glaucoma from retinal fundus images [16]. This feature includes CDR method and ratio of Neuroretinal Rim inferior. Optic disk is the brightest yellow colored part of the eye. The green part of the eye is extracted from the optic cup and then converted it into gray scale image and then the gray scale image converted into binary image. The CDR is calculated by threshold morphological method which gives enhanced combination of the optic cup. Some other researchers [17] detected the glaucoma from the optic nerve head ONH segmentation from the retinal image. A machine learning classifier is used after segmenting is done automatically. The automatic segmentation method segments the optic cup and disk. The results are highly accurate on different glaucoma images.

Moreover, a 2012 study introduced an innovative method for automated disease detection, utilizing retinal image analysis and data mining techniques to accurately classify retinal images into Normal, Diabetic Retinopathy, and Glaucoma affected categories [18]. Similarly, another paper in 2012 reviewed and discussed the utilization of image processing techniques for automatic detection of eye diseases [19]. The paper outlines key image processing methods including image registration, fusion, segmentation, feature extraction, enhancement, pattern matching, image classification, analysis, and statistical measurements in the context of detecting eye diseases.

Table 1 provides a concise overview of various techniques utilized by different authors for the detection of glaucoma from retinal fundus images. The table includes the author names, a brief description of their methodology, techniques employed, and drawbacks identified in their respective works.

Table 1. Summary of Glaucoma Detection Techniques

Author Name	Working of Author	Technique Used	Drawback of Their Work
Preeti et al. [4]	Diagnosing glaucoma through feature extraction.	Optic disk segmentation, image enhancement,	Lack of discussion on the robustness of the method against varying image qualities.

		feature extraction	
Noronha et al. [5]	Detecting eye abnormalities using fundus images.	Hough transforms, feature detection	Limited discussion on the generalizability of the method to diverse datasets.
Chandrika et al. [6]	Segmenting color fundus images and detecting glaucoma.	Gabor wavelet transform, segmentation	The effectiveness of the method on noisy or low-quality images is not addressed.
Anusorn et al. [7]	Calculating Cup-to-Disk ratio with edge detection and threshold methods.	Edge detection, thresholding	The method's performance with highly irregular optic disks is not discussed.
Lamani et al. [8]	Glaucoma detection using fractal dimension.	Grayscale conversion, binary image conversion	The method's sensitivity to noise in the image is not addressed.
Nyul [9]	Automatic retina image analysis for glaucoma detection.	Nonuniform illumination correction, GRI	Lack of discussion on the system's performance with varied image acquisition conditions.
Thorat [10]	Preprocessing and super pixel classification for glaucoma detection.	Image filtration, super pixel classification	Limited discussion on the scalability of the method to large datasets.
Sakthivel & Narayanan [11]	Early glaucoma detection with magnitude and phase features from fundus images.	Local binary patterns, histogram method	The method's performance with different fundus image resolutions is not discussed.
Parul [12]	Medical image purification and affected part segmentation using image processing operations.	Basic filtration methods	Lack of evaluation on the method's performance with diverse image qualities.
Jayanthi, Sagayee, &	Optic disk and cup detection using LDA and medical axis.	LDA, threshold level set method	The method's robustness to variations in optic disk and cup

			appearances is not discussed.
Arumugam [13]	Hough circle techniques for improved boundary detection of optic disk and cup.	Hough circle method, morphology	Lack of discussion on the method's performance under different lighting conditions.
Shruti & Harangouda [14]	Automated glaucoma classification without segmentation using a data-driven approach.	Feature extraction, data-driven approach	Limited discussion on the method's performance with diverse populations or ethnicities.
Ahmad et al. [16]	Glaucoma diagnosis from retinal fundus images using feature extraction methods.	CDR method, morphological operations	Lack of discussion on the method's performance with varying levels of glaucoma severity.
Guerre et al. [17]	Glaucoma detection from optic nerve head segmentation using machine learning classifiers.	Optic nerve head segmentation, ML classifiers	Limited discussion on the method's performance with diverse optic nerve head morphologies.

3. Materials and Methods

This paper's methodology is focused on diagnosing Glaucoma. Glaucoma is a serious eye condition that can lead to blindness if it's not caught early. The researchers are introducing a new method or "framework" they've developed to spot signs of Glaucoma in eye images. For this purpose, researchers used 400 eye images from Kaggle. They ran their experiments using MATLAB R 2017, a popular tool among engineers and scientists for crunching numbers and processing images. A step wise procedure used in a research context to analyze a fundus image of eye for detection of glaucoma is presented in the following figure diagram.

Following is the explanation of the employed methodology:

Input Image: Initially a fundus camera is used to take a colored picture of the eye. By taking high-quality retinal photos with this specialist camera, many eye problems can be identified. The first step in the discovery of glaucoma is to use a fundus camera to take a picture of the retina. High-resolution color images of the retina, retinal vascular system, optic disc, and macula, as well as other internal surfaces of the eye, can be captured using this specialist imaging apparatus. The clarity of the image taken is crucial because it must identify minute features in the structures of the eye, which are necessary for a precise diagnosis. Fundus cameras are designed to visualize the fundus, or rear of the eye, using integrated illumination and low-power microscopy. In the context of glaucoma detection, capturing the optic disc and the surrounding retinal nerve fiber layer is particularly important, as changes in these areas are indicative of the disease.

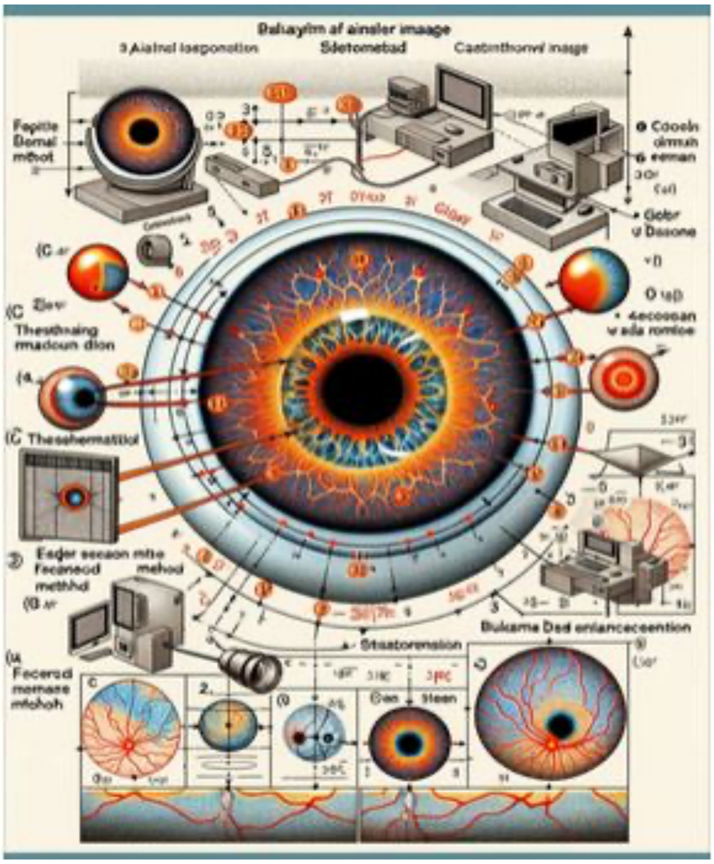

Figure 4. Step by Step Process

Image Enhancement: Once the retinal image is captured, the focus shifts to image enhancement, a pivotal step in preparing the image for further analysis. Image enhancement aims to improve the interpretability or perception of information in images for human viewers, or to provide 'better' input for other automated image processing techniques.

To improve the visibility of retinal features, image enhancement techniques are applied. There are two main methods:

Spatial Domain Method: In this method, the enhancement techniques are applied directly to the pixels of the image. The spatial method relies on direct manipulation of the image matrix, F(x,y), where each pixel's value is adjusted to enhance the overall image quality. The transformation function TT that is applied can be something as simple as brightness adjustment or contrast stretching, or more complex operations based on the image's local features, such as spatial filtering for noise reduction or sharpening. The outcome g (x,y) is the enhanced image that should ideally have improved visibility of important features for further processing.

Frequency Domain Method: The frequency domain method involves converting the image data from the spatial domain to the frequency domain using a mathematical operation, typically the Fourier Transform. Once in the frequency domain, various filters can be applied to modify the image's low-frequency (broad features) and high-frequency (fine details) components. Modifying these elements can greatly enhance the general contrasting qualities and brightness of the image. The inverse Fourier transform is then used to return the improved image to the spatial domain. This technique works especially well for photos with changing illumination or to bring out certain patterns that are easier to see in the frequency range.

Binary Image: From the improved image, a binary image is produced, which is reduced to two potential pixel values: black and white. Simplifying the original image into these two pixel value levels is that stage which is essential in terms to decrease complexity and increase computing performance in later processing steps. This binary format essentially reduces the image to its most basic form, with pixel values of 0 and 1, respectively.

Nonetheless, this process of simplifying is important not only for visual clarity but also to improve computing efficiency for further analysis. As reducing the pixel to only two numbers also reduces the complexity of the picture, it facilitates the processing and analysis of the image by algorithms. This step is of crucial value in the context of medical imaging, especially emphasizing certain structures or characteristics, like the optic disc or blood vessels in retinal pictures. This binary transformation of the image helps to identify traits and analyze them independently of color fluctuations and other visual noise.

Image Segmentation: It is the process of dividing a digital image into several segments for simplifying and transforming the image into more meaningful and understandable representation so that it can be analyzed. This critical stage involves segmenting the image into smaller, more manageable parts that further consisted of following stages:

Thresh-holding: Thresh-holding is a technique to convert a grayscale image into a binary image. This is one of the simplest segmentation techniques and works by turning a grayscale image into a binary image. The process involves selecting a threshold value, and then all the pixels above this value are turned to white, and all the pixels below are turned to black. This method is particularly effective when the object to be segmented has a high contrast against the background.

Edge-Based Segmentation: This method focuses on finding the edges within an image which correspond to abrupt changes in intensity. This technique aims to identify the edges within an image. Edges are significant local changes in intensity, which often correspond to object boundaries. Techniques such as the canny edge detector or the Sobel operator are commonly used to detect these edges. Edge-based segmentation is useful for locating objects in an image and for shape analysis.

Region-Based Segmentation: This approach clusters pixels or regions based on their similarities and can be further categorized into hierarchical and partitioning clustering methods. This technique divides an image based on regions according to predefined criteria. The similarity of pixels, such as intensity, color, or texture, is assessed, and pixels are grouped into regions. This can be further decomposed into partitioning clustering, in which the image is separated into clusters without nested structures, and hierarchical segmentation, in which clusters are nested according to a hierarchy of criteria. Therefore, finding homogenous objects and regions of the image that also meet the selected similarity criteria can be accomplished through this technique.

Image Classification: This is the stage that utilized controlled or independent learning techniques to classify the segmented image into various groups. Box counting method for determining the fractal measurement of images can also be employed. This stage includes understanding the image segments and classifying them into predetermined groups for which intensity, texture, color, and other elements that were taken out of the picture can be used. This grouping can be achieved using one of the two ways: either with supervision or control that uses labeled images to train the system, or unsupervised or independent technique, using no labeled training data at all. Meanwhile, in case of pattern identification, the fractal dimension of the image can be determined by applying the box counting method.

Identification of Glaucoma: Finally, after all the processing and analysis, the eye image is examined for signs of glaucoma, a condition that can lead to vision loss. The final step is the identification of glaucoma. Following the enhancement, segmentation, and classification, the image is meticulously examined for indicators of glaucoma, which is a critical condition that can lead to irreversible vision impairment if not detected early.

4. Results

The findings obtained from the process are presented in a table that compares their system's accuracy to previous studies. The proposed system hit an accuracy of 94.9%, which proves the method to be reliable and effective for the diagnosis of Glaucoma through images. The table shows several other researchers and their accuracy scores, ranging from around 90% to just over 93%. It is for a reason to highlight how a new approach might be a step forward in the right direction and could potentially offer a more reliable way to catch Glaucoma early on through image analysis.

Table 2. Comparison of Results

Author	Accuracy (%)
Proposed System	94.9
Nyul (2009)	90.7
Jayanthi et al. (2014)	92.57
Lamani et al. (2014)	93.52
Sakthivel & Narayanan (2015)	92.61
Thorat (2014)	91.70

Parul (2015)	92.52
Shruti & Harangouda (2015)	90.28
Guerre et al. (2014)	92.0
Noronha et al. (2006)	91.83

Above table demonstrates the precision of framework while dividing and arrangement of fundus images. As indicated by the correlation of our outcome with different results, our framework will have more exact results as contrast with alternate results. Hence, our proposed framework has better accuracy when contrasted with prior studies' system.

5. Discussion

The findings presented in the research paper highlight a significant advancement in the diagnosis of glaucoma through automated image analysis. The introduction sets the stage by emphasizing the importance of early detection and effective management of glaucoma, a condition characterized by elevated intraocular pressure and optic nerve damage leading to gradual vision loss. The literature review outlines various methodologies employed in previous studies for glaucoma detection, ranging from feature extraction to image segmentation and analysis.

The methods section presented a new framework that the researchers created to diagnose glaucoma from 400 eye photos that were obtained from Kaggle. MATLAB R 2017 was utilized for analysis to evaluate fundus photos and identify glaucoma symptoms. The image analysis methodology was explained through a stepwise process.

The findings indicated a better accuracy rate than previous methods highlighting value of the new strategy allowing for quick intervention and preventing visual loss that may provide a more reliable way to detect glaucoma early on.

This study's findings supported and expanded upon earlier investigations into automated image processing for the diagnosis of glaucoma. The construction of the unique framework proposed in this study was made possible by the approaches used in these earlier publications, as described in the literature review.

As an example, a study [4] focused on the cup-to-disk ratio calculation to aid in the diagnosis of glaucoma utilizing feature extraction techniques. Similar to this, a different study [5] used Hough transforms to identify abnormalities in eye fundus images and stressed the significance of characteristics such the optic disk, blood vessels, and fovea in aiding in the detection of glaucoma. These investigations offered insightful information about the critical components and methods required for a precise diagnosis of glaucoma.

Moreover, additional investigations, such the ones conducted by Thorat et al. [10] and the study that employed automatic retinal image analysis [9] emphasized the importance of image preprocessing, segmentation, and feature extraction in enhancing the precision of glaucoma diagnosis. These research showed how several image processing methods, such as segmentation algorithms, super pixel classification, and Gabor filtering, might improve the sensitivity and specificity of glaucoma diagnosis.

Utilizing cutting-edge image processing tools, the current research introduced a new framework for glaucoma diagnosis, building upon the approaches and conclusions of these earlier investigations. Through the use of MATLAB R 2017 and 400 eye scans, the suggested system was able to identify glaucoma with an astounding 94.9% accuracy rate—a higher rate than that of earlier research.

The Table 2 describes how much the proposed system is accurate as compared with the previous findings. The proposed system performs better as compared to the previous researches such as [8, 9, 13] This paper offers insightful information about the diagnosis of glaucoma and how automated image processing methods can improve the precision and effectiveness of disease detection in ophthalmology. The findings pave the way for additional study and advancement in this field, with the ultimate objective of enhancing patient outcomes and maintaining the health of the eyes.

6. Conclusion

The paper has outlined a method for diagnosing glaucoma using fundus images captured from a fundus camera. The introduction provided an overview of glaucoma, discussing its nature, causes, symptoms, and the associated hypertensive retinopathy. Additionally, it highlighted the working of the retina, crucial for understanding how to combat this disease, which gradually leads to optic nerve damage and vision loss. The literature review examined past segmentation and image enhancement methods employed in glaucoma diagnosis, along with exploring various procedures and systems used in glaucoma analysis. The framework utilized for diagnosing glaucoma through retinal images detailed the steps involved in the process, including retinal image input, enhancement using 2D Gabor filtering, image segmentation via thresholding and match filtering techniques, and optic disk detection using Circular Hough transform, which yielded precise results compared to alternative methods. This research represents a significant stride towards the development of an effective and widely applicable system for diagnosing glaucoma. Future research endeavors could further refine and expand upon these methodologies to enhance diagnostic accuracy and accessibility for clinicians.

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