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COMPARISON OF GLAUCOMA DETECTION TECHNIQUES

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Abstract: Glaucoma stands as a leading cause of irreversible blindness among individuals aged 40 and above. In Colombia, the prevalence of this disease is notably high, exacerbated by a shortage of ophthalmologists relative to the population's needs. Fundus imaging emerges as the primary screening method for glaucoma due to its favorable balance of portability, size, and affordability. This paper introduces a computational tool designed for automated glaucoma detection. We showcase enhancements in disc segmentation compared to existing literature, introduce a novel cup segmentation method employing thresholding, and propose a fresh metric assessing the ratio between cup and disc sizes. Our results stem from analyzing a collection of fundus images in partnership with the Center of Prevention and Attention of Glaucoma in Bucaramanga, Colombia, achieving an 88.5% success rate in glaucoma detection.

I. Introduction

Glaucoma poses a significant threat to eye health, particularly near the optic nerves, and has emerged as a notable public health issue globally. Second only to cataracts, it ranks as a leading cause of blindness worldwide, with approximately 57 million people affected, primarily by primary open-angle glaucoma, according to survey data.

This condition leads to vision loss and eventual blindness by causing damage at the back of the eye, resulting in impairment of the visual field. The root cause lies in elevated intraocular pressure from the aqueous humor fluid, which adversely affects the optic nerve system. If left unaddressed, it can lead to irreversible vision loss over time.

Glaucoma manifests in various forms, each resulting in damage to the nerve connecting the eye to the brain, typically due to elevated intraocular pressure. Open-angle glaucoma, the most common type, often presents with gradual vision loss as its sole symptom. Conversely, acute angle-closure glaucoma, a rarer form, manifests suddenly with symptoms such as eye pain, nausea, and visual disturbances. Treatment typically involves a combination of eye drops, medication, and surgery.

In our technologically advanced era, various techniques are available for identifying glaucoma using cutting-edge technologies. Machine learning, for instance, offers a promising avenue for disease detection by analyzing diseased eyes and comparing them to healthy ones.

There are two main types of Glaucoma:

1.Open-angle glaucoma: This type occurs when there is a gradual buildup of resistance in the eye's drainage canals over months or years. As a result, the fluid inside the eye accumulates, exerting pressure on the optic nerve.

2.Closed-angle glaucoma: This type occurs when the angle between the iris and cornea becomes too narrow. This narrowing may occur suddenly, especially when the pupil dilates rapidly. As a result, the drainage canals become blocked, preventing the aqueous fluid from exiting the eye, which leads to an increase in eye pressure.

For our research, we are focusing specifically on Open-angle glaucoma.

II. Literature Review

Given the dangerous and irreversible nature of Glaucoma on eyesight, extensive research is underway to improve clinical approaches for its detection. One globally recognized technique is Tonometry, which measures intraocular pressure inside the eye. Additionally, Optical Coherence Tomography (OCT) is a well-established method known for its high-resolution images of the Retinal Nerve Fiber Layer (RNFL), allowing for assessment of parameters such as RNFL thickness and Optic Nerve Head (ONH) topography.

Ophthalmoscopy is another essential tool, used to examine blood vessels, retina, optic nerve, and optic disc, while Pachymetry measures corneal thickness. Scanning Laser Polarimetry (SLP) provides valuable information on RNFL decline. These diverse techniques leverage various approaches to effectively measure and diagnose Glaucoma.

Fundus images, captured by specialized cameras, offer detailed insights into the retina and play a crucial role in identifying various eye conditions, including age-related detachment of the retina, macular degeneration, and diabetic retinopathy. Recognizing the complexity and potential for human error in clinical eye diagnosis, there is a growing trend toward automated diagnosis systems. Many methods have been proposed for detecting Glaucoma using fundus images, aiming to ensure consistent and accurate diagnoses.

The following section presents fundus images in Fig. 1.

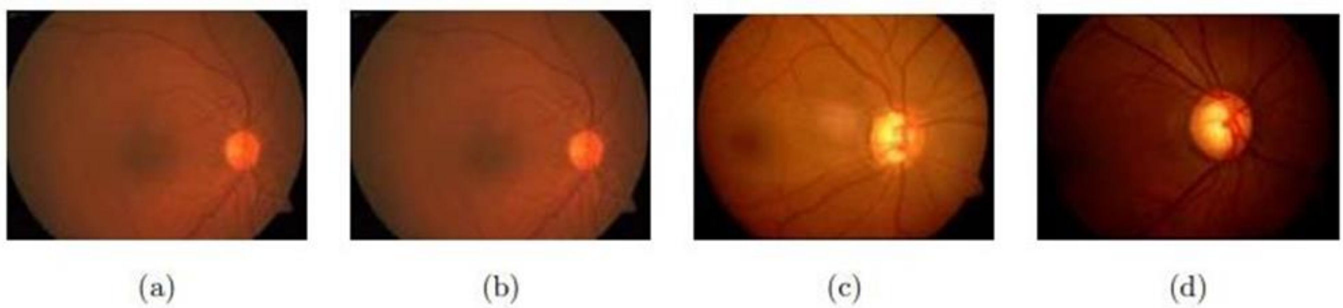

Fig.1 Specimen images of fundus

The assessment of Glaucoma relies on distinct indicators such as an elevated Cup-to-Disc Ratio (CDR), increased cup volume, and reduced rim area. However, determining a critical boundary value, often referred to as the threshold value, significantly influences the performance of CDR techniques, leading to potential inconsistencies in classification accuracy.

The challenge is further compounded by the Mach Bands effect, a perceptual phenomenon that complicates precise cup boundary delineation in fundus images. To address this, feature-based classification algorithms have been implemented, leveraging various machine learning techniques to enhance Glaucoma identification accuracy.

In one study, statistical analysis of maximum order and texture-based features, including Radon transform and bi-spectrum analysis, achieved an accuracy of 91% with a dataset of 60 images. Another approach utilized third-order Higher-Order Statistics (HOS) cumulant coefficients, combined with linear discriminant analysis (LDA) and support vector machine classification, achieving a 92.65% accuracy in classifying healthy and glaucomatous images.

Wavelet-based feature analysis methods have also been explored, with one study achieving a notable accuracy of 93.33% using discrete wavelet transform (DWT) wavelet energy features. Empirical Wavelet Transforms (EWT) method achieved an impressive 98.33% accuracy with correntropy-based features.

Geometric moment features of image texture, in conjunction with wavelet transform, were utilized for Glaucoma detection, achieving an 86.57% classification accuracy. Additionally, the amalgamation of HOS and DWT-based features achieved a 95% accuracy, while the integration of Trace Transform (TT), HOS, and DWT-based features yielded a 91.67% accuracy.

Various transform-based mechanisms, such as B-spline coefficients, Gabor Transform, and Fast Fourier Transform (FFT) coefficients, have been employed for Glaucoma detection. Nonlinear entropy-based features extracted from Variational Mode Decomposition (VMD) components achieved a 95.19% accuracy using Least Square Support Vector Machine.

Researchers have also explored different features such as Histogram, Haralick, Self-Organizing Maps (SOMs), and Local Connected Patterns (LCP) for Glaucoma detection. Convolutional Neural Network (CNN) models have proven effective for Glaucoma detection, achieving high accuracy and sensitivity, particularly when integrated with deep learning techniques.

In one study, a method utilizing non-parametric spatial envelope energy and features related to Radon Transform (RT) achieved a 97% accuracy with a Support Vector Machine classifier. Integrating a CNN model into the research further improved accuracy to 98.13%. The study reported high sensitivity and specificity using a smartphone and handheld ophthalmoscope image set, demonstrating the effectiveness of deep learning techniques for Glaucoma detection.

III. Conclusion

The presence of the cup within the disc serves as a robust indicator of glaucoma. This study proposes a method for glaucoma detection by accurately identifying the cup's location. Disc segmentation was achieved through thresholding, while vessel segmentation utilized edge detection. For cup segmentation, a method leveraging vessel and cup intensities was introduced.

Authors	**Methods**	**Classifier used**	**No. of images**	**No. of features**	**Performance (%)**
Chrastek et al.10	Morphological operations, Hough transform (HT) and anchored active contour model	LDA, classification trees, and bootstrap aggregation	159		acc:72.3
Yin et al.11	Circular Hough transform	Unsupervised	325		CDR error:0.10
Acharya et al.15	HOS bispectrum	Random Forest	60	12	acc:91
Noronha et al.16	HOS cumulants	SVM	272	35	acc:92.65, sen:100,spe92
Annu and Justin17	WEF	Probabilistic neural network (PNN)			acc:95
Gayathri et al.18	WEF	ANN		3	acc:97.6
Dua et al.19	WEF	SMO	60	14	acc:93.33
Maheshwari etal.20	2-D EWT and correntropy	SVM	Pri:60 Pub:55 5	6	acc:98.33, sen:100, spe:96.67
Gajbhiye et al.21	Wavelet and geometric moment features	SVM, KNN and EBPTA	350		acc:86.57
Mookiah et al.22	HOS and wavelet	SVM	60	13	acc:95, sen:93.33, spe:96.67

Future endeavors involve expanding the dataset of fundus images to conduct a more comprehensive evaluation of the algorithm

Improvements are needed for vessel segmentation, addressing issues encountered in various images and residual noise post-segmentation. Additionally, the integration of convolutional neural networks into the classification process is planned to enhance performance.

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