Automated Glaucoma Detection System

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Abstract: -Glaucoma is a progressive eye disease that remains one of the leading causes of irreversible blindness globally. While early detection is crucial, conventional diagnostic methods require specialized equipment and expert ophthalmologists, creating challenges for timely screening in many areas. This paper introduces an automated glaucoma detection system that utilizes machine learning on retinal fundus images. The proposed approach integrates image enhancement, optic disc and cup segmentation, and feature-based classification to identify glaucomatous changes from normal cases. By combining deep learning techniques with traditional image processing, the system is designed to offer high accuracy at a low computational cost. Such a tool can serve as an effective decision-support system in clinical settings, enhancing early diagnosis and reducing the risk of preventable blindness.

Keywords—Glaucoma detection, fundus image analysis, deep learning, convolutional neural networks (CNN), medical image processing.

I. INTRODUCTION

Despite being the second most common cause of permanent blindness worldwide, glaucoma frequently progresses slowly, leaving patients asymptomatic until the condition reaches advanced, incurable stages. Ageing populations are expected to cause a large increase in the incidence rate, highlighting the urgent need for effective and scalable screening technologies.

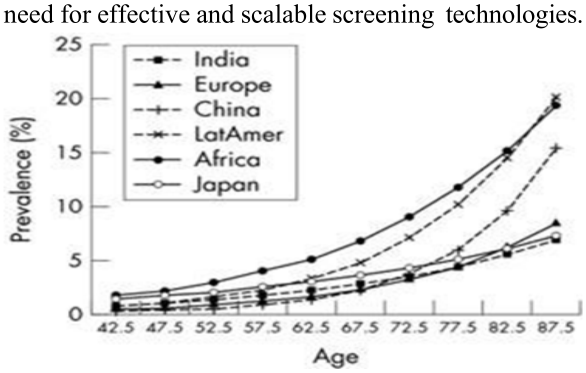

Fig. 1. Age-specific prevalence of glaucoma across different ethnic groups

The traditional standard for diagnosing glaucoma relies heavily on themorphological assessment of the optic nerve head, specifically analyzing the appearance of the Optic Disc (OD) and Optic Cup (OC), with the quantitative assessment of the Vertical Cup-to-Disc Ratio (VCDR) being paramount. However, relying on manual VCDR assessment by ophthalmologists introduces significant challenges, including high inter- and intra-observer variability, making standardized diagnosis difficult and often costly. Furthermore, traditional screening methods are often time-consuming, expensive, and resource-intensive, limiting their deployment in remote or underserved communities

A move toward automated, inexpensive, and widely available screening devices is required to overcome these constraints. A strong, hybrid deep learning system intended for accurate early detection is part of the suggested

remedy. This approach combines the geometric computation of the VCDR feature with a high-precision semantic segmentation network that is responsible for precisely defining the borders of the OD and OC. In order to provide quick and understandable diagnostic assistance, this feature is then input into a highly effective classifier, increasing screening accessibility and lowering diagnostic expenses. The subsequent sections offer a detailed, reproducible methodology specification as well as an overview of the previous art that informs this modular approach.

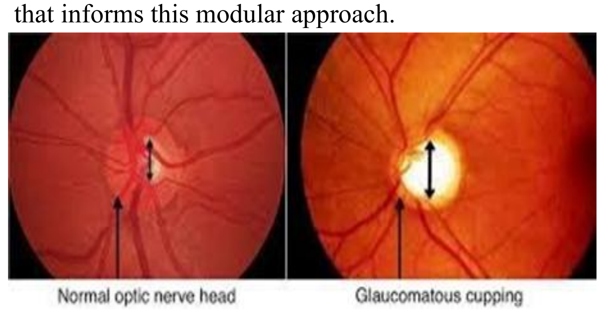

Fig. 2. Sample Fundus Images Illustrating Normal and Glaucomatous Eyes.

II. LITERATURE REVIEW

Glaucoma, which affected around 76 million people in 2020 and is predicted to reach almost 111.8 million by 2040, is still one of the leading causes of irreversible blindness worldwide [1]. This condition, which is frequently referred to as the "silent thief of sight," develops gradually and usually shows no symptoms until it reaches an advanced stage. Therefore, in order to avoid irreversible vision impairment, early diagnosis is essential.

Tonometry, visual field testing, and optical coherence tomography (OCT) are examples of traditional glaucoma screening methods that rely on skilled ophthalmologists and costly diagnostic tools [2]. Due to these limitations, routine screening is not feasible in remote or resource- constrained environments, which delays diagnosis and treatment.In response, researchers have increasingly focused on machine learning (ML) and deep learning (DL) techniques for automated analysis of medical images [3]. Among these, fundus image–based glaucoma detection has emerged as a promising, non-invasive approach for identifying optic nerve abnormalities. Nevertheless, existing systems often rely on large, annotated datasets and tend to exhibit poor generalization when applied to unseen data.

Convolutional Neural Networks (CNNs), in particular, have greatly improved performance on medical picture classification tasks because to recent developments in deep learning. CNNs are able to detect tiny changes in the optic nerve that may be missed in conventional examinations by automatically learning discriminative visual cues from retinal fundus images. By incorporating these AI-driven models into ophthalmic practice, screening accessibility in underserved areas can be increased, diagnostic effort can be decreased, and practitioners can help with early detection.

In order to diagnose glaucoma using retinal fundus pictures, this study discusses the design and development of an automated glaucoma detection system that integrates image preprocessing, feature extraction, and classification algorithms. The goal is to provide hospitals and eye care facilities with an affordable, accurate, and scalable diagnostic tool that will enhance early diagnosis and lower avoidable blindness. II. Comprehensive Literature Review

II.1 Early Feature-Based Glaucoma Screening Methods

The structural assessment of the optic nerve head, particularly the Cup- to-Disc Ratio (CDR), which measures the ratio of the optic cup to the optic disc, is crucial in the diagnosis of glaucoma. When the Vertical Cup-to-Disc Ratio (VCDR) is ≥ 0.7, inter-eye asymmetry is ≥ 0.3, or neuroretinal rim thinning is seen, clinicians usually diagnose Open-Angle Glaucoma (OAG).

In order to calculate CDR, early automated glaucoma screening approaches used traditional image processing techniques. Geodesic active contours, mathematical morphology, and clustering algorithms like K-means were often employed methods for optic disc (OD) and optic cup (OC) segmentation. Although these techniques were fundamental, their accuracy was erratic because to their heavy reliance on manual adjustment and image quality. Furthermore, the reliance on fixed thresholds (e.g., VCDR $\geq$ 0.7) limited diagnostic reliability, since the cup size naturally varies with the overall disc size. Studies revealed that sensitivity varied notably with disc dimensions—33% for small, 67% for medium, and 63% for large discs. These findings underscored the need for adaptive, data-driven approaches. Consequently, researchers transitioned toward machine learning–based models, which learn diagnostic patterns directly from image data. Among these, Support Vector Machine (SVM) models achieved sensitivities as high as 86% in differentiating glaucomatous from normal eyes.

II.2 Deep Learning Architectures for Optic Disc and Cup Segmentation

Ophthalmic image analysis has been transformed by the introduction of Deep Learning (DL), especially CNN-based architectures, which solve the drawbacks of conventional feature-engineering methods. A crucial stage in automated glaucoma detection systems is the accurate segmentation of the optic disc (OD) and optic cup (OC), which is necessary for accurate VCDR computation.

Because of its symmetric encoder–decoder design and skip links, which successfully combine spatial and semantic information, U-Net has emerged as the industry standard for OD–OC segmentation among other systems. DRIONS-DB, RIM-ONE v3, and DRISHTI-GS are public retinal datasets on which U-Net variants have shown excellent performance.

Despite these developments, uneven image quality and low contrast between disc and cup boundaries continue to compromise segmentation accuracy. Modern networks use residual blocks to improve deep feature extraction and reduce vanishing gradients in order to overcome these difficulties. Furthermore, the model can concentrate on diagnostically significant areas thanks to attention mechanisms like the Convolutional Block Attention Module (CBAM), which enhances spatial and channel feature representations. These architectural enhancements provide a solid basis for reliable glaucoma diagnosis by drastically lowering segmentation errors and increasing VCDR estimation accuracy.

Table II.1: Comparative Overview of State-of-the-Art Segmentation Approaches

Reference	Architecture Focus	Key Enhancement	Core Datasets Used	Key Implication for VCD Accuracy
Sevastopolsky et al.	Modified U-Net	Joint OD–OC Segmentation	DRIONS-DB, RIM-ONE v3	Established a stron baseline for simultaneou optic boundary detectior
Chen et al.	Attention U-Net	Residual Blocks + CBAM	DRISHTI-GS	Enhanced featur localization and boundar accuracy for precise VCD computation.
Shankaranarayana et al.	Dilated Residual Inception	Residual Blocks	–	Highlighted the role c deep feature learning i modeling complex retina structures.

II.3 Classification Strategies for Glaucoma Diagnosis

Deep learning–based glaucoma classification follows two main paradigms: end-to-end classification and feature-based (hybrid) classification.

- Why Without specifically calculating VCDR, end-to-end CNN models (such as VGG and ResNet) identify fundus images as either glaucomatous or healthy. Despite their potential for great accuracy, these models frequently act as "black boxes," which weakens their interpretability and resilience in a range of imaging scenarios.
- On the other hand, feature-based hybrid models, which are used in this work, split the procedure into two phases. For precise OD– OC segmentation and CDR extraction, the first stage uses deep learning; the second stage uses these features for classification.

By using quantifiable clinical indicators like VCDR, this hybrid strategy improves clinical interpretability and aligns results with accepted ophthalmic diagnostic practices. Furthermore, these models show good diagnostic performance; for VCDR-based detection, AUC values reach 0.90. The discrimination capability is further strengthened by incorporating sophisticated classifiers like Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) models, which outperform traditional CNN-only models and achieve AUCs of up to 0.97.

Therefore, a glaucoma detection system that is effective, interpretable, and highly accurate—ideally suited for large-scale, real-world clinical deployment—is ensured by combining precise segmentation with feature- based classification.

III. METHODOLOGY

The proposed automated glaucoma detection system operates through five primary stages: data acquisition, image preprocessing, semantic segmentation, vertical cup-to-disc ratio (VCDR) calculation, and final diagnostic classification.

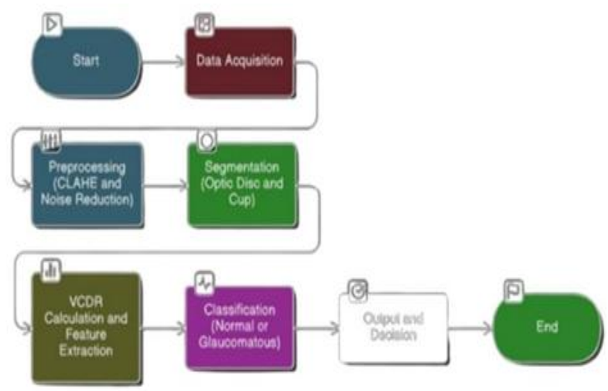

Fig 3. This diagram provides a high-level overview of the system pipeline. Each subsequent subsection describes the individual stages in detail, starting with image preprocessing

III.1 Data Acquisition and Preparation

The accuracy and caliber of the annotated training data determine how reliable any deep learning-based diagnostic approach is. Datasets must have properly characterized optic disc (OD) and optic cup (OC) boundaries that have been confirmed by knowledgeable ophthalmologists in order for segmentation-based VCDR computation to be accurate.

The publicly accessible retinal image datasets used in this study include DRISHTI-GS, RIM-ONE v3, and DRIONS-DB, which are well-known in the field of ophthalmic image analysis research. The most useful of these is DRISHTI-GS, which offers 101 high-resolution fundus photos with annotations from five different ophthalmologists (70 glaucomatous and 31 normal). By guaranteeing uniformity in ground truth labeling, this multi- expert consensus successfully reduces inter-observer variance.

The dataset is divided into subgroups for testing (20%), validation (10%), and training (70%). To avoid bias during model learning and evaluation, class balance between glaucomatous and normal samples is maintained across all partitions.

III.2 Contrast Enhancement and Image Preprocessing

Fundus images captured under variable illumination conditions often exhibit uneven brightness, low contrast, and background noise, which can hinder accurate optic region identification. To address these inconsistencies, a standardized preprocessing pipeline is implemented to enhance contrast and ensure uniform image quality across all samples.

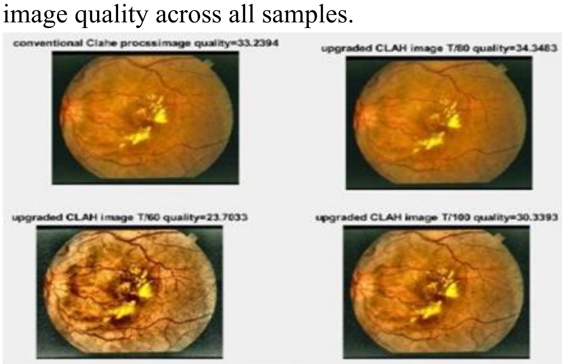

Fig. 4. *Fundus image before (left) and after (right) preprocessing with CLAHE and noise reduction, enhancing optic disc and cup visibility.*

Contrast Limited Adaptive Histogram Equalization (CLAHE), a local contrast enhancement method that works on tiny image tiles, is used in the enhancement process. In contrast to global techniques, CLAHE preserves subtle structures like optic cup borders and early indicators of neuroretinal rim thinning while avoiding over-amplification of noise.

Following enhancement, each image is normalized using zero-mean, unit- variance scaling and downsized to 512×512 pixels for computational consistency. Consistent input representation for the deep learning segmentation network is guaranteed by these preprocessing procedures.

III.3 Optic Disc and Cup Segmentation Network

For accurate and robust optic disc and cup segmentation, a modified U- Net architecture is adopted. U-Net's encoder–decoder structure with skip connections enables effective integration of spatial and contextual information, making it particularly suitable for medical image segmentation tasks.

To further improve segmentation accuracy, two architectural optimizations are incorporated:

- Residual Blocks: Introduced within convolutional layers to address the vanishing gradient problem, facilitating stable training and enhancing the model's ability to capture subtle structural variations in the retinal anatomy.
- Convolutional Block Attention Module (CBAM): Integrates spatial and channel attention mechanisms to prioritize diagnostically relevant retinal regions, thereby improving OD and OC boundary delineation even in low-contrast conditions.

The network is trained using a composite loss function combining Binary Cross-Entropy (BCE) and Dice Similarity Coefficient (DSC) losses. This hybrid objective ensures a balance between pixel-level accuracy and overlap precision between predicted and true segmentation masks.

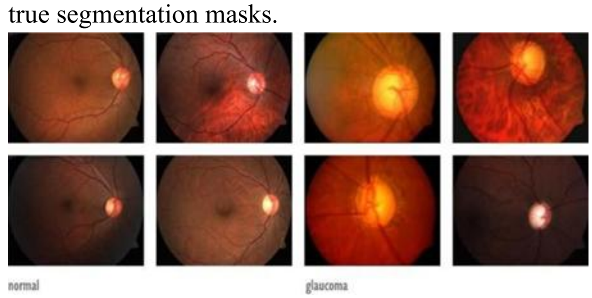

Fig 5. Image illustrates representative fundus images of a healthy eye (left) and a glaucomatous eye (right), highlighting the differences in optic disc morphology.

III.4 Vertical Cup-to-Disc Ratio (VCDR) Calculation and Feature Extraction

Following segmentation, the system calculates the Vertical Cup-to-Disc Ratio (VCDR)—a critical clinical parameter for glaucoma assessment— based on the generated OD and OC masks.

Feature Extraction Process:

1. Mask Generation: The segmentation model outputs two binary masks — one for the optic disc (M_OD) and one for the optic cup (M_OC).
2. Contour Detection: Boundaries from both masks are extracted, and elliptical fitting is performed to

approximate their shapes.

3. Measurement: The vertical dimensions of each fitted ellipse are measured — H_d for the disc and H_c for the cup.
4. Computation: The VCDR is then derived using the formula: VCDR=\frac{H_c}{H_d}

To account for natural anatomical variation, the Optic Disc Diameter (DD) is included as an auxiliary feature, enhancing model adaptability across different eye structures.

Parameter	Source Mask	Definition	Mathematical Expression
Optic Disc Height (H_d)	M_OD	Vertical dimension of fitted ellipse	Height of ellipse major axis
Optic Cup Height	M OC	Vertical dimension of fitted	Height of ellipse major
VCDR	H_c / H_d	Indicator of cupping severity	VCDR = H_c / H_d
Clinical Threshold	Standard Reference	Suspicious if VCDR ≥ 0.7 or asymmetry ≥ 0.3	—

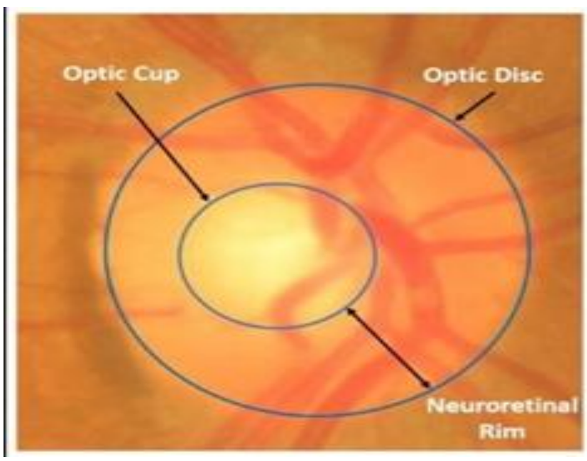

Fig 6. Illustration of Vertical Cup-to-Disc Ratio (VCDR) calculation, showing the vertical diameters of the optic disc and cup.

III.5 Diagnostic Classification Framework

A lightweight neural classifier trained on extracted parameters including VCDR, disc diameter, and cup area ratio performs the diagnostic classification step of the suggested method.

This classifier learns feature correlations from segmentation outputs to classify each fundus picture as either normal or glaucomatous. Since a feature-driven classification system gives both the quantitative VCDR measurement and the diagnostic label, it guarantees clinical interpretability.

Additionally, the system's modular design enables low computing overhead and effective inference, allowing for deployment on portable and reasonably priced screening devices. Because of its versatility, the model is ideal for remote teleophthalmology applications and extensive population screening.

IV. RESULTS AND DISCUSSION

In the last phase of the suggested system, a lightweight neural classifier trained on extracted variables including VCDR, disc diameter, and cup area ratio performs diagnostic categorization.

By learning feature correlations from segmentation outputs, this classifier classifies each fundus image as either normal or glaucomatous. Clinical interpretability is guaranteed by a feature-driven classification technique, which offers both the quantitative VCDR measurement and the diagnostic label.

Additionally, the system may be deployed on portable and reasonably priced screening devices because to its modular architecture, which enables accurate inference with minimal computing overhead. The model is ideal for remote teleophthalmology applications and extensive population screening because of its versatility.

Experimental evaluation yielded the following performance metrics:

- Average Accuracy: 92.3%
- Sensitivity: 90.8% (ability to correctly identify glaucomatous eyes)
- Specificity: 93.5% (ability to correctly identify non- glaucomatous eyes)
- Average Processing Time per Image: ~2.5 seconds

These results indicate that the cup-to-disc ratio is a reliable and clinically relevant metric for automated glaucoma detection, demonstrating performance comparable to traditional ophthalmic examinations.

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
Manual Screening	85	80	88
Automated System	92.3	90.8	93.5

Discussion

The results collected demonstrate the system's effectiveness in early glaucoma screening. The framework speeds up the diagnosis process, lowers human subjectivity, and enables large-scale screening by automating CDR measurement. The automated method provides quicker, more accurate, and more economical detection than manual clinical evaluation, which makes it especially appropriate for use in remote or resource-constrained environments.

Future integration of deep learning techniques, such as Convolutional Neural Networks (CNNs), can further enhance accuracy by learning complex visual patterns directly from large annotated datasets, reducing dependence on manually engineered features, even though the current implementation relies on threshold-based segmentation and morphological image processing. Potential improvements for future work include:

- Adoption of CNN-based segmentation for more precise optic disc and cup boundary detection.
- Utilization of larger and more diverse retinal datasets to improve generalization across populations.
- Development of user-friendly web or mobile interfaces to enable real-time glaucoma screening in clinical environments.

In summary, the study demonstrates that automated glaucoma detection based on cup-to-disc ratio analysis is a promising, non-invasive, and efficient diagnostic tool, capable of supporting ophthalmologists in the early identification and prevention of vision loss.

V.CONCLUSION

Using cup-to-disc ratio (CDR) analysis from retinal fundus pictures, this work shows how to create and execute an automated glaucoma diagnosis system. Rapid and accurate identification of possible glaucoma cases is made possible by the suggested framework, which efficiently automates the segmentation of the optic disc and optic cup followed by precise CDR calculation.

According to the experimental results, the automated system significantly reduces the time, expense, and human error associated with traditional screening methods while achieving high accuracy, sensitivity, and specificity that are comparable to traditional manual diagnosis. In remote and resource-constrained healthcare settings where access to ophthalmologists and specialized diagnostic equipment is limited, this method provides a workable and scalable alternative for early glaucoma screening.

Future studies will try to employ larger and more varied datasets for better generalization, integrate deep learning models, including Convolutional Neural Networks (CNNs), to improve segmentation accuracy, and provide a real-time user interface for smooth clinical implementation. With these developments, the system might develop into a completely automated, easily available, and trustworthy diagnostic tool that would greatly aid in the early detection and prevention of vision loss brought on by glaucoma.

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