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An Overview On Glaucoma Detection By Retinal Imaging

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Abstract: One of the major causes of irreversible blindness is Glaucoma. It causes progressive damage to the optic nerve, often without noticeable symptoms in the early stages. Detection of this condition is vital for averting vision loss. Recent technological advancements in medical imaging technologies coupled with new and improved computational methods have enabled significant progress in glaucoma diagnosis. This literature review examines the evolution of automated glaucoma detection, with a focus on the role of image preprocessing, feature extraction, and the use of machine learning (ML) along with deep learning (DL) techniques. The review highlights essential preprocessing methods to enhance image quality, such as contrast enhancement and noise reduction, which are critical for accurate analysis of fundus and OCT images. Additionally, it explores various feature extraction approaches that bridge raw image data to meaningful clinical insights. This comprehensive review also provides an overall picture of different ML and DL models employed to detect glaucoma, evaluating their strengths, limitations, and performance metrics. Furthermore, it addresses the challenges faced in the field, such as dataset imbalance, the need for diverse and high-quality datasets, and the integration of these automated systems into clinical practice. The paper concludes by discussing future directions for research, including the potential of hybrid models, multimodal frameworks, and improved interpretability in advancing glaucoma detection and management.

Index Terms - Glaucoma, Retinal Imaging, Optical Coherence Tomography (OCT), Fundus Images.

I. Introduction

Glaucoma is a long-term eye condition that gets worse over time. It damages the optic nerve, which connects the eye to the brain. This damage often causes increased pressure inside the eye (intraocular pressure – IOP). It is a chief cause of irreversible blindness worldwide, commonly known as the “silent thief of sight” because at initial stages it is asymptomatic [1]. Glaucoma harms the optic nerve head (ONH), the part of the eye that sends visual information from the retina to the brain. This results in progressive vision loss and can ultimately cause blindness if it goes untreated.

Glaucoma can develop when the fluid inside the eye, called aqueous humor, isn't produced and drained properly, leading to increased pressure (intraocular pressure or IOP). High IOP is the biggest risk factor for glaucoma, but some people develop optic nerve damage even with normal IOP, suggesting that other factors like blood flow problems and genetics are also important. The two main types of glaucoma are Primary Open-Angle Glaucoma (POAG) and Primary Angle-Closure Glaucoma (PACG). POAG is the most prevalent, making up about 70% of glaucoma cases worldwide. It develops gradually and is often undetected until significant vision loss occurs. PACG, on the other hand, can cause sudden symptoms such as pain, nausea, and blurred vision, requiring immediate medical intervention. Other forms, such as congenital and secondary glaucoma, are less common but can occur due to developmental abnormalities or other ocular or systemic conditions.

Glaucoma affects approximately 76 million people globally as of 2020, with projections indicating this number could rise to over 111 million by 2040. The economic burden of glaucoma is significant, encompassing direct medical costs like consultations, diagnostics, and medications, as well as indirect costs such as lost productivity and caregiver expenses [3]. The social impact is equally profound. Glaucoma patients often face limitations in mobility, difficulty performing daily tasks, and a reduced quality of life. These challenges are further exacerbated in low-income regions where access to diagnostic tools and treatment options is limited.

A major challenge in combating glaucoma is its asymptomatic nature in early stages. By the time patients seek medical attention, substantial optic nerve damage may have occurred, resulting in permanent vision loss. Early detection is critical but often hindered by the need for regular eye exams and access to specialised diagnostic tools, underscoring the importance of community awareness and affordable screening programs [4]. Glaucoma's asymptomatic onset often delays diagnosis, allowing extensive optic nerve damage to occur before detection. This underscores the importance of routine eye examinations, especially for high-risk groups such as individuals over 60, those with a family history of glaucoma, and patients with systemic conditions like hypertension or diabetes [5]. Traditional methods, including tonometry, fundoscopy, and visual field testing, have long been used to diagnose glaucoma. However, these techniques have limitations, including reliance on subjective interpretation, cost, and the need for specialised equipment [6]. While imaging techniques like Optical Coherence Tomography (OCT) provide more objective information about the retina and optic nerve head, their availability and cost can be limiting factors.

Retinal imaging technologies, such as OCT, fundus photography, and adaptive optics, have revolutionised glaucoma management by enabling non-invasive, high-resolution assessments of retinal and ONH structures. These technologies are essential for detecting structural changes that suggest early glaucoma progression, such as the thinning of the retinal nerve fiber layer (RNFL). Modern artificial intelligence (AI) has led to the development of automated image analysis tools that improve the accuracy of retinal image diagnosis [7]. Machine learning coupled with deep learning algorithms, trained on extensive datasets, can detect subtle changes caused by glaucoma, providing a more efficient and dependable option compared to traditional methods.

This paper aims to provide a comprehensive overview of advancements in glaucoma detection, focusing on the integration of traditional diagnostic methods with emerging technologies in machine learning (ML) and deep learning (DL). It emphasises the growing importance of automated techniques that enhance diagnostic accuracy, reduce subjectivity, and offer scalable solutions for clinical and research applications.

This literature review examines key aspects of detecting glaucoma, including preprocessing methods, feature extraction, and the use of sophisticated machine learning (ML) and deep learning (DL) models. Preprocessing steps, such as contrast enhancement and noise reduction, are highlighted for their role in ensuring image clarity and preparing data for further analysis. The significance of feature extraction, including clinical metrics like Cup-to-Disc Ratio (CDR) and advanced texture analysis methods, is discussed as a foundation for effective glaucoma detection.

This review closely examines the role of deep learning architectures, especially convolutional neural networks (CNNs). These models, along with ensemble and hybrid approaches, demonstrate remarkable potential in improving diagnostic outcomes. Techniques like segmentation using U-Net and its variants, as well as innovative hybrid frameworks integrating optimization algorithms, are reviewed for their contributions to precision and efficiency in glaucoma detection workflows. This survey also sheds light on emerging trends, such as explainability in AI models through visual tools like Grad-CAM, and the integration of clinical data with imaging features in multimodal frameworks. By synthesising findings across diverse datasets and methodologies, the paper identifies gaps in traditional practices and highlights the transformative role of AI driven solutions in early glaucoma detection and management. It aims to serve as a valuable resource for researchers and clinicians, fostering further innovation in this critical area of ophthalmology.

II. DATASETS IN GLAUCOMA STUDY

Large, well-curated datasets have been crucial for progress in glaucoma detection and severity assessment research. These carefully curated datasets, which include detailed annotations and various imaging techniques, are essential for developing and testing machine learning (ML) and deep learning (DL) models. Using images ranging from retinal fundus photos to Optical Coherence Tomography (OCT) scans, each dataset offers unique characteristics that contribute to different aspects of glaucoma diagnosis. These include optic disc and cup segmentation, Cup-to-Disc Ratio (CDR) calculation, and neuro-retinal rim analysis.

One important dataset in this field is the Brazil Glaucoma (BrG) dataset, which contains 2,000 fundus images from 1,000 individuals, equally split between glaucomatous and healthy cases. The dataset is particularly accessible as it uses smartphones paired with Welch Allyn panoptic ophthalmoscopes for image capture, making it suitable for resource-limited environments. The images are accompanied by manual annotations, such as segmentation masks for the optic disc and cup, enabling measurements like the Cup-to-Disc Ratio (CDR) and neuroretinal rim thickness. Researchers have used models like ResNet50, DenseNet, and MobileNet with transfer learning, as well as ensemble models, to achieve impressive performance—90% accuracy, 85% sensitivity, and 96.6% specificity, with an AUC of 96.5% [8]. This dataset is significant in addressing healthcare disparities by offering scalable and cost-effective screening solutions.

Another useful resource is the Online Retinal Image Glaucoma Analysis (ORIGA) dataset, which includes 650 retinal fundus images (168 glaucomatous and 482 healthy). The images come with manual annotations for optic disc and cup boundaries, which enable precise CDR calculations [9]. Advanced feature selection techniques, such as combining Whale Optimization Algorithm (WOA) with Grey Wolf Optimizer (GWO) have been applied to extract both structural and texture-based features. These features have been fed into classifiers like SVM and XGBoost, leading to excellent diagnostic results with a sensitivity of 99.2% and an overall accuracy of 96.8% [10]. The ORIGA dataset has been instrumental in improving tools for early-stage glaucoma detection.

A dataset known as RIM-ONE, consisting of 485 retinal fundus images, is another important resource for glaucoma research. Its detailed annotations of the optic disc and also cup boundaries make it well-suited for segmentation and classification tasks [11]. The dataset has been used to evaluate advanced architectures like ResNet50, VGG19, and MobileNet. Models trained on RIM-ONE have shown exceptional results, with AUC values reaching 0.9867 and a sensitivity of 100% in some cases [12]. The dataset's varied imaging conditions and standardized structure make it an extremely valuable tool for evaluating deep learning models for glaucoma diagnosis.

The REFUGE dataset contains 1,200 fundus images evenly split between glaucomatous and healthy cases, has been central in supporting global clinical challenges. It includes comprehensive annotations about optic disc along with cup segmentation, which help with accurate CDR measurement [13]. Researchers have used U-Net-based models on this dataset, achieving high segmentation accuracy, and it has become a benchmark for glaucoma detection systems [14]. The REFUGE dataset is not only used in academia but also serves as a gold standard for developing and evaluating advanced diagnostic methods.

The DRISHTI-GS dataset offers 101 high-resolution fundus images with annotations validated by ophthalmologists, particularly useful for segmentation tasks [15]. Advanced methods like entropy-based sampling combined with CNNs have achieved Dice scores of 0.973 for optic disc segmentation and classification accuracies above 90%. This dataset has been essential for advancing innovation in both classification techniques and segmentation techniques for reliable glaucoma diagnosis.

The ACRIMA dataset contains 705 fundus images, including 396 glaucomatous and 309 healthy cases, annotated by glaucoma specialists. It has been used extensively to develop interpretable AI systems, integrating Grad-CAM visualisations to enhance model transparency. Studies using ResNet50 on this dataset have achieved 98.03% accuracy and a recall of 99%. The ACRIMA dataset has been crucial in advancing trustworthy AI systems for automated glaucoma detection, contributing significantly to clinical applicability.

The Labelled Glaucoma (LAG) dataset is another valuable resource, containing 5,824 fundus images, with 2,392 glaucomatous and 3,432 normal cases. It includes attention maps and detailed annotations, supporting robust feature extraction for glaucoma classification. Researchers using CNN-based approaches have reported accuracies exceeding 94%. The LAG dataset is one of the key resources for training and validating automated glaucoma detection models on a large scale.

The STARE dataset, which includes 20 retinal fundus images and also having detailed annotations for the optic disc, optic cup, and retinal vessels, is widely used for evaluating segmentation algorithms. Methods like Glowworm Swarm Optimization (GSO) combined with XGBoost classifiers have achieved accuracies over 98.5%. The precision of the annotations makes it ideal for developing and testing high-precision segmentation models.

Though originally intended for diabetic retinopathy research, the MESSIDOR dataset, which contains 1,200 fundus images, has also been used for glaucoma studies due to its detailed retinal imaging. CNN models like ResNet50 and DenseNet121 have achieved accuracies above 91%, showing the dataset's adaptability for multi-condition diagnostics. It continues to be a valuable resource for refining classification models in glaucoma research.

The DRIONS-DB dataset includes 110 annotated fundus images, focusing on segmentation and classification tasks, particularly aimed at optic disc and cup boundaries. Models using U-Net and CNN-based architectures have reported Dice scores above 0.85 for segmentation and AUC values over 0.97 for classification. This dataset has played an important role in validating advanced glaucoma detection methods under varying imaging conditions.

The Optical Coherence Tomography Image Database (OCTID) dataset, with 2,000 OCT scans split between glaucomatous and healthy cases, focuses on structural analysis like macular thickness and retinal nerve fibre layer (RNFL) thinning. Researchers have used 3D ResNet models to analyse this volumetric data, achieving AUC values of 0.94 and sensitivity of 89.2%. OCTID highlights the importance of volumetric imaging in glaucoma research.

Table 1: Summary of the characteristics of the datasets

Dataset Name	No. of Images	Image Type	Glaucomatous/ Healthy Cases
Brazil Glaucoma (BrG)	2,000	Fundus Images	1,000 / 1,000
ORIGA	650	Retinal Fundus Images	168 / 482
RIM-ONE	485	Retinal Fundus Images	-
REFUGE	1,200	Retinal Fundus Images	600 / 600
DRISHTI-GS	101	Fundus → Images (High-res)	-
ACRIMA	705	Fundus Images	396 / 309
LAG	5,824	Fundus Images	2,392 / 3,432
STARE	20	Retinal Fundus Images	-
MESSIDOR	1,200	Fundus Images	-
DRIONS-DB	110	Fundus Images	-
OCTID	2,000	OCT Scans	1,000 / 1,000

Table 1 provides a summary of key datasets used in research for detecting glaucoma, highlighting the count of images, image types, and the distribution of glaucomatous versus healthy cases for each dataset. It offers a quick reference to understand the size and structure of each dataset, helping to identify the variety of data available for training and testing machine learning models in glaucoma diagnosis.

The variety and depth of these datasets highlight their critical role in advancing glaucoma detection and diagnosis. By offering high-quality images, comprehensive annotations, and insights into the disease's characteristics, these datasets have allowed researchers to refine machine learning algorithms and improve automated diagnostics. Their widespread use has led to the development of robust and scalable diagnostic systems, ultimately helping with earlier detection, better management, and improved outcomes for glaucoma patients. With ongoing advancements in imaging technology and data curation, these datasets will remain essential in overcoming challenges in ophthalmology and advancing precision medicine for glaucoma.

III. METHODOLOGY

Glaucoma detection has traditionally relied on manual evaluation of optic nerve health by means of fundus images along with Optical Coherence Tomography (OCT). More recent advancements have provided better scope by utilising machine learning (ML) in conjunction with deep learning (DL). These techniques have transformed this field, offering automated, accurate, and scalable solutions. By leveraging image preprocessing, feature extraction, and advanced model architectures, they enhance diagnostic reliability. The various techniques used in preprocessing, feature extraction, segmentation, and ML/DL models for glaucoma detection, showcasing their application and effectiveness across different datasets, are discussed below.

A. Preprocessing Techniques

Image preprocessing is essential in glaucoma detection workflows, as it ensures the clarity and consistency of fundus images before analysis. The diversity of imaging conditions, such as variations in lighting and noise, necessitates robust enhancement techniques [8]. A very common preprocessing technique is the Contrast Limited Adaptive Histogram Equalization (CLAHE) method. The technique adaptively adjusts image contrast, thereby improving the visibility of the optic disc and cup regions, which are critical in glaucoma diagnosis. CLAHE is particularly effective in datasets with low-contrast images, a common occurrence in clinical environments with diverse lighting conditions.

Noise reduction is another critical aspect of preprocessing. Techniques such as Gaussian and median filtering are applied to remove speckles and artefacts without compromising image details. Median filtering is especially effective in retaining sharp edges, which are essential for accurately segmenting retinal structures like the optic disc and cup [11]. These preprocessing steps prepare images for downstream tasks, ensuring the reliability of extracted features. Channel selection is employed to enhance specific image properties. Among RGB channels, the green colour channel is often preferred due to its higher contrast and ability to delineate retinal structures more effectively. Additionally, cropping methods are utilized to isolate the region of interest (ROI), typically the optic nerve head, focusing computational resources on relevant areas and reducing noise from peripheral regions.

Data augmentation addresses dataset imbalance, a prevalent issue in medical image datasets where glaucoma cases are underrepresented. Techniques like image rotation, flipping, zooming, and shearing are applied to generate synthetic variations of existing images. Augmentation not only balances the dataset but also improves model robustness by exposing it to a broader range of visual scenarios [12]. This also helps in creating the perfect version of the image, clear for further processing.

B. Feature Extraction

Feature extraction forms the backbone of glaucoma detection, bridging raw image data and analytical models. Clinically, the Cup-to-Disc Ratio (CDR) remains a cornerstone feature. It represents the ratio of optic cup's diameter to the diameter of optic disc, with values exceeding 0.6 often indicative of glaucoma. CDR offers a straightforward yet powerful metric for assessing optic nerve health. Additional clinical features include neuroretinal rim thickness and peripapillary atrophy, which provide insights into the structural integrity of the optic nerve and aid in glaucoma detection.

Texture analysis supplements clinical features with rich spatial information. Techniques like Grey-Level Run Length Matrix (GLRM) and Grey-Level Co-occurrence Matrix (GLCM) quantify pixel intensity relationships. These methods provide descriptors such as contrast, homogeneity, and entropy, which capture subtle textural variances between normal and glaucomatous eyes. Such features are particularly valuable in detecting early-stage glaucoma, where structural changes may be less pronounced. Wavelet transform is another powerful feature extraction technique, breaking images into multi-scale frequency components. By analysing variations in texture and patterns across different scales, wavelet features provide a nuanced representation of retinal structures. These multiresolution features are particularly effective in capturing the irregularities associated with glaucomatous progression.

In deep learning-based approaches, feature extraction is inherently integrated into model architectures. Convolutional neural networks (CNNs) which are pre-trained such as ResNet50, DenseNet121, and VGG19 have proven highly effective for extracting hierarchical features. These models leverage transfer learning by utilising weights pre-trained on large datasets like ImageNet. Transfer learning significantly reduces the computational burden and enhances model accuracy by adapting generalizable patterns to specific glaucoma detection tasks.

C. Deep Learning-Based Methods

Deep learning has revolutionised glaucoma detection, with CNNs playing a pivotal role. CNN architectures process fundus images in a layered manner, progressively learning hierarchical features. For example, ResNet50 uses residual connections to overcome the vanishing gradient problem, which allows for the training of deeper networks. This architecture has demonstrated high accuracy in distinguishing glaucomatous from healthy eyes, particularly when fine-tuned on domain-specific datasets. DenseNet architectures take the concept of connectivity further, ensuring that every layer receives input from all preceding layers. This dense connectivity improves feature reuse as also the gradient flow, making DenseNet very effective for medical imaging applications, such as segmenting the optic disc and cup. Inception networks, including InceptionV3, utilise multi-scale filters to capture features at varying resolutions. This makes them particularly suitable for detecting subtle textural changes in fundus images, such as those associated with early glaucoma.

Custom CNN architectures tailored to specific applications have also emerged. U-Net and its variations, for instance, are widely employed for segmentation tasks. U-Net++ enhances the original design with nested skip connections, improving segmentation accuracy for optic disc and cup boundaries. Architectures like these are critical for calculating clinical metrics like CDR with high precision. Ensemble methods integrate multiple CNNs to leverage their individual strengths.

By aggregating predictions through majority voting or weighted averaging, ensemble models attain higher accuracy and sturdiness [15]. For instance, frameworks combining ResNet50, VGG19, and InceptionV3 have demonstrated superior performance across diverse datasets. Emerging trends include 3D CNNs, which process volumetric data from Optical Coherence Tomography (OCT) images. These models utilise three-dimensional convolutions to capture spatial and depth information, offering a richer representation of retinal structures. Although promising, 3D CNNs face challenges like overfitting due to limited volumetric data.

Explainability is gaining traction as a critical component of deep learning models used in clinical settings. Techniques like Gradient-weighted Class Activation Mapping (Grad-CAM) and Grad-CAM++ produce heatmaps highlighting the regions most influential in the decision-making procedure of the model. These visualizations build trust by giving clinicians understandable insights, connecting AI predictions with clinical validation.

Table 2 provides a comprehensive summary of various papers focused on glaucoma detection, highlighting the methods employed and the results achieved in the field. Each entry reflects different approaches to utilizing deep learning and image analysis techniques for diagnosing glaucoma at early stages. The table not only presents the specific datasets used for training and validation but also compares the performance metrics of different models, such as sensitivity, specificity, accuracy, and area under (AUC) for the receiver operating characteristic.

Table 2: Summary of some Glaucoma Detection Studies

Paper / Study	Dataset	Algorithm	Accuracy	Other Metrics
Detection of Glaucoma Using Smartphone and CNN Ensemble	Brazil→Glaucoma (BrG): 2000 images	CNN→Ensemble→(ResNet50v2, MobileNet)	90%	Sensitivity: 85%; Specificity: 96.6%
An Improved Ensemble Framework for Glaucoma Detection	RIM-ONE, DRISHTI-GS, HRF	Ensemble:→ResNet50,→VGG19, InceptionV3	98.58%	Sensitivity: 98.8%; Specificity: 98.17%
Deep ensemble learning for retinal image classification	Retinal Fundus Multi-Disease→Image Dataset (RFMiD)	Ensemble of five CNN architectures (including SE-ResNeXt); optimized using asymmetric loss function	96.13%	AUROC: 92.95%
Computer-Aided Design (CAD) System for Early Glaucoma Detection	DRISHTI-GS, DRIONS-DB, HRF, PSGIMSR, → and Combined Dataset	Ensemble-based Deep Learning Model→(ResNet, VGGNet, GoogLeNet)	88.96%	Sensitivity: 85.55%; Specificity: 95.20%
Automated Glaucoma Detection in Retinal Fundus Images Using Machine Learning Models	RIGA: 2664 images	VGG16, AlexNet	92%	F1-score: 0.93
Deep Learning With Grad-CAM for Glaucoma Diagnosis	RIM-ONE, ACRIMA	Inception V3 with Grad-CAM	98.97%	Sensitivity: 99.42%; Specificity: 95.59%
Integrating Deep Learning with Electronic Health Records for Early Glaucoma Detection	EHR data from 1,652 participants (826 control, 826 glaucoma patients)	Random → Forest, → Gradient Boosting, → Sequential → Model (Keras/TensorFlow)	67.5%	ROC AUC: 0.67
Deep learning for glaucoma detection: R-CNN ResNet-50 and image segmentation	ACRIMA, ORIGA	Pre-trained → ResNet-50 + → Gradient-based → CDR Segmentation	95%	Average → Confidence Score: → 0.879 (ResNet-50), → 0.84 (Segmentation)
Assessing the Efficacy of 2D and 3D CNN Algorithms in	UK → Biobank (Macular), → ONH (Maetschke)	Pre-trained → 2D ResNet18, → 3D ResNet18, DenseNet121, Custom 3D CNN	96% → (2D), 94.5% (3D)	AUC: → 0.960 → (2D Macular), 0.943 (2D

OCT-based Glaucoma Detection				ONH); → AUC: → 0.945 (3D DenseNet121)

D. Hybrid and Advanced Techniques

Hybrid models that combine traditional machine learning with deep learning are becoming increasingly popular. Grey Wolf Optimizer (GWO) is one such feature selection technique integrated with CNN architectures. By optimising feature subsets before classification, GWO enhances model efficiency and accuracy. Similarly, Whale Optimization Algorithm (WOA) has been hybridised with CNNs to improve feature selection and reduce computational overhead.

Segmentation techniques are also witnessing innovation.

Modified U-Net++ models employ advanced loss functions, such as a combination of focal loss and dice coefficient, to handle class imbalances. This is particularly beneficial for datasets where glaucomatous cases are underrepresented. Synthetic data generation methods like Adaptive Synthetic Sampling (ADASYN) further bolster model performance by augmenting minority class samples. Another advanced approach involves integrating clinical data with imaging features. Electronic health records (EHR) containing demographic and lifestyle information are combined with image-based features in multi-modal frameworks. Such integrations enable comprehensive analyses that account for both structural and systemic factors contributing to glaucoma risk.

E. Evaluation Metrics

Evaluating the performance of glaucoma detection models requires a suite of metrics that capture both accuracy and reliability. Sensitivity calculates the proportion of rightly identified glaucomatous cases, whereas specificity quantifies the capacity to correctly classify non-glaucomatous cases. These metrics are particularly critical in medical diagnostics, where false negatives can have severe consequences.

Precision and F1-score provide additional insights into model performance by balancing the trade-offs between false positives and false negatives. State-of-the-art AI / ML models frequently achieve high F1-scores, often above 0.9, demonstrating strong performance across a variety of datasets. The AUC-ROC (Area Under the Receiver Operating Characteristic Curve) is another commonly used measure. It calculates the model's discriminatory power across various decision thresholds. AUC values close to 1.0 signify excellent model performance, underscoring the reliability of CNN-based approaches for glaucoma detection.

IV. CONCLUSION

The current work emphasizes the prospect of automated systems leveraging deep learning to address the challenges associated with traditional diagnostic methods. By employing advanced image pre-processing techniques, balanced training data, and a robust architecture like EfficientNetB3, our proposed system achieves higher accuracy and reliability in detection of glaucoma from retinal fundus images. The use of classification measures such as the confusion matrix, precision, recall, and also the F1-score highlight the efficacy of the model in recognizing glaucoma cases accurately.

While the results demonstrate significant promise, challenges such as dataset diversity, scalability, and their use in clinical practice remain. Future research should focus on developing hybrid models, incorporating multimodal data, and improving the interpretability of these systems to boost their applicability in real-world settings. This work paves the way for scalable, cost-effective, and efficient diagnostic tools, potentially transforming the landscape of glaucoma detection and management.

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