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A Review of Glaucoma Optic Disk Localization and Classification Machine Learning and Deep Learning Models

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Abstract:- This review aims to comprehensively synthesise recent advancements in machine learning (ML) and deep learning (DL) models specifically designed for localising and classifying the optic disk in glaucoma diagnosis. Glaucoma, a leading cause of irreversible blindness, is characterised by distinctive changes in the optic disk. Manual evaluations, although invaluable, face challenges due to inconsistencies, subjectivity, and the considerable time required. With the emergence of artificial intelligence, ML and DL models have become potent tools for enhanced and automated optic disk evaluations. An exhaustive literature search of primary studies from 2010 to 2023 focused on models to localise and classify the optic disk in glaucoma diagnosis. Selection criteria included novelty, accuracy, and clinical relevance of the models. Various architectures, datasets used, training techniques, and performance metrics were critically analysed. Numerous ML and DL models have shown promising optic disk localisation and classification results. Convolutional Neural Networks (CNN) have predominantly led the DL paradigm, with innovative architectures improving specificity and sensitivity. Hybrid models integrating traditional ML techniques with DL have also emerged, demonstrating enhanced robustness and generalizability. ML and DL models possess transformative potential in glaucoma care, offering a blend of accuracy, efficiency, and consistency. As these models evolve, integrating larger datasets and multimodal imaging, their role in clinical settings is poised to expand, bridging the gap between technological advancements and patient-centric care.

Keywords:- Glaucoma, Optic Disk, Machine Learning, Deep Learning, Convolutional Neural Networks, Diagnosis

I. INTRODUCTION

Glaucoma, often referred to as the "silent thief of sight", stands as a major public health concern due to its status as one of the predominant causes of irreversible blindness globally. The optic disk plays a central role in diagnosing, monitoring, and understanding glaucoma in the eye's retina, where the optic nerve fibres converge to exit the eyeball. Alterations in the optic disk's appearance and structure, particularly the optic cup's enlargement within the disk, serve as pivotal indicators of glaucomatous damage. Historically, the evaluation of the optic disk relied predominantly on manual methods, with ophthalmologists interpreting fundus photographs or Optical

Coherence Tomography (OCT) scans to discern any glaucomatous changes. However, this method, while invaluable, is not without its drawbacks. Subjectivity in assessments, inconsistencies across evaluations, and the required time are challenges faced in traditional optic disk assessment.

Moreover, the scarcity of specialists in many parts of the world exacerbates the problem, leaving vast populations at elevated risk. Enter the era of artificial intelligence. With the blossoming of Machine Learning (ML) and its sophisticated subset, Deep Learning (DL), we have witnessed a paradigm shift in various domains, including medical imaging. These computational techniques have allowed for automating, enhancing, and standardising optic disk evaluations, providing speed and consistency. This review delves into the burgeoning realm of ML and DL models tailored for glaucoma optic disk localisation and classification. We traverse the current research landscape, exploring methodologies, innovations, and findings that have shaped the frontier of automated glaucoma detection. We aim to offer insights into the capabilities and potentials of these models, fostering a deeper understanding of their role in revolutionising glaucoma care in the 21st century.

II. BACKGROUND STUDY

Glaucoma is one of the leading causes of irreversible blindness worldwide. Characterised by the damage to the optic nerve and subsequent visual field loss, early detection and appropriate intervention are critical to halting its progression and preventing visual impairment. The optic disk, especially the proportion and relationship between the optic cup and the overall disc, plays a vital role in diagnosing and monitoring glaucoma. Traditionally, ophthalmologists evaluate the optic disk using fundus photography and Optical Coherence Tomography (OCT). These evaluations can be subjective and vary between observers, leading to inconsistencies in diagnosis and treatment decisions.

Furthermore, in many regions globally, especially in low-resource settings, there's a shortage of ophthalmologists, which leaves a significant portion of the population at risk of undiagnosed and untreated glaucoma. In the digital age, the convergence of medical imaging and computational techniques offers a promising solution. Machine Learning (ML) and Deep Learning (DL), subsets of artificial intelligence, have shown remarkable achievements in image recognition tasks across various domains. In ophthalmology, these tools present an opportunity to provide consistent, objective, and high-speed evaluations of the optic disk, thereby aiding in glaucoma detection and management. In recent years, there has been a surge in research focusing on applying ML and DL models for optic disk localisation and glaucoma classification. These models, trained on vast datasets of labelled fundus images, aim to identify the optic disk's location and assess its morphology for signs of glaucoma. Given the rapid advancements and the diverse approaches in this domain, there's a need to critically review the existing literature, understand the state-of-the-art models, identify their strengths and weaknesses, and chart out the future research direction. This review aims to provide a comprehensive overview of ML and DL models designed for glaucoma optic disk localisation and classification, evaluating their performance, discussing the challenges, and highlighting potential areas for future exploration.

III. LITERATURE REVIEW

Latif et al. (2022) designed a novel deep-learning model to automate optic disc localisation and classify glaucoma using fundus images. Thanki (2023) utilised a combination of deep neural networks and machine learning to classify retinal fundus images, as detailed in Healthcare Analytics. Brown et al. delved into using deep learning to detect optic disc haemorrhages in a localised manner, a contribution featured in the American Journal of Ophthalmology. Nawaz et al. (2022) introduced an efficient deep-learning methodology for glaucoma detection, relying on localising the optic disc and optic cup. Archana et al. (2023) analysed various machine learning and deep learning techniques used in glaucoma detection. Alawad et al. (2022) reviewed the machine learning and deep learning techniques available for segmenting the optic disc and cup, with their findings published in Clinical Ophthalmology. Rasheed et al. (2023) introduced RimNet, a deep neural network pipeline engineered for the automated identification of the optic disc rim, with their findings showcased in Ophthalmology Science. Zedan et al. (2023) reviewed various deep-learning approaches for glaucoma screening and diagnosis, primarily utilising retinal fundus images as the data source. Charng et al. (2023) discussed various deep learning applications in diagnosing retinal and optic nerve diseases. Fan et al. (2023) explored a unique method of glaucoma detection from fundus photographs using deep learning, specifically by employing transformers instead of conventional convolutions, offering insights into improved generalisation, as detailed in Ophthalmology Science. Panahi et al. (2023) developed a method to autonomously assess spontaneous retinal venous pulsations based on fundus videos documented in Scientific Reports. Braeu et al. (2023) delved into the use of Geometric Deep Learning to determine critical 3D structural features of the Optic Nerve Head, a significant advancement in diagnosing glaucoma. Musthafa (2023) utilised Deep Reinforcement Learning for precise localisation of the optic disc region, aiming to enhance the accuracy of glaucoma diagnosis. Vali et al. (2023) differentiated glaucomatous optic neuropathy from nonglaucomatous ones using advanced deep learning algorithms, as detailed in the American Journal of Ophthalmology. Thamilselvan et al. (2023) analysed various machine learning and deep learning techniques and their effectiveness in diagnosing glaucoma.

Oguz et al. (2023) proposed a novel hybrid model based on CNN for glaucoma detection, with detailed methodology and results documented in Multimedia Tools and Applications. Jumanto et al. (2023) proposed an enhanced glaucoma prediction method combining histogram and grey-level cooccurrence matrix techniques. Xu et al. (2023) introduced E-Net, a novel deep-learning framework integrating expert knowledge specifically for segmenting glaucoma optic disc haemorrhage. Parkhi and Hambarde (2023) developed a deep learning method to segment the optical cup and disc critical for accurate glaucoma detection, documented in the International Journal of Next-Generation Computing. Shoukat et al. (2023) introduced an automatic diagnosis system for glaucoma, drawing data from retinal images and utilising a state-of-the-art deep learning approach. Chan et al. (2023) showcased a cutting-edge Deep Learning System designed explicitly for evaluating the quality of optic disc photographs, aiming to benefit the diagnosis and treatment of neuro-ophthalmic disorders. Janani and Rajamohana (2021) performed a survey on early glaucoma detection methods, emphasising techniques focusing on the segmentation of the optic disc and optic cup. Lamba and Rani (2023) discussed machine learning-based segmentation and classification algorithms tailored for glaucoma detection, marking advancements in diagnostic capabilities. Ahmed et al. (2023) introduced an efficient deep-learning network to detect and classify the glaucomatous eye. David, D.S. (2023) proposed an enhanced glaucoma detection approach integrating an ensemble-based CNN with a spatially oriented ellipse fitting curve model for better diagnosis precision. Prananda et al. focused on retinal nerve fibre layer analysis, aiming to enhance the efficiency of glaucoma detection during eye disease assessment by incorporating deep learning. Veena et al. (2020) delved into various optic disc and optic cup segmentation methodologies and their application in detecting glaucoma using retinal fundus images. Liu et al. (2022) presented a glaucoma screening tool employing an attention-guided stereo ensemble network, bringing forward an innovative approach to detect the disease. Guergueb and Akhloufi (2023) provided a thorough overview of deep learning techniques available for glaucoma detection, discussing their advantages and challenges. CH, M. (2023) proposed a method for detecting glaucoma using convolution neural networks, emphasising the potential of CNNs in revolutionising diagnostic processes. Hemelings et al. (2023) introduced a deep-learning regression model for automated glaucoma screening, emphasising its generalizability using fundus images for early disease detection. Varma et al. (2022) provided insights on automatic glaucoma detection techniques utilising fundus images, compiling and discussing recent advancements. Hussain and Basak (2023) presented UT-Net, a novel integration of U-Net and Transformer networks, offering joint optic disc and cup segmentation for enhanced glaucoma detection.

Lenka et al. (2023) emphasised a glaucoma detection technique based on specularity removal and a low-rank model applied to retinal fundus images. Shan et al. (2023) introduced a deep learning method classifying angle closure using anterior segment OCT, showcasing advancements in glaucoma detection in Ophthalmology Glaucoma. Elangovan et al. (2023) proposed an enhanced method for classifying glaucoma stages using the Efficientnet-b0 CNN and RNN from colour fundus images. Fang and Qiao (2023) delved into glaucoma multi-classification through a novel syndrome mechanism-based dual-channel network. Kitaguchi et al. (2023) focused on a deep-learning approach to detect childhood glaucoma based on periocular photographs, emphasising early diagnosis. Selvathi (2023) discussed classification techniques for ocular diseases utilising transfer learning approaches and offering insights into glaucoma severity grading. The chapter addressed fundus image classification using deep learning architectures and their impact on choosing deep learning architectures. Krishna et al. (2023) integrated multimodal imaging to provide a more accurate glaucoma diagnosis. Naidana and Barpanda (2023) presented a unique polynomial-driven deep-learning approach tailored for glaucoma classification, showcasing innovative techniques in the field. Muramatsu (2020) concentrated on diagnosing glaucoma using retinal fundus images, focusing on detecting nerve fibre layer defects and analysing the optic disc. Hasan et al. (2023) provided a comprehensive review of the

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applications of artificial intelligence in diagnosing glaucoma and neurodegenerative diseases, presenting the intersection of AI and optometry.

Ref	Method	Result	Limitation
1	ODGNet: Deep learning for optic disc localisation and glaucoma classification	Accurate optic disc localisation and glaucoma classification	Limited discussion on model interpretability. Specific performance metrics may not be provided. Scalability considerations are not explored.
2	Network and machine learning approach for retinal fundus image classification	Improved retinal fundus image classification using deep learning	There is limited discussion on the choice of deep learning architectures and their impact. Scalability challenges are not explored.
3	Deep learning for localised detection of optic disc haemorrhages	Accurate detection of optic disc haemorrhages using deep learning	There is limited discussion on the specifics of the deep learning model architecture. Specific performance metrics may not be provided. Scalability considerations are not discussed.
4	Deep learning approach for automatic glaucoma detection using optic disc and optic cup localisation	Efficient automatic glaucoma detection using deep learning	There is limited discussion on the choice of deep learning algorithms and their impact. Scalability challenges are not explored.
5	Machine learning and deep learning techniques for glaucoma detection	Overview of machine learning and deep learning techniques for glaucoma detection	Does not focus on a specific method or result. General review article. Scalability considerations are not addressed.
6	Review of machine learning and deep learning techniques for optic disc and cup segmentation	A comprehensive review of optic disc and cup segmentation techniques	Does not present specific results. Review the article without specific methods. Scalability considerations are not discussed.
7	RimNet: A deep neural network pipeline for automated identification of the optic disc rim	Automated identification of the optic disc rim using a deep neural network pipeline	There is limited discussion on the specifics of the deep neural network architecture. Specific performance metrics may not be provided. Scalability considerations are not discussed.
8	Automated glaucoma screening and diagnosis based on retinal fundus images using deep learning approaches	Efficient glaucoma screening and diagnosis using deep learning approaches	There is limited discussion on the choice of deep learning approaches and their impact. Scalability challenges are not explored.
9	Applications of deep	Applications of	Overview article without specific

	learning in retinal and optic nerve diseases	deep learning in retinal and optic nerve diseases	methods or results. Does not address scalability considerations.
10	Transformer for improved generalisation in glaucoma detection from fundus photographs	Glaucoma detection using a Transformer for improved generalisation	There is limited discussion on the choice of Transformer parameters and their impact. Scalability considerations are not discussed.
11	Autonomous assessment of spontaneous retinal venous pulsations using deep reinforcement learning	Autonomous assessment of retinal venous pulsations using deep reinforcement learning	There is limited discussion on the specifics of deep reinforcement learning. Scalability challenges are not explored.
12	Geometric Deep Learning for critical 3D structural features of the optic nerve head for glaucoma diagnosis	Identification of critical 3D structural features using geometric deep learning	There is limited discussion on the specifics of the geometric deep learning model. Specific performance metrics may not be provided. Scalability considerations are not discussed.
13	Precise Localisation of Optic Disc Region for Accurate Glaucoma Diagnosis Using Deep Reinforcement Learning	Precise localisation of optic disc for accurate glaucoma diagnosis	There is limited discussion on the specifics of deep reinforcement learning. Scalability considerations are not explored.
14	Differentiating Glaucomatous Optic Neuropathy From Nonglaucomatous Optic Neuropathies Using Deep Learning	Differentiation of glaucomatous optic neuropathy using deep learning	There is limited discussion on the specifics of deep learning algorithms and their impact. Scalability challenges are not explored.
15	Diagnosing Glaucoma Disease Using Machine Learning and Deep Learning Techniques	Diagnosing glaucoma using machine learning and deep learning techniques	Overview article without specific methods or results. Scalability considerations are not addressed.
16	CNN-based hybrid model to detect glaucoma disease	Detection of glaucoma disease using a CNN-based hybrid model	There is limited discussion on the specifics of the hybrid model architecture. Scalability challenges are not discussed in depth.
17	Mix histogram and grey level cooccurrence matrix to improve glaucoma prediction machine learning.	Improved glaucoma prediction using histogram and matrix-based machine learning	There is limited discussion on the specific machine learning parameters and their impact. Scalability considerations are not explored.
18	Deep learning framework for glaucoma optic disc	Deep learning framework for	There is limited discussion on the specifics of the deep learning

	haemorrhage segmentation	glaucoma optic disc haemorrhage segmentation	framework. Specific performance metrics may not be provided. Scalability considerations are not discussed.
19	Optical cup and disc segmentation using deep learning technique for glaucoma detection	Segmentation using deep learning for glaucoma detection	There is limited discussion on the choice of deep learning technique parameters and their impact. Scalability challenges are not explored.
20	Automatic Diagnosis of Glaucoma from Retinal Images Using Deep Learning Approach	Automatic diagnosis of glaucoma from retinal images using deep learning	There is limited discussion on the specifics of deep learning approaches and their impact. Scalability challenges are not explored.
21	Deep Learning for automated quality evaluation of optic disc photographs in neuro-ophthalmic disorders	Automated quality evaluation of optic disc photographs	Limited discussion on specific deep learning architecture details. Scalability considerations not addressed.
22	Survey on early detection of glaucoma using optic disc and optic cup segmentation	Overview of early detection methods using Segmentation	Does not present specific results. General survey article. Scalability considerations are not discussed.
23	Machine learning-based segmentation and classification algorithms for glaucoma detection	Effective deep learning network for detecting and classifying glaucomatous eyes	There is limited discussion on the choice of deep learning algorithms and their impact. Scalability challenges not explored.
24	Effective deep learning network for detecting and classifying glaucomatous eyes	Efficient detection and classification of glaucomatous eyes	There is limited discussion on deep learning architecture specifics. Specific performance metrics may not be provided. Scalability considerations not addressed.
25	Enhanced glaucoma detection using ensemble-based CNN and spatially based ellipse fitting curve model	Improved glaucoma detection using ensemble-based CNN	There is limited discussion on the specifics of ensemble-based CNN. Scalability challenges are not explored.
26	Retinal nerve fibre layer analysis using deep learning to improve glaucoma detection.	Improved glaucoma detection using deep learning	There is limited discussion on deep learning model specifics. Specific performance metrics may not be provided. Scalability considerations not discussed.
27	Review of optic disc and optic cup segmentation and classification	Overview of segmentation and classification	Does not present specific results. General review article. Scalability considerations are not addressed.

	approaches for glaucoma detection.	approaches	
28	Glaucoma screening using an attention-guided stereo ensemble network	Efficient glaucoma screening using an ensemble network	There is limited discussion on the choice of network parameters and their impact. Scalability considerations not discussed.
29	Review of deep learning techniques for glaucoma detection	Overview of deep learning techniques for glaucoma detection	Does not focus on specific methods or results. General review article. Scalability considerations are not addressed.
30	Glaucoma detection using convolutional neural networks	Glaucoma detection using CNN	There is limited discussion on the choice of CNN architecture specifics. Scalability challenges are not explored.
31	Generalisable deep learning regression model for automated glaucoma screening	Generalisable deep learning regression model for glaucoma screening	There is limited discussion on deep learning regression model specifics. Specific performance metrics may not be provided. Scalability considerations not discussed.
32	A short review on automatic detection of glaucoma using fundus image	Short review on automatic detection of glaucoma	General review article without specific methods or results. Scalability considerations are not addressed.
33	Combining U-Net and Transformer for joint optic disc and cup segmentation and glaucoma detection	Joint segmentation and glaucoma detection using U-Net and Transformer	There is limited discussion on the combined U-Net and Transformer model specifics. Scalability challenges are not explored.
34	Glaucoma detection based on specularity removal low-rank model from retinal fundus images	Glaucoma detection based on specularity removal low-rank model	There is limited discussion on the model specifics. Specific performance metrics may not be provided. Scalability considerations are not discussed.
35	Deep learning classification of angle closure based on anterior segment OCT	Deep learning classification of angle closure using anterior segment OCT	Limited discussion on specific deep learning architecture details. Scalability considerations not addressed.
36	Improved classification of glaucoma stages from colour fundus images using EfficientNet-B0 CNN and RNN	Improved classification of glaucoma stages using EfficientNet-B0 CNN and RNN	Limited discussion on the specific architecture details of EfficientNet-B0 CNN and RNN. Scalability challenges are not explored.
37	Glaucoma multiclassification using a novel syndrome	Multiclassification of glaucoma using a dual-channel	There is limited discussion on the specific architectural details of the dual-channel network. Scalability

	mechanism-based dual-channel network	network	challenges are not explored.
38	Glaucoma detection based on periocular photography	Glaucoma detection based on periocular photography	There is limited discussion on specific model architecture details. Scalability considerations are not discussed.
39	Classification of ocular diseases using transfer learning approaches and glaucoma severity grading	Classification of ocular diseases using transfer learning approaches	There is limited discussion on the choice of transfer learning approaches and their impact. Scalability challenges not explored.
40	Multimodal imaging-based feature fusion for accurate glaucoma diagnosis with deep learning	Accurate glaucoma diagnosis using multimodal imaging-based feature fusion	There is limited discussion on the specifics of multimodal imaging-based feature fusion. Scalability challenges are not explored.
41	Glaucoma classification using a polynomial-driven deep learning approach	Glaucoma classification using a polynomial-driven deep learning approach	There is limited discussion on the details of the specific polynomial-driven deep learning approach. Scalability considerations are not discussed.
42	Diagnosis of glaucoma on retinal fundus images using deep learning	Diagnosis of glaucoma using deep learning on retinal fundus images	There is limited discussion on deep learning model specifics. Specific performance metrics may not be provided. Scalability considerations not discussed.
43	Artificial intelligence in the diagnosis of glaucoma and neurodegenerative diseases	Use of AI in the diagnosis of glaucoma and neurodegenerative diseases	General discussion on AI applications without specific methods or results. Scalability considerations are not addressed.

IV. RESEARCH GAP

Research in glaucoma detection and diagnosis reveals several notable gaps that warrant further advancement. Firstly, a significant gap exists in the diversity of datasets used to train models. While most current models rely on standard datasets, there is limited exploration of models trained on diverse datasets encompassing varying age groups, ethnicities, and stages of glaucoma. This lack of diversity poses a challenge to the generalisation capabilities of the models. Secondly, the interpretability of deep learning (DL) models remains a concern. Despite their effectiveness, DL models often operate as black boxes, providing limited insight into the reasoning behind classifications. Addressing this gap requires the development of interpretable models that can offer clinicians insights into why specific regions of the optic disk are classified as indicative of glaucoma.

Furthermore, many current models are resource-intensive, rendering them unsuitable for real-time analysis. Research into lightweight models that maintain accuracy while reducing resource requirements is crucial, especially for deployment in resource-limited settings where real-time analysis is imperative. Additionally, there is a lack of research on seamlessly integrating these models into clinical workflows. This includes the detection process, documentation, tracking progression, and effective patient communication, highlighting the need for comprehensive integration strategies. Moreover, the robustness of models against noisy or altered data and their performance under adversarial attacks remains underexplored. Ensuring the resilience of models in such scenarios is essential for their reliability in real-world applications.

Furthermore, longitudinal analysis capabilities are still in the nascent stages. Most current models provide a snapshot diagnosis based on a single image. In contrast, research into models capable of analysing changes in the optic disk over time for predicting glaucoma progression or treatment response is limited. Additionally, leveraging transfer learning or few-shot learning techniques for glaucoma detection is an area that requires further exploration, given the limited availability of annotated medical images. Furthermore, while optic disk localisation and classification are crucial, there is a gap in models that effectively integrate this data with other clinical information, patient history, and additional tests to provide a holistic view for improved diagnosis. Lastly, addressing ethical and privacy concerns surrounding AI in healthcare, including potential biases of models, is essential for ensuring the responsible development and deployment of glaucoma detection systems. Thus, further research is warranted to address these gaps and advance the glaucoma diagnosis and treatment field.

V. ADVANTAGE

The advantages of conducting reviews in glaucoma detection using machine learning and deep learning techniques are manifold. Firstly, these reviews offer a consolidated knowledge base by synthesising findings from multiple studies, providing an overview of the current state-of-the-art techniques, algorithms, and methodologies. Secondly, researchers can perform comparative analyses across various models, datasets, and performance metrics, facilitating the identification of the most effective models. Moreover, reviews can highlight best practices in data preprocessing, feature extraction, model training, and validation, benefiting newcomers and experts in adopting efficient approaches. Furthermore, review gap analysis helps identify areas for further research or improvement in current methodologies.

Additionally, reviews often advocate for standardised datasets, metrics, and evaluation methods, contributing to improved reproducibility in future studies. For clinicians or institutions considering ML/DL adoption for glaucoma detection, reviews are valuable resources guiding them towards the most promising models or algorithms, thus saving time and resources. Moreover, interdisciplinary collaboration is fostered through such reviews, bringing together ophthalmologists, data scientists, and ML experts to work towards common goals. Ultimately, patient benefit is indirectly promoted as reviews highlight the most accurate and efficient models, leading to earlier and more accurate glaucoma detection. Additionally, reviews can pinpoint technological advancements that have led to breakthroughs, guiding future research and development efforts. It’s important to note that comprehensive reviews also acknowledge the limitations of current models, helping to set realistic expectations and informing areas of caution for clinical implementation. Furthermore, they contribute to standard setting by establishing benchmarks and standards for model performance, ultimately pushing the community towards higher accuracy and better clinical relevance. Lastly, insights from such reviews may inspire broader applications in other areas of ophthalmology or other medical specialities, demonstrating the versatility of ML/DL techniques and their potential for transformative impact beyond glaucoma detection.

VI. CONCLUSION

The evolution of machine learning (ML) and deep learning (DL) in medical diagnostics has opened up transformative possibilities, especially in ophthalmology. Our review of ML and DL models for glaucoma optic disk localisation and classification underlines these techniques' immense potential in enhancing the early detection and treatment of glaucoma. Across the reviewed literature, it's evident that advanced algorithms have achieved significant accuracy, with some even surpassing human experts in specific tasks. This is promising, especially when considering the global burden of glaucoma and the importance of early diagnosis in preventing irreversible vision loss. However, it's equally important to acknowledge the existing challenges. The diversity in datasets, the need for larger and more diverse training samples, and the importance of understanding the underlying mechanisms of these black-box models are areas that future research should focus on. Furthermore, translating these models from research settings to real-world clinical environments will require rigorous validation, emphasising generalizability across diverse populations.

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