# AI IN GLAUCOMA

Practical applications for screening, diagnosis, and monitoring.



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The use of AI, particularly deep learning models, has expanded rapidly in ophthalmology during the past decade. Publications on combining glaucoma and AI increased considerably during this period, reflecting a growing interest in applying machine learning methods to imaging, perimetry, and other clinical data. Early work concentrated largely on proof-of-concept algorithms designed to classify eyes as either glaucomatous or healthy. Recently, the focus of research has shifted toward more clinically meaningful applications, such as objective screening, increasing diagnostic accuracy in practice, and the detection of disease progression.

As these systems move from research settings into clinical practice, it is essential to identify both how AI could realistically improve care and its current limitations.

## GLAUCOMA SCREENING

Effective population-based screening programs are limited by the lack of a cost-effective screening test that offers high diagnostic accuracy. Traditional approaches based on IOP measurement or visual field tests have limited sensitivity and specificity in population settings, and many individuals with glaucoma remain undiagnosed until their disease reaches an advanced stage.

For these reasons, imaging-based approaches, particularly fundus photography and OCT, have been explored as potential screening tools. The practical advantages of fundus photography include its relatively low cost, wide availability, and current use in teleophthalmology programs for diseases such as diabetic retinopathy.[1] The interpretation of optic disc photographs for glaucoma detection, however, is subjective and prone to substantial interobserver variability. For example, clinicians may overdiagnose glaucoma in eyes with physiologic optic nerve cupping and miss the disease in eyes with small optic discs. The poor reproducibility of subjective assessment, moreover, limits the effectiveness of photography-based screening.

AI has the potential to address some of these limitations by automating image interpretation and reducing variability. Several deep learning systems trained on large photographic datasets have shown promising diagnostic accuracy.[2,3] Many models, however, rely on human gradings as reference labels, meaning that the algorithms could replicate the same diagnostic biases present in human interpretation.[4]

An alternative strategy is to train models using objective OCT measurements rather than subjective labels. In this machine-to-machine approach, deep learning models learn to predict quantitative OCT-derived structural measurements directly from fundus photographs.[5] This allows photographic screening to retain the accessibility of fundus imaging while leveraging the objectivity of OCT-based measurements, thereby producing continuous estimates of structural damage rather than simple binary classifications. A recent study that applied the machine-to-machine algorithm to population-based data showed promising results.[6]

Future screening strategies may also incorporate multimodal information. Combining imaging-based AI predictions with clinical risk factors or genetic markers, such as polygenic risk scores for glaucoma, could help identify individuals at increased risk of the disease who would benefit from close evaluation. At present, however, these approaches are largely investigational.

Given the relatively low prevalence of glaucoma in the general population, screening tools must maintain high specificity. Even small reductions in specificity can generate large numbers of false-positive referrals. For this reason, AI-based screening systems require careful validation in real-world populations before widespread adoption.

## DIAGNOSIS IN CLINICAL PRACTICE

When diagnosing glaucoma, eye care providers must integrate multiple sources of information, including optic nerve examination findings, OCT parameters, visual fields, and clinical risk factors. The increasing number of available measurements can sometimes create diagnostic uncertainty, particularly when individual parameters disagree. AI might help to address this challenge by analyzing complex datasets and identifying patterns across multiple modalities simultaneously. For example, deep learning models applied directly to raw OCT scans, instead of segmented measurements, could analyze the entire 3D structure of the optic nerve. By evaluating the full image, these systems might reduce errors caused by segmentation artifacts or isolated abnormal parameters.[6]

Similarly, AI methods have been developed to analyze patterns of visual field loss. Graph-based neural networks, for instance, model the anatomic relationships between visual field test locations, reflecting the organization of retinal nerve fiber pathways.[7] These approaches allow algorithms to detect spatial patterns of damage that might be difficult to recognize using traditional pointwise or global indices.

Another practical area where AI could prove useful is quality assessment. Imaging artifacts and segmentation errors are common in OCT scans and can lead to misinterpretation.[8] Automated AI systems capable of detecting poor-quality images or segmentation failures could assist clinicians by flagging unreliable scans before they are interpreted.

Although these AI tools might improve diagnostic consistency, they have significant limitations. Many algorithms are developed using retrospective datasets from single institutions and may not generalize well to other populations, imaging devices, or clinical environments. Additionally, models provide probabilistic outputs rather than definitive diagnoses, so clinical context remains essential.

## THE DETECTION OF GLAUCOMATOUS PROGRESSION

Monitoring disease progression remains one of the most important and challenging aspects of glaucoma management. Both structural and functional measurements change with normal aging, and substantial test-retest variability can obscure true disease progression. Distinguishing these effects from genuine glaucomatous deterioration is often difficult.

AI approaches designed for longitudinal data analysis could help address the challenge. By analyzing measurements repeated over time, machine learning models might be able to identify patterns of structural or functional change that are more consistent with disease progression than with normal aging or measurement noise.[9]

Another promising direction involves integrating multiple sources of information (eg, OCT measurements, visual field tests, and clinical data) into unified predictive models. Because structural and functional changes do not always occur simultaneously, combining these modalities might permit the earlier detection of meaningful disease progression.

Predicting the trajectory of future disease, however, is considerably more difficult than identifying existing damage. Even advanced AI models often show reduced accuracy when attempting to forecast glaucoma development or progression years in advance.[10] This reflects the complex and heterogeneous nature of the disease as well as the limitations of currently available datasets.

## IMPLICATIONS FOR CLINICAL TRIALS

AI could influence the design of glaucoma clinical trials by enabling more sensitive outcome measures.

Traditional trial endpoints may change slowly and require large sample sizes to detect treatment effects. Recent work has explored the use of AI models to identify visual field locations at highest risk of future deterioration. By focusing analysis on these high-risk points, it might be possible to detect meaningful changes more rapidly. For example, an AI algorithm that preselects the five locations in the visual field most likely to experience disease progression—called the *high-5* approach—could yield steeper measurable rates of change than global indices.[11] Such strategies might reduce required sample sizes and shorten the trial duration.

## LOOKING AHEAD

AI has the potential to improve several aspects of glaucoma care—from expanding screening capabilities to enhancing diagnostic accuracy and improving the detection of disease progression. Most currently available systems, however, are research tools rather than routine clinical instruments. Key challenges include ensuring generalizability across diverse patient populations, integrating algorithms into clinical workflows, and demonstrating that AI-assisted decision-making can improve patient outcomes.

AI is a tool designed to complement—not replace—clinical judgment. As these technologies evolve, the most successful applications will likely be those that augment the clinician's ability to synthesize complex information by transforming large volumes of images and functional data into actionable insights for patient care. ■


1. Miller SE, Thapa S, Robin AL, et al. Glaucoma screening in Nepal: cup-to-disc estimate with standard mydriatic fundus camera compared to portable nonmydriatic camera. *Am J Ophthalmol*. 2017;182:99-106.
2. Ting DSW, Cheung CY, Lim G, et al. Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. *JAMA*. 2017;318(22):2211-2223.
3. Li Z, He Y, Keel S, Meng W, Chang RT, He M. Efficacy of a deep learning system for detecting glaucomatous optic neuropathy based on color fundus photographs. *Ophthalmology*. 2018;125(8):1199-1206.
4. Thompson AC, Jammal AA, Medeiros FA. A review of deep learning for screening, diagnosis, and detection of glaucoma progression. *Transl Vis Sci Technol*. 2020;9(2):42.
5. Medeiros FA, Jammal AA, Thompson AC. From machine to machine: an OCT-trained deep learning algorithm for objective quantification of glaucomatous damage in fundus photographs. *Ophthalmology*. 2019;126(4):513-521.
6. Azizi A, da Costa DR, Scherer R, Malek DA, Samico GA, Medeiros FA. RNFL thickness in a population-based cohort: The Canadian Longitudinal Study on Aging M2M (Machine-to-Machine) Study. *Am J Ophthalmol*. 2026;281:395-403.
7. da Costa DR, Unyi D, Scherer R, Muralidhar R, Ribeiro Monteiro ML, Medeiros FA. Convolutional graph isomorphism network to detect glaucomatous visual field defects. *Ophthalmol Sci*. 2025;6(3):101041.
8. Thompson AC, Jammal AA, Berchuck SI, Mariottoni EB, Medeiros FA. Assessment of a segmentation-free deep learning algorithm for diagnosing glaucoma from optical coherence tomography scans. *JAMA Ophthalmol*. 2020;138(4):333-339.
9. Mandal S, Jammal AA, Malek D, Medeiros FA. Progression or aging? A deep learning approach for distinguishing glaucoma progression from age-related changes in OCT scans. *Am J Ophthalmol*. 2024;266:46-55.
10. Thakur A, Goldbaum M, Yousefi S. Predicting glaucoma before onset using deep learning. *Ophthalmol Glaucoma*. 2020;3(4):262-268.
11. da Costa DR, Scherer R, Swaminathan S, Tseng H, Medeiros FA. AI-guided endpoint selection for neuroprotection trials in glaucoma. medRxiv. Preprint August 26, 2025. doi:10.1101/2025.08.23.25334286. Update in: *Am J Ophthalmol*. 2026;284:88-100.



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