

AI IN THE DIAGNOSIS AND TREATMENT OF GLAUCOMA

Sakshi Gandhi^{*1}, Anjali Patel¹, Hemani Mistry¹, Riddhi Gandhi¹, Satyajit Sahoo², Dhananjay B. Meshram³

¹Student, Pioneer Pharmacy College, Ajwa-Nimeta Road, Vadodara, Gujarat, India -390019.

²Associate Professor, Pioneer Pharmacy College, Ajwa-Nimeta Road, Vadodara, Gujarat, India -390019.

³Principal, Pioneer Pharmacy College, Ajwa-Nimeta Road, Vadodara, Gujarat, India -390019.

Article Received: 22 August 2026 || Article Revised: 12 September 2026 || Article Accepted: 02 October 2026

***Corresponding Author: Sakshi Gandhi**

Student, Pioneer Pharmacy College, Ajwa-Nimeta Road, Vadodara, Gujarat, India -390019.

DOI: <https://doi.org/10.5281/zenodo.23233747>

How to cite this Article: Sakshi Gandhi, Anjali Patel, Hemani Mistry, Riddhi Gandhi, Satyajit Sahoo, Dhananjay B Meshram (2026) AI IN THE DIAGNOSIS AND TREATMENT OF GLAUCOMA. World Journal of Pharmaceutical Science and Research, 5(10), 422-434.



Copyright © 2026 Sakshi Gandhi | World Journal of Pharmaceutical Science and Research.

This work is licensed under creative Commons Attribution-NonCommercial 4.0 International license (CC BY-NC 4.0).

ABSTRACT

As the leading cause of permanent vision loss worldwide, glaucoma poses a significant public health problem because it is a condition that progresses slowly and has highly complex multi-modal diagnostic needs. This paper offers a broad review of how Artificial Intelligence (AI) has developed through the clinical spectrum of glaucoma treatment, ranging from initial diagnosis and glaucoma severity, to now personalized treatment planning and surgical guidance. The AI models use deep learning architectures, such as Convolutional Neural Networks (CNNs) and multi-modal transformers, to automatically process intricate diagnostic data like color fundus photography, Optical Coherence Tomography (OCT) scans, visual field perimetry, and Electronic Health Records (EHRs). In addition, predictive algorithms can enable personalized treatment based on the prediction of disease progression rates, intraocular pressure fluctuations and the selection of more appropriate surgical candidates. Although the advantages are clear, there are important obstacles to broader adoption in clinical practice, such as variations in hardware across different devices, risk of bias in the algorithms used by different patient populations, data privacy issues, and the 'black-box' nature of deep learning. Newly developed concepts such as the Explainable AI, the use of wearable sensors for continuous monitoring, and the use of genomic risk profiles are bridging these gaps. In the end, AI is an objective, rapid, clinical decision support tool to assist clinical practice, improve the efficiency of teleophthalmology screenings and protect the patient's visual function.

KEYWORDS: Artificial Intelligence, Glaucoma Screening, Deep Learning, Optical Coherence Tomography (OCT), Retinal Nerve Fiber Layer (RNFL), Cup-to-Disc Ratio, Teleophthalmology, Visual Field Perimet.

1. INTRODUCTION

Artificial Intelligence (AI)

Artificial Intelligence (AI) is a branch of computer science that focuses on creating computer systems that perform tasks which are normally associated with human cognitive abilities. These abilities include natural language translation, complex decision making, speech recognition and visual perception. The ability to ingest, process and analyze vast amounts of structured and unstructured data is at the heart of the modern AI algorithms. Continuous pattern recognition allows AI models to make data-driven predictions, uncover the underlying relationships and continuously update medical knowledge base.^[1]

Overview of Glaucoma

Glaucoma is a collection of chronic, progressive neurodegenerative diseases of the eye that involves the progressive loss of the optic nerve. Structural excavation of the optic disc, loss of the neuroretinal rim border, thinning of the neuroretinal rim/border of the retinal nerve fibre layer (RNFL), and progressive apoptotic death of retinal ganglion cells (RGCs) are key pathological hallmarks. Glaucoma is the leading cause of irreversible blindness and is a huge public health burden worldwide.^[2]

Global Burden and Prevalence of Glaucoma

Glaucoma is rapidly becoming an epidemic problem worldwide. According to epidemiological models, the numbers of people infected with the virus globally would be increasing from 76 million in 2020 to about 112 million by 2040. This disease is usually insidious and initially produces no symptoms, so people may not be aware of it until there is a large amount of permanent, irreparable loss of vision. Glaucoma is a multi-factorial diagnosis that can be made only by a clinical assessment. Relying on data from a wide range of diagnostic techniques, ophthalmologists require an understanding of the interpretation of such equipment. This diagnostic complexity makes an effective resource-poor setting more problematic. In ophthalmology, AI can analyze retinal images and records automatically, aiding in early detection and consistent diagnosis.^[3]

Importance of Early Diagnosis and Timely Treatment

Early clinical interventions are directly related to preventing irreversible blindness due to glaucoma. The ability to detect structural damage early enables the clinician to apply more conservative, less invasive methods of treatment, including topical intraocular pressure (IOP)-lowering drugs, before significant axonal damage is seen. Early detection offers patients the opportunity to take therapeutic lifestyle modifications, such as regular exercise programs, mindfulness training, and personalised nutrition advice. In conjunction with medical adherence, early detection will maintain the long term functional visual fields and health-related quality of life.^[4]

Role of AI in Ophthalmology

Artificial Intelligence is revolutionizing clinical Ophthalmology. AI algorithms analyze multimodal diagnostic data and extract high-order, complex topological features and relationships between topology and function, which might otherwise be missed during routine clinical examination. AI models excel in many other eye diseases besides glaucoma, notably in screening and management of diabetic retinopathy (DR) and age-related macular degeneration (AMD).^[5]

2. Fundamentals of Glaucoma

Definition of Glaucoma

Glaucoma is a clinically and pathologically diverse group of optic neuropathies that can be distinguished by a gradual breakdown of the optic nerve head (ONH), loss of retinal ganglion cells and their axons, progressive thinning of the retinal nerve fiber layer (RNFL), pathological enlargement of the optic excavation, and peripapillary vascular damage.^[6]

Types of Glaucoma

- **Primary Open-Angle Glaucoma (POAG):** Most common clinical form. The anterior chamber drainage angle (between the cornea and the iris) is always open, but the outflow of aqueous humor through the trabecular meshwork is increased. This silent, progressive rise in IOP leads to a progressive optic neuropathy that causes the optic nerve to be damaged over time.
- **Primary Angle-Closure Glaucoma (PACG):** This is closed angle glaucoma that is caused by the iris being pushed forward into the IRAD (iridocorneal filtration angle). The anatomical apposition prevents the aqueous humor from reaching Schlemm's canal, resulting in a sudden rise in IOP which has to be dealt with clinically in an emergency to prevent loss of vision.
- **Normal-Tension Glaucoma (NTG):** A type of POAG in which there is progressive optic nerve damage and characteristic visual field loss despite normal baseline IOPs. Pathogenesis is a combination of microvascular insufficiency, hypoperfusion of the optic nerve or increased susceptibility of optic nerves to mechanical stretch. There are strong correlations between NTG and VRD disorders such as migraines, Raynaud's phenomenon and systemic hypotension.
- **Secondary Glaucoma:** a group of glaucoma in which the increase in IOP and optic neuropathy is due to known secondary intraocular and/or systemic disease. Some of the causes are trauma, chronic intraocular inflammatory disease (uveitis), pigment dispersion syndrome, neovascularization, surgical problems or prolonged use of exogenous cortisone.
- **Congenital Glaucoma:** Rare congenital condition that occurs at birth or infancy as a result of malformation of the TM during embryogenesis. When the aqueous outflow is impaired, there is marked elevation of the IOP in the infant, classical buphthalmos (enlargement of the globe), clouding of the cornea and photophobia. It has been associated with genetic mutations and syndromes like Axenfeld-Rieger syndrome, Aniridia and Neurofibromatosis Type 1.^[7]

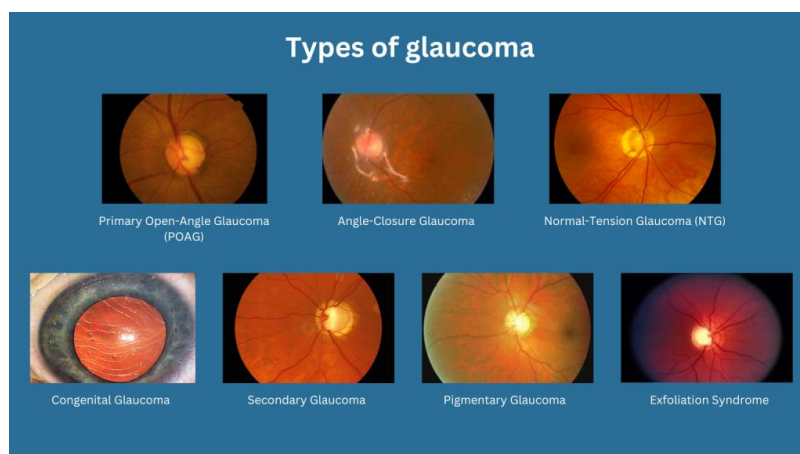


Figure 1: different types of glaucoma.^[8]

Risk Factors of Glaucoma

- Advanced Age: Incidence increases after age 40. Trabecular meshwork sclerosis is an age-related condition.
- Ethnicity: African populations have high rates of POAG and East Asian have high rates of PACG.
- Shallow depth of anterior chamber in females results in increased angle closure patterns (Biological Sex).
- Axial myopia is associated with greater susceptibility to the development of POAG, hyperopia predisposes to PACG.
- Familial Predisposition: 1st degree relatives increase risk of disease up to 9-fold.
- The most important modifiable risk factor for development and progression is Elevated Intraocular Pressure (IOP).
- Systemic Comorbidities: Type 2 diabetes mellitus, systemic hypertension and cardiovascular disorders.
- Pharmacological Exposure: Long-term topical, intraocular or systemic use of corticosteroid medications.⁹

Symptoms and Clinical Signs of Glaucoma

Patient's Symptoms	Clinical Signs
Early: No symptoms whatsoever, but IOP >21 mmHg	Elevated IOP: IOP >21 mmHg, but no symptoms whatsoever (early)
Late: Loss of side (peripheral) vision	Increased Cup-to-Disc Ratio
Tunnel vision (late stage)	Localized RNFL thinning
Bright lights surrounded by halos	Neuroretinal rim notch
Severe eye pain (acute angle-closure glaucoma)	Peripapillary haemorrhages
Headaches, nausea and vomiting	Arcuate visual field defect

Pathophysiology of Glaucoma

The non-pigmented ciliary epithelium of the posterior chamber continually produces aqueous humour. Fluid exits from the pupil through the anterior chamber into the conventional Trabecular meshwork, Schlemm's canal and the episcleral veins. Pathological resistance in these outflow structures leads to accumulation of aqueous, and increases the IOP. From a mechanical perspective, elevated IOP causes shear stress to the lamina cribrosa which leads to structural deformation, blockade of retrograde axoplasmic transport, deprivation of trophic factors, neuroinflammation, and eventual death of retinal ganglion cells via apoptosis of the axons of retinal ganglion cells.^[10]

Complications of Glaucoma

In untreated glaucoma, there is gradual optic nerve atrophy and progressive loss of functions. Peripheral visual field loss progresses to central scotomas, to end stage “tunnel vision” and then to total bilateral blindness. In more advanced cases, it may progress to absolute glaucoma, which is a late stage clinical condition characterized by complete loss of vision, painful globe enlargement, secondary corneal bullae, chronic ocular inflammation.^[11]

3. Conventional Diagnosis and Treatment

Diagnostic Framework

- Medical History & Patient Evaluation: Detailed multi-generational family history, medical history and ocular trauma, comprehensive screening of systemic vascular disease and history of corticosteroid use.
- Tonometry: Goldmann Applanation Tonometry (GAT): Gold standard test for measuring static IOP. Physiological circadian fluctuations require a serial diurnal IOP reading. Values obtained from the diagnosis need to be corrected with reference to central corneal thickness (CCT) measurements.
- Gonioscopy: A diagnostic procedure which involves the use of a gonio-lens with a mirror surface to see the anatomical structures of the iridocorneal angle and to classify it as open- or angle-closure.

- Ophthalmoscopy: Direct and indirect stereoscopic assessment of the neuroretinal rim tissue integrity, disc hemorrhage and vertical cup to disc ratio (VCDR).
- Optical Coherence Tomography (OCT): Non-invasive optical imaging furnishing high resolution cross-sectional tomograms of retinal structure. Measures micro-scale thinning of the RNFL, Ganglion Cell Complex (GCC) loss and depth of lamina cribosa.
- Standard Automated Perimetry (SAP) usually employs central 24-2 and 30-2 threshold patterns, and is used to determine functional retinal sensitivity throughout the visual field to detect early arcuate scotomas.
- Ultrasonic or optical measurement of central corneal thickness (CCT): Pachymetry. Actually, eyes with thin corneas overestimate intraocular pressure and are a possible independent risk factor for disease progression.^[12]

Treatment Paradigms

- Pharmacotherapy: Topical monotherapy is the initial treatment. Uveoscleral outflow is improved with prostaglandin analogs (e.g., Latanoprost). Second line drugs are beta-blockers (Timolol), alpha-2-adrenergic drugs and Carbonic Anhydrase Inhibitors (CAIs) to reduce aqueous production. Some new drugs that inhibit the trabecular meshwork outflow directly, such as Rho Kinase (ROCK) inhibitors.
- Laser Interventions: Selective Laser Trabeculoplasty (SLT) applies laser energy to the cells in the pigmented trabecular meshwork, resulting in a biological remodeling that improves aqueous outflow. SLT is recommended by major guidelines (NICE, EGS and AAO) as an effective first-line therapy along with medical drops.
- Advanced and unmanaged disease – Invasive Surgical Procedures: Recommended. These include Trabeculectomy (Tracyanos scleral filtering bleb), Glaucoma Drainage Device (shunts) and Minimally Invasive Glaucoma Surgery (MIGS) devices which restore normal physiological outflow channels with minimal tissue involvement.
- Long-Term Monitoring: Should involve serial IOP, OCT structural parameter and SAP functional field monitoring over time to detect progressive loss and alter target IOP goals throughout the patient's lifetime.^[13]

4. AI in Glaucoma Diagnosis

Early Detection Approaches

- High-Risk Population Screening: AI algorithms interpret multiple types of data inputs (such as demographic information, family history and fundus images) to identify high-risk groups within community populations and route them to specialist clinical care.
- What is unique about this is that deep learning networks are used to detect micro-structural changes within the optic nerve head, peripapillary RNFL layer, and ganglion cell architecture long before sub-clinical damage occurs, thereby making it easier to detect the structural changes before they cause measurable defects in the visual field.
- Predictive Risk Modeling: Machine learning models combine together clinical risk factors to produce probabilistic forecasts for the risk of developing structural neuropathies based on standardized time frames over a period of time.^[14]

Retinal Image Analysis

- Fundus Photograph Analysis: Deep Convolutional Neural Networks (CNNs) accurately and sensitively detect neuroretinal rim thinning, focal RNFL loss, and optic disc hemorrhages in digital fundus photographs.
- Optic Disc & Cup Segmentation: Semantic segmentation architectures, like UNet architectures, automatically segment boundaries of optic discs and cups, which removes manual tracing variability.

- AI Models can be used for "automated CDR Computation" to generate objective measurements of progressive optic cup expansion over time from segmented masks.
- Computer vision techniques identify localized areas of dark wedges corresponding to axonal bundle dropouts of RNFL, which map early structural insults; Focal RNFL Defect Mapping.^[15]

OCT Image Analysis

- Automated OCT Interpretation: Using deep neural networks, the raw 3D-OCT volumetric data was analysed directly without errors caused by automated layer segmentation failures in highly pathological eyes.
- The deep learning architectures quantify micro-structural parameters like circumferential RNFL thickness, ganglion cell-inner plexiform layer (GCIPL) loss and lamina cribosa displacement to identify early stage of the disease.
- True structural degradation is distinguished from the inherent measurement noise of the machine in real-world OCT data using AI algorithms that overlay longitudinal cross-sections with time.^[16]

Visual Field Analysis

- Automated Perimetry Parsing: Machine learning methods analyze complex SAP sensitivity maps and identify glaucomatous scotomas from generalised sensitivity loss and artifactual variations, as well as cataract.
- Progression forecasting: Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models are used to classify eyes based on longitudinal series of visual fields, and identify those with quick progression.
- Functional Vision Loss Quantification: AI maps the visual field defects directly to the functional metrics of everyday activities, giving direct estimates of patient visual impairment.^[17]

5. AI in Glaucoma Treatment and Management

Personalized Treatment Planning

- Individualized Therapy Selection: AI algorithms compare patient risk profile, structural parameters and comorbidities to suggest the right therapy – medical drop, laser or MIGS.
- Risk-Stratified Management: High risk patients are treated aggressively in a timely fashion, thanks to machine learning models that categorize patients into fast, moderate, or slow progression groups.
- Treatment Response Analytics: Predictive models analyze baseline eye and systemic characteristics to determine what IOP reduction to anticipate with specific classes of topical drugs or surgery.^[18]

Disease Progression Prediction

- Automated Optic Nerve Tracking: Computer vision engines can be used to register and mark small neuroretinal rim lost within multiple-years of serial optic disc photography.
- Visual Field Decay Trajectory: Predictive models based on longitudinal visual field data can be utilized to preemptively adjust the course of treatment in order to prevent mean deviation (MD) loss before it occurs and before central visual acuity is affected.
- Medical Therapy Evaluation: AI algorithms flag patients whose medical management isn't successfully halting structural deterioration, signaling those that need immediate surgery.^[19]

Follow-Up and Remote Monitoring

- **AI-Enabled Teleophthalmology:** Automated triaging of retinal scans captured in the primary care setting using cloud platforms, and routing of suspect cases to sub-specialist evaluation.
- **At-Home Visual Testing:** Deep learning models are used to analyze data from home perimetry platforms, or tablet-based visual testing apps, which can help overcome variable testing environments to monitor functional trends at home.
- **Smartphone Support Apps:** AI applications: track patient medication adherence, medication administration schedule and patient reported symptoms.
- **Wearable Sensor Analytics:** Algorithms analyze real-time IOP data from an IOP sensor on the contact lens or from an intraocular pressure sensor that is placed in the eye, detecting acute elevations in IOP that can damage optic nerve integrity.^[20]

Surgical Decision Support

- **Surgical Candidate Selection:** Risk analytics considered in this section include individual disease trajectory, target IOP requirements, life expectancy and medication tolerance to identify patients that are most likely to benefit from early surgical intervention.
- **Outcome Forecasting Models:** Supervised learning models use pre-operative ocular characteristics and surgical factors to predict the likelihood of surgical success and/or target pressure achievement.
- **Postoperative Bleb Evaluation:** Convolutional models are used to analyse slit-lamp images of post-trabeculectomy filtering blebs, identifying early bleb failure, avascularity or leakage to encourage early intervention.^[21]

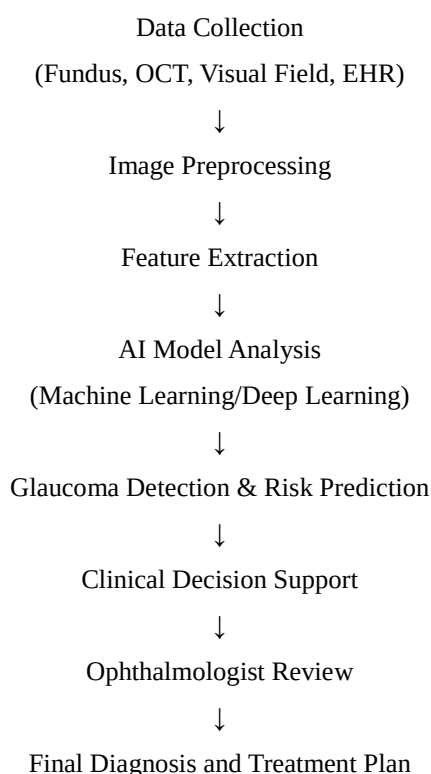
6. Primary Data Sources for AI Models

Data Source	Core Features	Advantages
Fundus Photographs	Optic cup-to-disc ratio (CDR), optic disc morphology, neuroretinal rim notch, RNFL defects	Low cost, non-invasive, and widely available for large-scale screening
OCT Scans	RNFL thickness, GCIPL, GCC, lamina cribrosa measurements	High-resolution imaging with quantitative three-dimensional structural assessment
Visual Fields	Visual sensitivity loss, pattern deviation, mean deviation (MD), visual field progression patterns	Direct assessment of functional vision loss and disease progression
Electronic Health Records (EHRs)	IOP history, demographic information, systemic diseases, medication history	Provides holistic patient information and supports personalized clinical decision-making
Genetic / Biomarker Data	Single nucleotide polymorphisms (SNPs), genetic risk markers, molecular biomarkers	Enables high-precision risk prediction and personalized glaucoma management

- **Fundus Photography:** This is an easily accessible two-dimensional colour image of the optic disc, optic cup and peripapillary area. AI processing is applied to detect CDR, identify focal RNFL loss and detect the boundary of the discs.
- **Optical Coherence Tomography (OCT):** Quantitative measurements of RNFL thickness, ganglion cell-inner plexiform layer (GCIPL) integrity and optic nerve head topography, high-resolution 3D volumetric structural data.
- **Visual Field (VF) Reports:** Threshold maps that are standardized to show mean deviation (MD), pattern standard deviation (PSD), and numeric dB sensitivity results for individual quadrants and grids.

- Structured and unstructured patient data, including previous IOP logs, systemic conditions, systemics medication records, previous ocular interventions, and longitudinal notes, that have been parsed using Natural Language Processing (NLP) as part of Electronic Health Records (EHRs).
- Intraocular Pressure (IOP) Time-Series: Analyze pressures modeled over time, with time-series analytics, for both baseline and post-treatment pressure measurements, and for intraocular pressure (IOP) spikes.
- Patient Demographics: Contextual inputs such as biological age, sex, race, self-reported ethnicity, and family history, all used to make adjustments to baseline risk calculations.
- Genomic and Biomarker Profiles: Polygenic Risk Scores (PRS) and specific genetic polymorphisms associated with glaucoma susceptibility were calculated with clinical features for precision risk modeling.^[22]

7. Operational AI Workflow in Glaucoma Care



- Multimodal Data Collection: Fundus photos, OCT scans, perimetry matrices, IOP logs and EHR metrics are all fed into centralized secure pipelines.
- Image preprocessing/standardization: raw images are preprocessed to optimize contrast, correct illumination, reject images with artifacts, crop around ONH, and normalize, to standardize variation across platforms.
- Automated Feature Extraction: Deep Convolutional Neural Networks extract spatial visual features, and other parallel pipelines calculate other clinical structural variables such as RNFL thickness and CDR.
- Latent features are analysed by using dedicated deep learning architectures (e.g., ResNet, EfficientNet, U-Net) or ensemble networks, to produce diagnostic outputs.
- The model provides binary classification (Glaucoma vs. Healthy), probabilistic suspect scores and classifies the disease severity as mild, moderate or severe.
- Treatment Decision Support Generation: Longitudinal trend analysis of the information to provide individualized target IOP ranges, medical adjustments, or referrals for surgery.

- Longitudinal Tracking & Alerting Systems: Incoming follow-up imaging and functional data are continually compared to the baseline scans, and alerts are sent when significant structural and/or functional loss is detected.²³

8. Comparative Analysis: AI Advantages vs. Implementation Limitations

Advantages of AI in Glaucoma	Limitations of AI in Glaucoma
Pre-symptomatic detection of glaucoma before noticeable vision loss	Algorithmic bias may affect performance in underrepresented populations
Eliminates intra-observer variability and improves diagnostic consistency	Cross-device variability can reduce model generalizability
Rapid image analysis and processing within seconds	Limited interpretability due to the 'black box' nature of many AI models
Supports large-scale screening and teleophthalmology programs	Availability of high-quality annotated datasets remains limited
Integrates multimodal data (fundus images, OCT, visual fields, EHRs) for comprehensive assessment	Regulatory approval and data privacy concerns can hinder implementation
Enables continuous longitudinal monitoring and disease progression tracking	Clinical validation and standardization across healthcare settings are still required

Key Clinical Advantages

- AI models recognise subtle axonal loss and ganglion cell dropouts that are not picked up on by normal perimetry until functional damage can be measured.
- Diagnostic Precision and Consistency: Deep learning models have consistent diagnostic criteria, which reduces the inter- and intra-observer variability in assessing the optic nerve.
- Automated image evaluation significantly cuts down interpretation times to mere seconds, thus optimizing the throughput of the clinical workflow in a busy clinic.
- Scalable Screening for Remote Populations: Use of AI-powered automated screening for population level triage, to increase access to expert level care in rural or under-resourced areas.
- Personalized Care Pathways: Structural, functional and systemic inputs all integrated, personalised progression risk models and personalised therapy plans.
- Automated routine image segmentation and baseline screening reduces the burden for clinicians that can be spent on more complex therapeutic decision making and patient care.^[24]

Implementation Challenges and Limitations

- Dataset Scarcity & Domain Shift: Performance of models are highly reliant on the availability of large and well-annotated training data. Limited availability of a diverse set of ground truth data could lead to poor performance in external clinic populations.
- Hardware & Acquisition Device Variability: When models are not properly domain adapted, performance differences between different hardware platforms such as users of different manufacturers of the OCT or fundus camera can lead to diagnostic errors.
- Algorithmic Bias: Training models using mainly homogenous datasets may result in misclassification in underrepresented individuals who have different baseline optic nerve and retinal pigmentation.
- The black-box nature of interpretability limitations: Deep learning networks often do not have a clear pathway for decision-making, and clinicians are not confident in fully trusting the automatic outputs for irreversible decisions.
- Regulatory & Data Security Hurdles: Adhering to privacy laws (HIPAA, GDPR) and multi-phase validation for regulatory clearance (FDA, EMA) for multi-center data integration.^[25]

9. Real-World Applications and Illustrative Case Scenarios

Screening via Fundus Photography

Community screening programs have portable non-mydriatic fundus cameras with cloud-based AI networks. These systems automatically assess optic disc characteristics, notifying CHWs of individuals at risk of referral to specialists, improving the ability to diagnose at a higher rate in areas that lack specialists.^[26]

Clinical Case 1: AI for detecting primary open-angle glaucoma through OCT

The patient's history was familial glaucoma with slightly high IOP (28 mmHg OU) and was a 58-year-old male.

Clinical Findings: CDRs on both sides were symmetrically enlarged (CDR=0.7) on stereoscopic exam.

AI Tool Integration: Deep learning models were able to detect areas of localized RNFL thinning in the superior and inferior peripapillary RNFL bundles from raw spectral domain OCT volumes.

Early arcuate scotomas were found in the exact location as the structural lesions by the AI model and confirmed by the SAP.

Clinical management: The integrated AI evaluation determined that this patient had moderate POAG, and treatment with topical prostaglandins was started early, as well as automated tracking over time.^[27]

Clinical Case 2: Community Screening & Referral for Early-Stage Glaucoma

Patient's Age: 62 years old female, came to the Vision health screening camp in rural area without any eye history.

Primary Triage: Non-mydriatic colour fundus photos were taken and analysed by an edge-AI model.

The model identified neuroretinal rim thinning and computed an abnormal VCDR of 0.75 and made an automatic specialist referral.

Secondary Evaluation: Specialist examination showed raised IOP (24mmHg) and focal visual field defect.

Result: Early detection led to topical therapy to be started before central vision was affected.^[28]

10. Future Horizons in AI-Driven Ophthalmic Care

- Smart Ophthalmology Clinics: Clinical environments that are integrated with ambient AI elements that provide an all-in-one display of real-time imaging, diagnostic reports, and EHR entries to give doctors in the clinic a consolidated, concise diagnostic summary for patients in their chair.
- Portable & Point-of-Care Diagnostic Edge Devices: Smartphone-mounted fundus cameras and handheld OCT devices with compact AI models to achieve high diagnostic accuracy at point-of-care settings.
- Digital Twin Patient Modeling: Developing a dynamic computational model of the eye of an individual patient based on structural, physiological and pressure dynamics data. These digital twins enable the simulation of disease progression, virtual modelling of surgical options vs. pharmaceutical options, before the treatment of the patient.
- Continuous Monitoring via Wearables: Combining smart contact lenses and implantable sensors with deep learning systems for real-time IOP monitoring throughout the day, to alert users of therapy when pressures increase.
- Explainable AI (XAI): Using feature attribution techniques like visual saliency maps and Grad-CAM overlays to show precise image regions contributing to AI-driven results, fostering clinician trust and facilitating regulatory clearance.

- Genomic Integration & Precision Medicine: Multi-modal deep learning and Polygenic Risk Scores (PRS) for individual risk and targeted therapeutic selection based on genetic susceptibility.^[29]

11. Ethical, Regulatory, and Governance Frameworks

- Patient Privacy & Informed Consent: Ensuring high-quality patient information is securely anonymized and patient informed consent regarding the use of imaging and health data in model training.
- Transparency & Visual Explainability: Demand on XAI architectures to give visual overlays (e.g. heatmaps) together with the diagnostic prediction, providing the physician with a comprehension of the model output.
- Reducing Algorithmic Bias: Ensuring multi-ethnic, multi-center data sets with diverse demographic groups and anatomical variations, to mitigate diagnostic disparities in underserved populations.
- Clinical Validation Standards: Prospective, multi-center real world trials are required to validate model accuracy, safety and applicability in various clinical environments before deployment.
- Regulatory Approval Processes: Regulatory agencies (such as US FDA, European EMA) have all of the following requirements for adaptive algorithms: Clinical evidence of safety; Clinical evidence of efficacy; Ongoing performance monitoring; Version control.
- Human-in-the-Loop Governance: AI platforms need to be used as tools to assist in making decisions, not to make decisions. The final decision on diagnosis, risk assessment and choice of treatment is left to the licensed ophthalmologist.^[30]

12. CONCLUSION

AI is helping to revolutionize glaucoma care from screening to diagnosis, follow-up, and individual treatment. AI can perform the same diagnostic accuracy as expert clinicians, using the advanced deep learning architectures to analyze fundus images, OCT volumes, visual field maps and electronic health records. These platforms allow for larger screening programs, clinical workflow efficiency and uncover early structural degeneration without functional loss. As new technologies, such as point-of-care edge devices, wearable continuous sensors, explainable AI models, and dynamic digital twins evolve, AI will improve access to specialized eye care and help prevent avoidable blindness around the world. Most importantly, AI does not take the place of human expertise; it is a tool to help with it. The ideal clinical model is one that is able to fuse the high speed pattern recognition ability of AI with the caring clinical judgment, comprehensive evaluation and experience of the practicing ophthalmologist.

13. REFERENCES

1. Razavian N, Knoll F, Geras KJ. Artificial intelligence explained for nonexperts. *Semin Musculoskelet Radiol*, 2020; 24(1): 3-11.
2. Weinreb RN, Aung T, Medeiros FA. The pathophysiology and treatment of glaucoma: a review. *JAMA*, 2014; 311(18): 1901-1911.
3. Peng Y, Han L, Jiang Q, Liu J, et al. Global, regional and national burden of glaucoma from 1990 to 2021 and projections to 2050: a retrospective cross-sectional study. *BMJ Open*, 2026; 16(1): e108975.
4. De Francesco T, Bacharach J, Smith O, et al. Early diagnostics and interventional glaucoma. *Ther Adv Ophthalmol*, 2024; 16: 25158414241287431.
5. Rizwan Khan AY, Malik MB. Artificial intelligence in ophthalmology: practical applications, subspecialty evidence and real-world deployment. *Cureus*, 2025; 17(11): e96121.

6. Dietze J, Blair K, Zeppieri M, et al. Glaucoma. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing, 2026 [updated 2024 Mar 16].
7. Tripathy K, Zeppieri M. Open angle glaucoma. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing, 2026 [updated 2024 Mar 7].
8. Shah P. [Image of glaucoma/ophthalmic anatomy]. [Internet]. 2025 [cited 2026 Sep 22]. Available from: <https://www.drparthshah.com.au/wp-content/uploads/2025/01/image1-3.png>
9. Hamid SAT, Abdulmajeed SM, Chowdhury IH, Hasan MM, Noman SM. Risk factors and genetic markers associated with the development and progression of glaucoma: a review. *J Curr Glaucoma Pract*, 2025; 19(4): 216-222.
10. Sunderland DK, Sapra A. Physiology, aqueous humor circulation. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing, 2023 [updated 2023 Mar 12].
11. Dinsdale M, Guajardo-Beroiza JM, Mohamed-Noriega J, Vallabh NA. Optic neuropathies that mimic glaucoma. *Community Eye Health*, 2022; 35(117): 23-26.
12. Ali N, Law S, Patwardhan A. Selected abstracts from The Royal College of Ophthalmologists Annual Congress 2024, Belfast, UK. *Eye (Lond)*, 2024; 38(Suppl 3): 121-201.
13. Alm A. Latanoprost in the treatment of glaucoma. *Clin Ophthalmol*, 2014; 8: 1967-1985.
14. Du K, Zheng Y, Wang Z. Artificial intelligence-integrated multimodal retinal imaging for early detection and risk stratification of systemic vascular and neurodegenerative diseases. *Front Neurol*, 2026; 17: 1885303.
15. Thompson AC, Jammal AA, Medeiros FA. A deep learning algorithm to quantify neuroretinal rim loss from optic disc photographs. *Am J Ophthalmol*, 2019; 201: 9-18.
16. Park SJ, Ko T, Park CK, Kim YC, Choi IY. Deep learning model based on 3D optical coherence tomography images for the automated detection of pathologic myopia. *Diagnostics (Basel)*, 2022; 12(3): 742.
17. David JPF, Rosa AAM, Scherer R, Teixeira CEC, Costa D. Artificial intelligence-based model for the interpretation and reporting of standard automated perimetry. *Arq Bras Oftalmol*, 2025; 88(5): e20240270.
18. Weyant C, Brandeau ML. Personalization of medical treatment decisions: simplifying complex models while maintaining patient health outcomes. *Med Decis Making*, 2022; 42(4): 450-460.
19. Mohammadzadeh V, Wu S, Davis T, Vepa A, Morales E, Besharati S, et al. Prediction of visual field progression with serial optic disc photographs using deep learning. *Br J Ophthalmol*, 2024; 108(8): 1107-1113.
20. Nikolaidou A, Tsaousis KT. Teleophthalmology and artificial intelligence as game changers in ophthalmic care after the COVID-19 pandemic. *Cureus*, 2021; 13(7): e16392.
21. Hassan AM, Rajesh A, Asaad M, et al. Artificial intelligence and machine learning in prediction of surgical complications: current state, applications, and implications. *Am Surg*, 2023; 89(1): 25-30.
22. Chen WS, Ko YC, Chen YC, Lu HH. Artificial intelligence-assisted glaucoma detection on color fundus images: with comorbidity and cross-institutional analysis. *J Chin Med Assoc*, 2025; 88(10): 747-759.
23. Sun S, Cai CX, Fan R, et al. Multimodal prediction of visual improvement in diabetic macular edema using real-world electronic health records and optical coherence tomography images. *medRxiv [Preprint]*. 2026 Apr 24.
24. Hassan B, Raja H, Hassan T, et al. A comprehensive review of artificial intelligence models for screening major retinal diseases. *Artif Intell Rev*, 2024; 57: 111.
25. Schäfer R, Nicke T, Höfener H, et al. Overcoming data scarcity in biomedical imaging with a foundational multi-task model. *Nat Comput Sci*, 2024; 4(7): 495-509.

26. Natarajan S, Jain A, Krishnan R, Rogye A, Sivaprasad S. Diagnostic accuracy of community-based diabetic retinopathy screening with an offline artificial intelligence system on a smartphone. *JAMA Ophthalmol*, 2019; 137(10): 1182-1188.
27. Carlà MM, Gambini G, Baldascino A, Boselli F, et al. Large language models as assistance for glaucoma surgical cases: a ChatGPT vs. Google Gemini comparison. *Graefes Arch Clin Exp Ophthalmol*, 2024; 262(9): 2945-2959.
28. Schuman JS, De Los Angeles Ramos Cadena M, McGee R, Al-Aswad LA, et al. A case for the use of artificial intelligence in glaucoma assessment. *Ophthalmol Glaucoma*, 2022; 5(3): e3-e13.
29. Rabbani SA, El-Tanani M, Sharma S, Rabbani SS, El-Tanani Y, Kumar R, et al. Generative artificial intelligence in healthcare: applications, implementation challenges, and future directions. *BioMedInformatics*, 2025; 5(3): 37.
30. Barucci A, Colcelli V, De Masi S, et al. Ethical and regulatory frameworks for artificial intelligence in clinical research: a European perspective on the Artificial Intelligence Act for ethics committees and researchers. *Eur Cardiol*, 2026; 21: e01.