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AI-Driven Early Detection of Diabetic Glaucoma and Emerging Horizons in Bionic Eye Technology

Gaurav Tiwari[1]*, Ankita Wal[1], Raghuraj Singh Suryavanshi[2], Rishi Shukla[1], Muzammil Khan[1], Brijesh Kumar Chaurasia[2]

[1]PSIT-Pranveer Singh Institute of Technology (Pharmacy), NH-19, Kanpur, Uttar Pradesh 209305, India
[2]Department of Computer Science & Engineering, Pranveer Singh Institute of Technology, National Highway, NH-19, Kanpur, Uttar Pradesh 209305, India

***Correspondence Author:**
Dr. Gaurav Tiwari, Professor,
PSIT- Pranveer Singh Institute of Technology (Pharmacy), National Highway, NH#19, Bhauti, Kanpur, Uttar Pradesh-209305, India.
ORCID: 0000-0003-2200-737X
Email ID: drgauravtiwari81@gmail.com

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Abstract

Background: Diabetic glaucoma is a serious eye disorder that can lead to permanent vision loss and is increasingly seen in individuals with long-term diabetes. With its rising global incidence, there is a critical need for early and reliable methods of detection to prevent severe complications. **Objective:** This study highlights the growing role of artificial intelligence (AI), especially deep learning technologies, in identifying diabetic glaucoma at an early stage. It also reviews progress in bionic eye technologies designed to help restore vision in affected individuals. **Methods:** Relevant scientific literature was reviewed by searching databases including PubMed, Taylor francis, ScienceDirect, MDPI, and Bentham. Articles published up to 2025 were considered, focusing on terms such as "diabetic glaucoma," "retinal imaging," "deep learning," "AI in eye care," "bionic eye," and "neuroprosthetics." Studies were selected based on their relevance to diagnostic innovations and vision-restoration technologies. **Results:** Recent developments in AI have enabled more accurate interpretation of retinal images, such as those from fundus cameras and optical coherence tomography (OCT), aiding in early detection of structural changes linked to glaucoma. At the same time, bionic eye systems—based on neuroprosthetic implants—are showing promise in partially restoring vision in cases of severe visual impairment. **Conclusion:** Combining AI-powered diagnostics with emerging bionic eye technologies represents a major shift in managing diabetic glaucoma. These innovations have the potential to improve early detection and offer new options for visual rehabilitation, paving the way for more effective patient care in ophthalmology.

Keywords Diabetic glaucoma, Artificial intelligence, Retinal imaging, Deep learning, Bionic eye, Visual prosthesis

1. Introduction

Glaucoma remains the second leading cause of irreversible blindness worldwide and is especially common among people with diabetes. Its development in diabetic patients is complex, largely driven by chronic high blood sugar, which damages the small blood vessels in the retina, raises intraocular pressure (IOP), and gradually leads to degeneration of the retinal nerve fiber layer (RNFL) and optic nerve. The two main forms seen in diabetes are primary open-

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angle glaucoma (POAG) and neovascular glaucoma (NVG), both of which present significant diagnostic challenges. Early changes in vision or retinal structure can be subtle and are often masked by overlapping damage from diabetic retinopathy [1].

Machine learning (ML) and deep learning (DL), two major advancements in artificial intelligence (AI), have become powerful tools for the early detection and diagnosis of diabetic glaucoma. These AI algorithms are trained on large datasets of OCT scans and retinal fundus images. As a result, they can now detect early signs of the disease with impressive accuracy, often outperforming human specialists in both sensitivity and consistency [2]. These technologies have the ability to raise patient outcomes and enable earlier leadership by recognizing glaucomatous damage before significantly higher vision loss starts.

At the same time as diagnostic innovations, therapeutic improvements like bionic eye technology are growing in popular. These devices use bioelectronic components and brain stimulation techniques to assist individuals with severe retinal degeneration repair functional vision. Bionic eyes, involving the new cortical implants and the Argus II retinal prosthesis, show especially promise for people with end-stage glaucoma for whom traditional therapies are inadequate. These technologies, and that remain in the preclinical and clinical trial stages, represent a frontier in visual neuroproteins with ongoing research aimed at improving visual resolution, biocompatibility, and brain integration (Figure 1).

This review examines the at present state of bionic eye technologies and potential future orientations, additionally worrying the revolutionary role of AI in detection and monitoring. It also looks at the clinical and the pathophysiology features of diabetic glaucoma. together all of these developments mark a paradigm shift in the knowledge, diagnosis, and management of diabetic glaucoma, offering those who have it hope for early intervention and visual rehabilitation [3, 4].

2. Essential Perspective on AI Application in Imaging and Medicine

By enabling more rapid more precise, and more personalized diagnosis and treatment in fields as radiology and pathology, AI has changed medicine, particularly in the field of medical imaging. AI tool integration into clinical workflows has the possibility to significantly enhance healthcare efficiency and quality. AI fundamentally involves machines copying human brain processes like learning, reasoning, and decision-making. Machine learning and deep learning, in particular convolutional neural networks (CNNs), are crucial to evaluating complex medical images like retinal scans, MRIs, and X-rays. However, unlike human experts, AI models were able to "understand" these

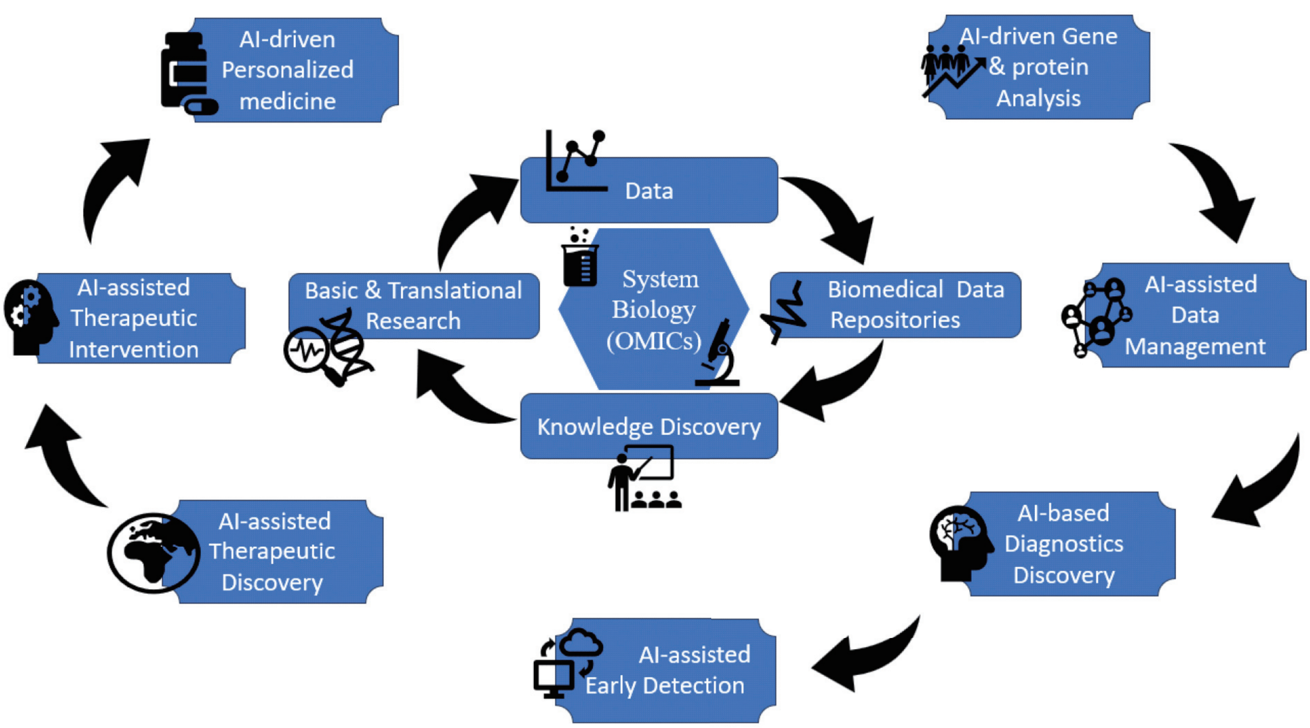

Figure 1. AI-Driven Workflow in Systems Biology and Precision Medicine

pictures or medical ideas; rather they find statistical patterns and relationships in huge datasets that physicians would not see. AI is quite powerful for this data-driven strategy, but it also heavily relies on high-quality and variety of the training data. AI technologies' accuracy and scalability rely substantially on large-scale, well-labeled datasets that include multiple types of patient demographics, illness stages, and imaging techniques.

Data biases can restrict model performance or even worsen healthcare inequities. Examples of these biases include the overrepresentation of specific clinical diseases or ethnicity. In addition, AI systems trained in a particular setting failed to operate as well in another due to variations in imaging tools and methods throughout institutions, highlighting the necessity for varied, representative datasets to create strong, dependable AI applications [5].

Because a lot of deep learning models serve as ‘black boxes’, which generate predictions without obvious explanations, transparency and interpretability still are big problems for medical AI. To trust and employ AI ideas properly in an area like medicine, where decisions can have life-or-death consequences, practitioners require interpretable outputs. To enhance physician adoption and regulatory monitoring, the explainable AI community is developing methods that elucidate how models reach their results—e.g., visual heatmaps that emphasize the image regions pertinent to a task. If AI is to really benefit health care, it must seamlessly integrate in today’s processes. Tools that clash with day-to-day work or require significant manual input often face adoption barriers. Rather than replacing human judgment, AI should ideally augment physicians’ capabilities by offering assistance with screening, organizing and decision support. Equally important is presenting AI output information in an intuitive clear way, allowing for rapid interpretation and medico-legal decisions. Today’s processes AI needs to easily fit into today’s processes if it is going to have a meaningful impact on healthcare. Tools that are disruptive, because they don’t work with existing tasks, or require a lot of manual input, have barriers to adoption. Instead of taking the place of human judgment, AI should ideally enhance physicians' ability by helping with screening, organizing, and decision support. Ensuring that the AI-generated data are simple, interpretable, and rational that allow quick answer and medical decisions is also important. Ethical and legal dilemmas are central when it comes to using AI in health. High privacy and security standards (e.g., GDPR and HIPAA) have to be respected to ensure the privacy of patients, as medical data are sensitive and confidential [6,7]. Furthermore, for the equitable provision of healthcare to diverse populations, developers should also work together to minimize bias in AI models. only based on (standard) static approval process, regulatory bodies are moving toward adapting their frameworks to manage particular issues related to AI. Among these challenges is that of necessary adaptive forms of oversight, which would need to accommodate the capability of AI systems to learn and improve even after deployment. Even as AI makes strides, it remains fundamentally broken. In order to maintain clinical safety and effectiveness, deployed models must be constantly monitored, acknowledged, and acted upon as warning signs to avoid false positives and negatives such as in rare and complex cases. To offer truly personalized medicine, it may be such as combining imaging data with genetic, clinical and lifestyle information.” Moreover, expanding the application of AI to cutting-edge fields such as neuroprosthetics and dynamic rehabilitation technologies, could further increase patient outcomes [8–10].

3. Approaches using artificial intelligence for detecting diabetic glaucoma

Millions of individuals worldwide are living with diabetes mellitus, a long-term metabolic condition that can lead to diabetic glaucoma, an unsafe eye consequence. This disorder is born out of the convergence of glaucoma and diabetic retinopathy, two main causes of vision loss. When high IOP, or vascular and metabolic changes carried on by diabetes damage the optic nerve, it can induce diabetic glaucoma, which, if unregulated, can cause slow irreversible visual impairment or blindness. Early diagnosis is important to prevent visual loss from diabetic glaucoma. But early stages of diabetic glaucoma can have no symptoms, or few ones that are easily overlooked; and commonalities of diabetic retinopathy (DR), such as retinal vascular abnormalities, could complicate the manifestation, and result in a difficult differentiation.

IOP measurement, funduscopic confirmation of optic nerve head (ONH), visual field testing to detect function loss, and imaging techniques such as OCT for visualization of structural changes in the retinal nerve fibre layer form part of conventional diagnostic algorithms. Although effective these techniques require special equipment and skilled interpretation. In addition, early diagnosis remains challenging in many regions with limited access to ocular specialists [11]. In this situation, AI is a promising tool that has a chance to transform diabetic glaucoma screening. AI, specifically ML and DL, uses a big data of clinical information and images to detect patterns that potentially describe evidence of early glaucomatous damage. These methods can interpret complex imaging, such as fundus images, OCT scans, and visual field reports, frequently detecting abnormalities that are not visible to human observers [12]. By automating the process of image interpretation, AI has the potential to improve the accuracy of diagnosis, decrease interobserver variability, and pave the way for large scale screening, to include under-served patient populations.

More broadly, leveraging AI to diagnose diabetic glaucoma represents a trend in healthcare towards precision medicine-- where personalized risk assessment and treatment are enabled by data-driven solutions. Nonetheless, AI needs broad, high quality datasets and careful testing in clinical environment in order to realize those potential benefits. Ethical considerations such as algorithmic fairness, data privacy and patient privacy must also be considered to facilitate safe and equitable deployment. With these advancements in mind, the application of AI in diagnosing diabetic glaucoma holds significant promise for transforming early detection, enhancing patient care, and ultimately reducing the burden of blindness associated with this complex condition. However, it remains crucial to explore how these emerging computational approaches can reshape ocular management by addressing the underlying pathophysiology, diagnostic challenges, and the role of AI-based tools in diabetic glaucoma [13].

3.1. AI in Early Detection of Diabetic Glaucoma

3.1.1. Role of Retinal Imaging and OCT

Given that they afford precise identification of important ocular structures associated with disease processes, retinal imaging and OCT have entirely transformed the diagnosis and treatment of glaucoma. The ONH, RNFL, and macula are the primary affected structures in glaucoma. These structures are critical and early targets for the diagnosis of glaucomatous damage. High-resolution fundus photography provides clear optic disc images for healthcare providers to examine glaucomatous optic neuropathy signs, such as increased cup-to-disc ratio, a decrease in neuroretinal rim, and optic dischaemorrhages. OCT, on the other hand, allows quantitative, cross-sectional measures of the macular ganglion cell complex and RNFL thickness to be captured, which has helped investigators in identifying subclinical, early structural losses predetermining functional visual field constraints. This characteristic is of special benefit to the detection of normal-tension glaucoma and early glaucoma because the disease may be present with a normal intraocular pressure, a situation in which conventional screening methods are usually inadequate. OCT programs have implications in both diagnosis and monitoring the disease process given their precise quantification and reproducibility, allowing for more tailored and timely treatment approaches [14]. The implementation of retinal imaging and OCT in AI systems has also transformed the management of glaucoma by improving the speed and accuracy of diagnosis. Artificial intelligence models trained on large retinal image datasets are able to detect glaucomatous damage earlier and more accurately as they can pick up subtlears and early structural changes outside the range of human perception (Figure 2). These emerging AI technologies show great promise for glaucoma screening, particularly in low-resource settings where access to specialized expertise is limited. Tools such as OCT and fundus photography play a vital role in this effort, as the integration of high-resolution retinal imaging with advanced computational analysis enables earlier diagnosis, more accurate risk assessment, and more cost-effective disease management—all with the ultimate goal of preserving vision.

3.1.2. Fundus Photography

Fundus photography is a fundamental imaging modality that has been widely used for the diagnosis and monitoring of glaucoma, for which it plays a crucial role by presenting vital visual information of the retina, ONH, and surrounding vasculature. By providing two-dimensional, colour images of the posterior pole, fundus photography allows clinicians to visualize and record the glaucomatous changes that occur within the optic disc and its surrounding retinal tissues. One of the diagnostic features of glaucoma that can be observed using fundus photography is optic disc cupping, which is defined as elevation of the cup-to-disc ratio (CDR). This is accompanied by ongoing axonal degeneration of retinal ganglion cell axons and progressive thinning of the neocortical rim, which results in the central depression (or “cup”) of the optic nerve head expanding relative to the entire disc area. Longitudinal CDR changes are crucial to achieve progression determination of the disease [15].

Fundus photography also facilitates to identify neuroretina rim thinning that frequently proceeds functional vision field defect. As glaucoma progresses, the rim (protective nerve fibers around the edge) thins, the way it thins can suggest the kind and degree of

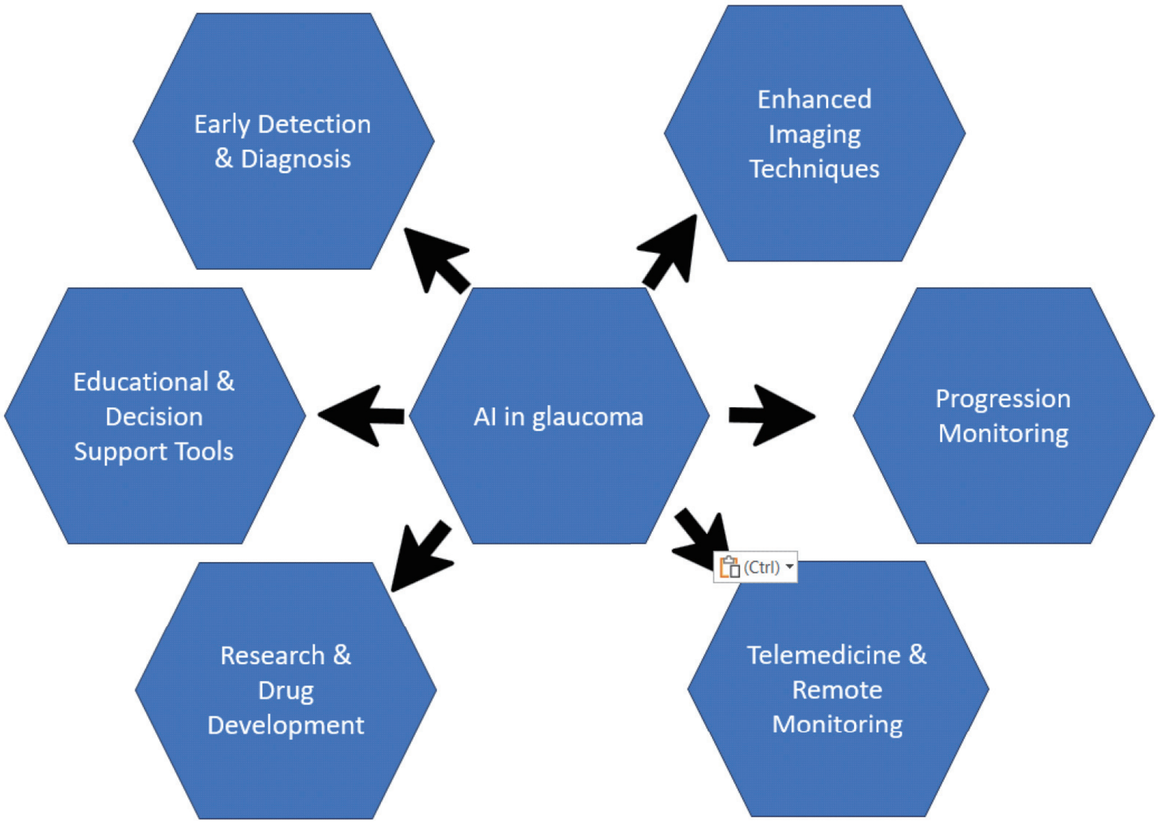

Figure 2. AI-Driven Innovations in Glaucoma Diagnosis and Treatment

glaucoma. Another common finding among glaucoma patients is periphery atrophy, which presents as an area of Chori retinal atrophy and retinal pigment epithelium surrounding the optic nerve head on a fundus image [16]. It is associated with glaucomatous optic neuropathy (GON), and it has been associated with the stage and nature of the disease.

Due to its non-invasive nature, short capture time and low cost, it is an ideal tool for use in community wide comprehensive glaucoma screening programs, particularly in low-resource settings. The screening can even be carried out in mobile units or community clinics - thanks to fundus cameras, which are simpler and more available than more sophisticated imaging techniques such as optical OCT. This makes early detection very easy and is very important as one can then be tested early enough leading to early intervention, since glaucoma itself does not generally have symptoms until it is at advanced stages.

The Uvea and Fundus Photography Advances in digital imaging and telemedicine also have significantly extended the usefulness of fundus photography. The storage, transmission and analysis of digital images at remote locations allows teleophthalmology consultations and AI-based screening programmes. AI-infrastructure that is capable of accurately detecting glaucomatous features such as peripapillary atrophy, rim thinning, and an elevated cup-to-disc ratio may be trained on a large number of fundus photographs. This might improve diagnostic consistency and decrease inter-operator difference in subjective clinical judgment [17].

The fundus photography is a helpful option in the diagnosis and treatment of glaucoma because it can contribute to a comprehensive visual assessment of the optic nerve head structure as well as changes of the peripapillary. Due to its ease of use, wide availability, and compatibility with modern AI technologies, fundus photography has become a critical tool in the global fight against glaucoma, enabling early detection and timely intervention before irreversible vision loss occurs.

3.1.3. OCT

OCT has gained popularity as an imaging modality helpful in the diagnosis and monitoring of glaucoma. It uses cross-sectional, high-resolution scans of the retina and optic nerve head that are acquired with near-infrared light waves. This non-invasive approach to assessing the key anatomical structures involved in glaucomatous optic neuropathy enables both rapid diagnosis and accurate monitoring of disease progression [18–20]. One of the most crucial factors seen with OCT in the evaluation of glaucoma is the thickness of the RNFL. Unmyelinated RGC axons converge at the optic nerve head to create RNFL, which sends visual data to the brain. Because the RNFL thins in glaucoma, these axons eventually vanish. OCT gives doctors a precise, repeatable measurement of the area around the optic disc, which enables them to identify any small alterations that could be occurring before obvious visual field loss. RNFL loss, a hallmark of glaucomatous damage, is a crucial biomarker for both detecting and tracking the course of the illness.

In addition to RNFL analysis, OCT assesses the Ganglion Cell Complex (GCC), which is made up of the inner plexiform layer, retinal ganglion cell (RGC) layer, and nerve fibre layer within the macula. Given that a sizable portion of RGCs is observed in the macular region, GCC analysis adds context to RNFL findings and can be especially helpful in the early detection of glaucoma. It has been demonstrated that alterations in GCC thickness, which contribute to ganglion cell death, correlate with functional impairment in glaucoma patients.

OCT can also provide a detailed view of the optic nerve head's architecture, particularly the lamina cribrosa, a sieve-like connective tissue structure through which RGC axons leave the eye. Structural alterations in the lamina cribrosa, such as posterior displacement, thinning, or focal defects, are implicated in glaucomatous optic nerve injury and axonal damage (Table 1). Advanced OCT imaging techniques, including enhanced depth imaging (EDI) and swept-source OCT, enable better visualization and quantification of lamina cribrosa changes, providing insights into the biomechanical effects of elevated intraocular pressure and other pathogenic mechanisms [21].

The high-resolution, objective, and quantitative nature of OCT imaging enhances its clinical utility in glaucoma management. It allows early identification of structural damage before functional deficits become apparent on standard automated perimetry.

Table 1. OCT-Derived Quantitative Biomarkers in Glaucoma Diagnosis and Monitoring

OCT-Derived Quantitative Biomarker	Description	Clinical Utility
RNFL Thickness	Measurement of the thickness of the nerve fiber layer around the optic nerve head.	A widely used and popular parameter for glaucoma diagnosis and monitoring progression. Thinning is a key indicator of glaucomatous damage.
Macular GCC Thickness	Measures the combined thickness of the macular RNFL, ganglion cell layer (GCL), and inner plexiform layer (IPL).	Macular parameters can be superior for detecting early glaucoma, especially in cases of high myopia. A key biomarker due to the high concentration of retinal ganglion cells in the macula.
Ganglion Cell-Inner Plexiform Layer (GCIPL) Thickness	Measures the thickness of the GCL and IPL.	The GCIPL and inferior GCIPL have been shown to have the best diagnostic value for glaucoma. Asymmetry across the horizontal raphe is a good indicator of early glaucoma.
ONH Parameters	Includes measurements like cup volume, cup diameter, and neuroretinal rim thinning.	These parameters are able to differentiate between healthy and glaucomatous eyes, and are correlated with structural damage.
Lamina Cribrosa (LC)	A fenestrated collagenous structure that is the primary site of retinal ganglion cell injury.	Enhanced-depth imaging (EDI) OCT allows for in-vivo examination of the LC, with changes in its morphology, deformation, and vascular perfusion serving as biomarkers.
Peripapillary Retinal Nerve Fiber Layer (cpRNFL)	Specific measurement of the circumpapillary RNFL.	Useful in the early detection of glaucoma, though measurements can be affected by individual variations like myopia.
Inner Plexiform Layer (IPL) Thickness	Measurement of the IPL thickness.	May serve as a biomarker to detect impairment of retinal ganglion cell function in early glaucoma, as morphological alterations in RGC dendrites might be seen in pre-perimetric and early glaucoma.

Moreover, serial OCT scans enable precise monitoring of disease progression, facilitating timely adjustments in therapy to prevent irreversible vision loss. The integration of OCT data with AI and machine learning algorithms further augments glaucoma care by improving diagnostic accuracy and risk stratification. AI systems trained on large OCT datasets can detect subtle patterns of RNFL and GCC thinning, predict progression, and assist clinicians in decision-making, especially in challenging cases such as normal-tension glaucoma or atypical optic nerve appearances [22].

OCT provides a comprehensive, non-invasive means of assessing critical retinal and optic nerve structures affected in glaucoma. Its ability to measure RNFL thickness, GCC integrity, and optic nerve head morphology, including lamina cribrosa status, makes it a cornerstone of modern glaucoma diagnosis and monitoring. By facilitating early detection and precise tracking of glaucomatous damage, OCT plays a vital role in preserving vision and improving patient outcomes (Table 2).

AI tools can now detect glaucoma with sensitivity >90% using only fundus photos or OCT scans, often outperforming general ophthalmologists in early-stage diagnosis.

3.2. DL and CNNs

CNNs, a subclass of deep learning algorithms, have transformed medical image analysis. Their specific capacity to automatically extract and learn hierarchical visual characteristics from retinal pictures makes them especially well-suited for ophthalmic applications. CNNs have proven to have outstanding diagnostic capabilities in the detection of diabetic glaucoma and other retinal pathologies. For important pathological markers like vascular abnormalities, RNFL thinning, and optic disc cupping- markers of glaucomatous damage and diabetic retinopathy—reported area under the curve (AUC) values frequently surpass 0.90. The layered architecture of CNNs—comprising convolutional, pooling, and fully connected layers—stands in contrast to traditional machine learning models, which rely on handcrafted features and domain-specific knowledge. This structure allows them to progressively learn complicated patterns by starting with low-level elements like edges and textures and working their way up to high-level features like blood vessel morphology or optic disc structure. Such a feature hierarchy is helpful in identifying traces of clinical symptoms that may not be apparent to the unaided eye or a conventional diagnosis, particularly in situations that are early stage or overlap, like diabetic glaucoma. The rise of CNN-based approaches involved the presence of large annotated datasets such as Eyepatch (heavily used for diabetic retinopathy detection), RIM-ONE (Retinal Images for Optic Nerve

Table 2. Imaging Modalities Ideal for AI Integration in Glaucoma and Their Benefits

Imaging Modality	Description	AI-Relevant Benefits
OCT	Cross-sectional imaging of retina and optic nerve	High-resolution data; layer segmentation; ideal for structural damage detection
Fundus Photography	2D images of the retina and optic disc	Widely available; large datasets; enables deep learning for optic nerve head analysis
Scanning Laser Ophthalmoscopy (SLO)	High-contrast retinal imaging using laser scanning	Detailed visualization of nerve fiber layer; aids in precise feature extraction
OCT-Angiography (OCT-A)	Non-invasive imaging of retinal and choroidal microvasculature	Provides vascular biomarkers; useful for detecting perfusion changes in glaucoma
Visual Field Testing (SAP)	Measures functional vision loss across the field of view	Enables AI to correlate structural-functional loss; prediction of disease progression
Ultrasound Biomicroscopy (UBM)	High-frequency ultrasound imaging of anterior segment structures	Structural input for angle-closure diagnosis; enhances anatomical interpretation
Corneal Topography/ Tomography	Maps corneal shape and curvature	Useful for detecting secondary glaucomas; supplementary input for comprehensive AI models
Anterior Segment OCT	Visualizes structures in the anterior chamber (e.g., angle, iris, lens)	High-definition input for angle-closure glaucoma; integration with clinical decision tools

Evaluation) and ORIGA (Online Retinal Fundus Image Database for Glaucoma Analysis) that have significantly contributed to the increase in CNN performance in ophthalmology, by providing representative and diverse image sets pair for supervised learning. These data have allowed CNN models to also generalize across differing populations and imaging conditions, having overall more robustness and translational efficacy.

Moreover, transfer learning—a technique where models pretrained on large, generic image datasets like ImageNet are fine-tuned on retinal data—has further improved model performance in settings where domain-specific datasets are limited (Figure 3) [23]. In ophthalmic AI applications, CNN-based models have been integrated into tools capable of segmenting optic nerve head boundaries, classifying the cup-to-disc ratio, detecting microaneurysms or neovascularization, and even predicting disease progression. Additionally, recent innovations such as attention mechanisms and hybrid models combining CNNs with recurrent layers or transformers are pushing the boundaries of performance and interpretability. CNNs have drawbacks despite their great accuracy; they frequently operate as "black boxes," providing no insight into their decision-making procedures, which makes clinical adoption difficult. Because of this, explainable AI frameworks that superimpose heatmaps or saliency maps to show which areas of the image affected the model's prediction are becoming more and more popular. These frameworks are crucial for gaining the trust of clinicians and obtaining regulatory approval (Table 3). Nonetheless, the application of CNNs in ophthalmology represents a significant advancement in automated diagnosis, with potential to democratize eye care, support early detection in underserved regions, and reduce the burden on overextended healthcare systems. Their continued evolution—alongside improvements in dataset diversity, interpretability, and multimodal integration—positions CNNs as a cornerstone of AI-driven solutions for complex ocular conditions such as diabetic glaucoma [24] (Table 4).

3.2.1. Fundus-AI in telemedicine: Cloud-based glaucoma screening

The integration of fundus-AI technology into telemedicine platforms is transforming the screening process for glaucoma by facilitating remote, cloud-based analysis of colour fundus pictures. This technology is particularly useful for the early diagnosis and treatment of this eye-threatening condition. Preventing permanent vision impairment requires prompt detection of glaucoma, which is characterised by progressive optic nerve injury that is sometimes only discovered after severe structural loss. In many

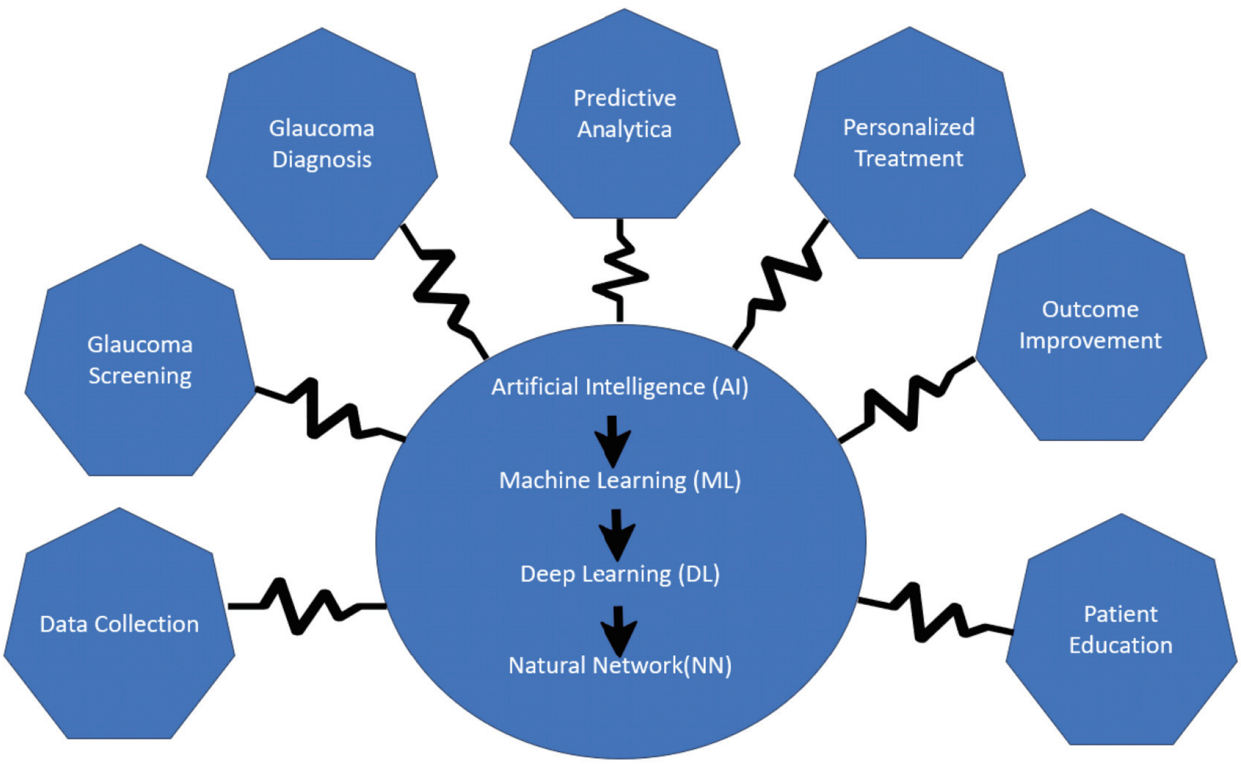

Figure 3. Application of AI/ML in Glaucoma Screening and Treatment.

Table 3. CNN-Detectable Glaucoma Features and Their Clinical Significance

CNN-Detectable Feature	Description	Clinical Significance
CDR	Ratio of the diameter of the optic cup to the entire optic disc	Increased CDR (>0.6) is a hallmark of glaucomatous optic neuropathy
Neuroretinal Rim Thinning	Loss of rim tissue around the optic nerve head	Early sign of glaucoma; especially significant in the inferior and superior regions
RNFL Defects	Focal or diffuse RNFL loss in fundus images	Indicates axonal damage and progression of glaucoma
Peripapillary Atrophy (PPA)	Atrophic changes around the optic disc	Often associated with glaucomatous damage; more common in myopic eyes
Optic Disc Hemorrhage	Flame-shaped hemorrhage at the disc margin	A strong predictor of glaucoma progression
Asymmetry in CDR Between Eyes	Unequal cup-to-disc ratio between the two eyes	Inter-eye asymmetry (>0.2) may suggest glaucomatous damage
Vessel Bending at Cup Edge	Blood vessels bend sharply into the optic cup	Associated with deepening of the cup and glaucomatous excavation
Bayonetting of Blood Vessels	Sharp angulation of blood vessels over the edge of the cup	Indicates advanced glaucomatous cupping
Laminar Dots Visibility	Exposure of lamina cribrosa within the optic cup	Sign of severe optic nerve head damage
Paracentral Visual Field Defects (*via indirect inference*)	Early glaucomatous field loss inferred from fundus and OCT patterns	Critical for early detection when central vision is still preserved

Table 4. Representative CNN Architectures in Glaucoma Diagnosis

CNN Architecture	Use/Benefit in Glaucoma Diagnosis
AlexNet	Used for glaucoma classification, achieving high accuracy on retinal fundus image datasets.
VGG, ResNet, MobileNet	Common architectures used for transfer learning in glaucoma detection from fundus images. They are effective for feature extraction and classification.
YOLO (You Only Look Once)	Used as a component in a two-step system to first detect the optic disc region in fundus photographs, and then classify it as glaucomatous or non-glaucomatous.
U-Net	Primarily used for segmenting the optic disc and optic cup, which is a crucial step in calculating the cup-to-disc ratio (CDR) for glaucoma screening.
GlauNet	A new CNN architecture specifically designed for glaucoma diagnosis using OCT-angiography (OCTA) imaging.
Hybrid Models	Combine CNNs with other deep learning techniques like Bidirectional Long Short-Term Memory (BiLSTM) or Vision Transformers (EViT) to leverage different feature types (e.g., spatial and temporal) for improved performance.
Custom 2D CNNs	Shallow CNN architectures can be designed with a few convolutional layers to be computationally efficient for real-time glaucoma diagnosis from fundus images.

places, access is limited by the requirement for specialised equipment and interpretation, which restricts the application of conventional screening methods. These challenges are addressed by fundus-AI systems that use deep learning algorithms trained to identify glaucomatous changes such as increased cup-to-disc ratio, neuroretina rim thinning, and peripapillary atrophy directly from fundus images. Internal validation experiments of these AI models have proved its great diagnostic accuracy (89.7%) and area under the curve of the receiver operating characteristic (AUC) of 0.93, with excellent sensitivity and specificity values in detecting glaucoma suspects. External validation in diverse populations has confirmed the robustness of these algorithms with an AUC of 0.85 and accuracy of 83.5%, thus highlighting their generalizability in clinical settings [25].

Images of the fundus are taken in the primary clinic or at a screening site and then securely transmitted to a cloud server as done in the telemedicine framework that utilizes cloud computing to facilitate remote assessment. These photos are then automatically analyzed by an AI system, which flags any individuals displaying signs that may suggest they have the potential to develop glaucoma. This computerized triage significantly lessens the burden on ophthalmologists. It also enables to diagnose at-risk patients early and conduct further examinations and intervention more objectively. Telehealth platforms such as Fundus-AI would lower barriers for individuals of low socioeconomic status or living in rural areas to be screened in communities with limited access to eye care specialists and without on-site expert evaluation [26].

Moreover, since it also facilitates the use of commercial fundus cameras rather than more expensive imaging equipment such as optical coherence tomography, this approach allows a cost-effective and scalable glaucoma screening in resource limited regions. Fast turnaround time for AI analysis also enhances the efficiency of clinical workflow through the potential for immediate referral and start of therapy before irreversible damage to the optic nerve. The data privacy and patient confidentiality measure of these systems is fundamental for retaining patient trust and ensuring compliance to healthcare law [27].

In conclusion, Fundus-AI integrated in telemedicine systems provides a robust method for glaucoma screening, which combines the performance of AI-based image evaluation with the convenience of an application for remote healthcare service. Such a technology is very promising and likely to revolutionize glaucoma detection worldwide, improve early diagnosis, prevent vision loss, and decrease the public health burden related to this chronic eye condition [28].

3.2.2. Smartphone-based offline AI screening in India

These challenges can be effectively tackled using Fundus-AI systems, which employ deep learning algorithms trained to identify glaucomatous changes—such as an increased cup-to-disc ratio, neuroretinal rim thinning, and peripapillary atrophy—directly from fundus images. Internal validation studies of these AI models have demonstrated strong diagnostic performance, achieving an AUC of 0.93 and an accuracy of 89.7%, along with excellent sensitivity and specificity in detecting glaucoma suspects. Type 2 DM risk prediction in addition, four external validations in different populations have verified the stability of the models, where AUC was 0.85 and accuracy of 83.5%, respectively, demonstrating the generalization characteristics of these risk prediction models in a real scenario [29].

Images of the fundus captured at primary care clinics or screening locations are securely transmitted to cloud servers, which are part of the telemedicine framework's cloud computing for remote image interpretation. By automatically scanning these photos, the AI system notifies those with symptoms that could be indicative of glaucoma. This computerized triage significantly reduces the burden on ophthalmologists and also makes it possible to detect patients at risk earlier and provide them with comprehensive eye exams and intervention. Fundus-AI telemedicine strategies overcome these health disparities by increasing screening coverage in low-income rural communities and by minimizing the need for on-site specialist examination [30].

Additionally, since this method requires only accessible fundus cameras rather than more advanced imaging techniques such as optical coherence tomography, it promotes low-cost glaucoma screening and is adaptable to resource-poor areas. Rapid turnaround for AI analysis also maximizes the clinical workflow to the overall benefit of allowing early referral and therapy to be started before the optic nerve is greatly damaged. Information security and patient privacy procedures are important for these systems to gain patient trust and ensure compliance with healthcare regulations [31, 32]. Combining the convenience of telehealth-based care delivery with the precision of AI-enhanced image analysis, telemedicine platforms-based Fundus-AI represents a powerful glaucoma screening tool. Such technology has great potential for changing the current paradigm of glaucoma diagnosis worldwide, and could contribute to the early detection of the disease, which in turn prevents vision impairment and subsequently reduces public health problems related to this chronic eye disease (Table 5).

3.2.3. Limitations and Ethical Considerations

Although AI-based tools for glaucoma screening and diagnosis hold significant promise, there are several limitations and ethical considerations that must be carefully considered to deploy these tools safely, equitably, and effectively. A first issue is the generalizability of AI models to varying populations and imaging devices. A large number of algorithms

Table 5. AI-Powered Platforms in Glaucoma Detection: Settings & Performance

Platform	Modality	Setting	Performance
Google DeepMind + Moorfields	OCT scans	Clinics/hospitals	94.5% accuracy in detecting diseases
IDx-DR (Digital Diagnostics)	Fundus photos	Primary care, retail clinics	87% Sens, 90% Spec for DR; now expanding
Cloud-based fundus-AI (telemedicine)	Fundus photos via cloud	Remote clinics	AUC 0.93 internal; AUC 0.85 external
Offline smartphone AI	Smartphone fundus	Community/rural outreach (India)	93.7% Sens, 85.6% Spec for referable glaucoma

are learned and tested from demographic or imaging system-specific data that potentially preclude their performance to other populations with distinct ethnic, anatomical or clinical conditions, or with different equipment and acquisition protocols. Such non-generalizability may contribute to diminished diagnostic accuracy and clinical utility in real-world (e.g., underserved or globally diverse) populations. The issue of algorithmic bias is closely connected, as this phenomenon occurs when training datasets are biased against specific social groups. If AI systems are based on data from one population (say people of European descent), they could be less accurate when it comes to spotting glaucoma in other racial or ethnic groups, making disparities in health worse instead of better. Another important concern is the interpretability (or transparency) of many AI-models, especially based on deep learning. These so-called "black box" systems only produce a diagnostic output but do not explain it, this resulting in a very difficult trust and verification path for clinicians. This lack of transparency raises concerns not only for clinical oversight, but also for regulatory authorization and the concept of patient consent. In addition, the application of AI systems in telemedicine and cloud seems to face the challenges on data safety and patient privacy. Retinal images and patient health information are sensitive medical records that should be processed in compliance with privacy regulations like HIPAA or GDPR. Patient trust and legal compliance can be weakened due to the risks of data breach, unauthorized access and misuse of data, particularly while data is exchanged and stored in cloud infrastructures. However, there is a need for transparency of how data is collected, processed and used, who has contributed to it, and what are the mechanisms for consent, anonymization and auditability as well as of the mechanisms for ethical deployment. Finally, the use of AI tools should not foster over-reliance or de-skilling of human administrators, but rather that AI should be a complement to, and not a replacement for, human clinical judgement. In summary, while AI holds transformative potential in glaucoma care, addressing these technical, ethical, and regulatory challenges is essential to ensure its equitable, trustworthy, and clinically sound integration into ophthalmic practice [33-36].

4. Artificial intelligence approaches to evaluate prognostication, treatment response and survival in Diabetic Glaucoma

Diabetic glaucoma represents a significant intersection of two chronic, vision-threatening conditions: diabetes mellitus and glaucoma. Characterized by elevated intraocular pressure, retinal ischemia, and progressive optic nerve damage, diabetic glaucoma often poses diagnostic and prognostic challenges due to its complex and multifactorial pathophysiology. Traditional clinical approaches to assess disease progression, treatment response, and long-term outcomes rely heavily on periodic imaging, visual field testing, and clinician expertise—methods that can be limited in predictive accuracy and scalability.

AI, especially ML and DL, has performed impressively in the past few years with potential to transform the management of glaucoma. By analyzing a vast amount of data from images, electronic health records (EHR), and clinical notes, AI models can approximate surgical specifics, evaluate the effectiveness of therapy, predict the pathological progression, and personalize individualized care. These technologies include CNNs for optic disc imaging and a survival model such as DeepSurv and random survival forests (RSF), which offer early intervention and improved clinical decision-making. AI may be able to integrate multiple clinical variables to augment prognostication and facilitate long-term visual preservation particularly in the setting of diabetic glaucoma for which systemic metabolic influences the ocular outcomes [37].

4.1. Prognostication & Progression Prediction

AI models are increasingly used to predict the progression of glaucoma, including the likelihood and timing of glaucoma surgery. For example, survival models such as DeepSurv, RSF, and Gradient Boosting Survival (GBS) applied to structured EHR data achieved strong predictive performance—DeepSurv reached a C-index of ~0.775 and mean AUC ~0.80 in forecasting progression to surgery. Important predictive features included age, baseline visual acuity, intraocular pressure, and use of multiple glaucoma medications, which aligned with clinician judgment [38]. Another study combined structured EHR features with free-text clinical notes via deep learning and NLP techniques. The combined model achieved an AUC of ~0.899 and F1 score ~0.757 in predicting near-term progression, outperforming models using only structured data or only text [39]. Key predictors included IOP, visual acuity, medication regimens, and terms from clinical notes indicating urgency or risk of surgery.

4.2. Treatment Response & Surgical Outcome Prediction

Machine learning and deep learning models have also been applied to predict treatment and surgical outcomes in glaucoma. At Stanford, ML models (including Random Forests and CNNs) were used to predict surgical failure—defined by inadequate IOP reduction, increased medication use, or need for revision. These achieved accuracy of ~75% and AUROC up to ~76%, with better performance for IOP outcomes (AUROC ~86%) than for medication changes (~70%). These predictive models can inform personalized surgical planning and patient counselling [40].

4.3. Predicting Diabetic Glaucoma Changes

Earlier neural network research specifically targeted ocular changes in patients with both diabetes and glaucoma. Simple feedforward and recurrent networks—for instance Jordan–Elman neural networks—were trained on clinical parameters such as cup-to-disc ratio, HbA1c, intraocular pressure, and visual field mean deviation. These models predicted progression with up to 95% accuracy for direct modelling and ±15% confidence intervals for predicting visual field decline [41] (Table 6).

4.4. Imaging-Based Prognostication

Beyond EHR data, AI-driven imaging approaches are being explored to predict progression or treatment response. Deep learning models analyses of optic nerve head focal notching and RNFL thinning via fundus segmentation achieve glaucoma detection accuracy of over 90%. While not explicitly focused on diabetic glaucoma, similar approaches could be adapted to quantify and predict progression in diabetic populations [42].

4.5. Explainability & Trust

AI survival models traditionally have lower interpretability. Yet, techniques like Shapley values and cumulative hazard curve visualizations help model transparency. Studies highlight explainable features such as age, visual acuity, and medication usage—mirroring clinicians' risk factors and boosting trust in AI predictions. Similarly, models incorporating clinical text used explainability tools like Grad-CAM to emphasize predictive note phrases such as "urgent referral [43].

5. The Bionic Eye: Future Vision Restoration

The bionic eye, or visual prosthesis, is a state-of-the-art innovation designed to restore functional vision in people affected by advanced degenerative retinal disorders. Conditions such as retinitis pigmentosa (RP) and age-related macular degeneration (AMD) involve

Table 6. AI Methodologies and Outcomes in Diabetic Glaucoma Prognostication

Task	AI Methodology	Key Outcomes
Progression to Surgery	DeepSurv, RSF, GBS survival models	C-index ~0.775, AUC ~0.80
Near-term Progression Risk	Structured + NLP deep learning models	AUC ~0.899, F1 ~0.757
Predicting Surgical Failure	Random Forest, CNN prediction models	Accuracy ~75%, AUROC up to 86% for IOP outcomes
Diabetic Glaucoma Progression	Feedforward/Jordan-Elman ANN models	Up to ~95% accuracy in progression prediction
Imaging-based Prognosis	CNNs for optic cup–disc segmentation	Glaucoma detection AUC >90%

the gradual loss of photoreceptors—rods and cones—ultimately causing severe vision loss and blindness. Crucially, while these diseases damage photoreceptors, the inner retinal neurons, optic nerve, and visual cortex may remain anatomically intact, providing a foundation for artificial stimulation. By utilizing this residual neural circuitry, bionic eye systems generate artificial visual signals, allowing patients to perceive light patterns and regain partial visual function [45].

The working principle of the bionic eye begins with visual scene capture using an external imaging device, typically a miniature video camera attached to glasses worn by the patient. The images are processed in real time by a portable processor, which converts them into electrical stimulation patterns. These signals are then transmitted wirelessly to an implantable microelectrode array surgically positioned on the retina (epiretinal or subretinal) or, in some designs, directly within the visual cortex. The electrodes stimulate remaining functional retinal ganglion cells or, alternatively, higher visual centers such as the lateral geniculate nucleus or primary visual cortex [46, 47]. The brain interprets this stimulation as phosphenes—flashes or spots of light—which the patient progressively learns to decode into rudimentary visual information.

Several types of bionic eye systems have been developed and tested in clinical settings. Among the most well-known is the Argus II Retinal Prosthesis System (Second Sight Medical Products), which uses an epiretinal implant with 60 electrodes and has received regulatory approval in Europe and the United States. The PRIMA system (Pixium Vision) represents a subretinal approach, placing a photovoltaic chip beneath the retina to convert pulsed near-infrared light into electrical currents that stimulate bipolar cells. Meanwhile, the Gennaris Bionic Vision System (developed by Bionic Vision Technologies in Australia) explores a cortical implant strategy for patients who lack a functional retina altogether. Each of these systems offers unique advantages and challenges. Retinal implants are more natural in preserving the visual pathway but require a functional optic nerve, while cortical systems can bypass retinal damage but demand more complex neurosurgical procedures and pose greater risks [48-50].

While current-generation bionic eye devices do not restore vision to normal levels, they can significantly improve spatial orientation, object localization, and navigation for individuals who are otherwise completely blind. Patients using these systems often describe perceiving outlines of objects, high-contrast edges, or motion, which aids in mobility and independence. However, several limitations persist. The resolution of current prosthetic vision is low, typically limited to coarse pixel arrays, and the learning curve for interpreting artificial visual stimuli can be long and demanding. Power consumption, biocompatibility, long-term implant stability, and individualized adaptation to neural variability remain active areas of research [51].

To overcome these limitations, recent efforts focus on integrating ML and AI into the visual processing units of bionic systems. AI algorithms can optimize image preprocessing, enhance contrast, detect key objects in the visual field, and translate scenes into simplified, interpretable visual patterns tailored to each user's perceptual capacity. Moreover, advances in neuromorphic engineering—which mimics biological neural processing—promise more efficient, low-latency, and energy-saving solutions for real-time visual information encoding. Future iterations may also incorporate closed-loop feedback, where real-time cortical responses inform adjustments to stimulation parameters for more natural visual perception [52].

In conclusion, the bionic eye offers transformative potential for patients with irreversible retinal degeneration, providing a viable pathway to partial visual restoration in cases where conventional therapies fail. As this field evolves, the convergence of neural interface technology, AI-driven processing, and precision medicine will play a pivotal role in enhancing the effectiveness, personalization, and accessibility of visual prosthetic systems. Continued interdisciplinary collaboration between ophthalmology, neuroscience, bioengineering, and computer science is essential to bring these innovations from experimental labs to widespread clinical reality [53].

5.1. Bionic Eye Works

In glaucoma—a neurodegenerative eye disease characterized by the progressive loss RGCs and damage to the optic nerve—vision loss is typically irreversible, particularly in advanced stages where significant portions of the optic nerve and associated RGCs have degenerated. In such cases, conventional treatments aimed at lowering IOP are no longer effective in restoring lost vision [54]. The advent of bionic eye technologies offers a potential breakthrough for patients with end-stage glaucoma by bypassing the damaged visual pathway and directly stimulating the remaining functional components of the visual system to restore a rudimentary form of sight. The bionic eye system operates through a multi-step process designed to mimic the natural visual pathway. First, visual input capture is achieved using external glasses fitted with a camera that records real-time video of the environment. This input is transmitted to an external signal processing unit, which processes the visual scene by extracting key features such as shapes, edges, and motion. The unit then converts this information into encoded electrical signals optimized for neural stimulation.

In the electrical stimulation stage, these signals are wirelessly transmitted to an implanted microelectrode array (MEA), which is strategically placed either on the retinal surface (epiretinal), beneath the retina (subretinal), or in some advanced designs, directly into the visual cortex. In glaucoma, where photoreceptors may still be intact but RGCs are compromised, the approach typically focuses on stimulating surviving RGCs or bypassing them entirely by targeting the visual cortex [55-57]. Once implanted, the MEA delivers precise electrical pulses to activate the remaining RGCs or cortical neurons. This neuron activation mimics the natural signalling that would have been generated by healthy photoreceptor-RGC interactions. These artificial signals are then transmitted via the intact portions of the optic nerve—if still functional—or directly to the brain in cortical systems.

Finally, in the perception formation phase, the brain interprets these electrical signals as visual stimuli, resulting in the perception of phosphenes—flashes or patterns of light. Though this does not restore normal vision, it enables users to recognize shapes, perceive movement, and navigate environments with greater autonomy [58]. For patients with advanced glaucoma and extensive optic nerve damage, cortical bionic systems may offer the most promise, as they bypass the eye entirely. While still experimental and limited in resolution, bionic eye technologies hold great potential for restoring functional vision in glaucoma patients with otherwise untreatable blindness (Table 7).

Future advancements in bionic eye technology, particularly for glaucoma patients who suffer from irreversible vision loss due to RGC or optic nerve degeneration, will depend on overcoming several key engineering and biomedical challenges. A primary focus is on improving visual resolution, which remains limited in current systems. Most bionic eyes can only produce low-resolution images consisting of coarse shapes or flashes of light (phosphenes), due to the limited number of electrodes in the MEA. Enhancing electrode density while maintaining spatial selectivity is essential for delivering more precise and localized electrical stimulation. This would enable users to perceive more detailed visual scenes, better recognize objects, and navigate complex environments with greater independence. However, increasing electrode count must be balanced with power consumption, thermal safety, and signal cross-talk, which pose engineering constraints [59].

Another promising direction is the development of closed-loop stimulation systems. In current open-loop designs, the stimulation patterns are pre-programmed and do not adjust based on user feedback or neural response. In contrast, closed-loop systems aim to incorporate real-time feedback from the brain or remaining visual pathways, allowing the device to modulate stimulation parameters dynamically. Such adaptive systems would significantly enhance visual function by personalizing stimulation patterns based on the patient's neural response, fatigue levels, or environmental context [60]. Implementing this requires integration of neural recording capabilities into the implant, as well as sophisticated signal processing algorithms capable of interpreting and

Table 7. Types of Visual Prostheses: Mechanisms and Notable Devices

Type	Implant Location	How It Works	Notable Devices or Trials
Retinal – Epiretinal	On the inner surface of the retina (above RGCs)	External glasses capture images; microelectrodes stimulate RGCs directly.	Argus II system (~60electrode array)
Retinal – Subretinal	Beneath photoreceptors, near bipolar cells	Photodiode chip converts captured light into electrical signals, stimulating deeper retinal layers.	Alpha IMS, PRIMA (photovoltaic implants)
Suprachoroidal	Between choroid and sclera	Electrode array placed less invasively; signals delivered to RGC via external camera.	Experimental devices in clinical trials
Cortical	Direct stimulation of the visual cortex	Bypasses eye and optic nerve; ideal when optic pathways are nonfunctional.	Orion (Second Sight), Debelle's cortical implant

responding to complex brain activity.

Biocompatibility and long-term stability of implanted components are also critical engineering concerns. The materials used in electrode arrays and implant casings must minimize the risk of inflammation, fibrosis, or rejection while maintaining consistent performance over many years. Advances in biomaterials and coating technologies can reduce immune responses and enhance electrical conductivity. Furthermore, ensuring mechanical durability in the dynamic environment of the eye or brain is essential to prevent device degradation or malfunction [61].

Thermal safety is another consideration, especially as devices become more complex and power-intensive. Excessive heat generation from continuous stimulation or wireless data transfer could damage surrounding neural tissue. Therefore, thermal management strategies such as passive heat dissipation structures and efficient circuitry are necessary.

Future of bionic eyes in glaucoma management lies in achieving higher resolution, real-time adaptive stimulation, and long-term biocompatibility and safety. These innovations will be crucial for transitioning bionic vision from basic light perception to meaningful, functional sight for patients with end-stage glaucoma.

5.2. Types of Bionic Eye Systems

Bionic eye systems are emerging as a revolutionary approach to restoring some degree of visual function in patients with end-stage glaucoma, where conventional treatments are no longer effective due to irreversible loss of RGCs and optic nerve damage. A variety of bionic eye systems—targeting different parts of the visual pathway—have been developed or are in advanced stages of research to address these complex needs. Retinal implants, such as the Argus II (by Second Sight, now under Cortigent), are designed to sit epileptically, on top of the retina, above the remaining RGCs. This system was approved in the EU in 2011 and the U.S. in 2013 for use in patients, with over 350 individuals implanted. Users reported improved light perception, motion detection, and basic navigation abilities, with about 60% showing significant visual improvements compared to only 5% when the device was turned off. However, the system offered limited resolution—only 60 electrodes producing roughly 60 phosphene points of light—and a relatively high adverse event rate (26%). Production ceased in 2020, but legacy support continues under Cortigent. While Argus II has not been approved specifically for glaucoma, it provides a foundational technology for future retinal prosthetics in glaucoma patients with partial RGC survival [62].

The PRIMA implant by Pixium Vision represents another class of retinal prosthetics—subretinal implants. These devices are placed beneath the photoreceptors and use photovoltaic stimulation powered by infrared light projected from smart glasses. In a clinical trial involving patients with AMD, a 2 mm chip improved visual acuity from around 20/450 to 20/160 in most participants, with some reaching 20/63 when using magnification features. PRIMA's ability to provide "form vision"—recognition of shapes and patterns—rather than just basic light flashes, represents a significant advancement and holds potential for glaucoma cases where outer retinal layers remain functional.

For advanced glaucoma with significant optic nerve damage, optic nerve and cortical implants are of greater interest. The Bionic Vision Australia consortium and its commercial spin-off, Bionic Vision Technologies, have explored suprachoroidal and epiretinal implants targeting residual optic nerve pathways. Their "Diamond Eye" system, incorporating biocompatible diamond electrodes, aims to reduce power consumption and improve stability. Initial prototypes have been tested in seven patients since 2012, with ongoing clinical evaluations for broader deployment [63]. In cases where both the retina and optic nerve are severely compromised—typical in late-stage glaucoma—cortical implants offer the most direct route to visual restoration. The Monash Vision Group's Gennaris system places an implant on the visual cortex, bypassing the eye entirely. Supported by Australia's MRFF "Cortical Frontiers" program, this technology is preparing for first-in-human trials. It targets completely blind individuals, including those with glaucoma, by stimulating the brain's visual processing centres directly.

Similarly, Neural ink's Blind sight project focuses on a cortical neural interface. It has received FDA Breakthrough Device designation and aims to begin human trials by late 2025. This system aspires to restore basic vision in totally blind individuals, including those with glaucoma, although current technology still produces grainy, low-resolution images. Challenges such as precise cortical mapping, long-term implant stability, and safe surgical procedures remain significant [64] (Table 8). While bionic eye systems were initially developed for retinal degenerative diseases, innovations in retinal, optic nerve, and cortical prostheses offer promising new avenues for restoring functional vision in glaucoma patients. These technologies, although still in developmental stages for glaucoma-specific use, mark

Table 8. Comparison of Different Bionic Eye Technologies

Implant Type	Systems	Target Patients	Vision Quality	Stage
Retinal (epiretinal)	Argus II	RP with intact optic nerve	Light/motion, basic shapes (60 electrodes)	Commercial (Argus II discontinued)
Retinal (subretinal)	PRIMA	Dry AMD with preserved inner retina	Form vision, improved acuity (~20/160)	Clinical trials
Suprachoroidal	BVA/BVT prototypes	RP, AMD	Early-stage; pending trials	Pre-commercial clinical
Cortical (surface)	Monash Vision Group (Gennaris)	Optic nerve/retina loss, glaucoma	Undetermined; upcoming trials	Preclinical → human trials ahead
Cortical (intracortical)	Neural ink “Blindsight”	Complete blindness	Low resolution; early data	Human trials expected late 2025

a transformative shift in how vision loss.

5.3. Integration with AI and Computer Vision

Integration of AI and computer vision is rapidly advancing the functionality of bionic eye systems, especially in enhancing visual perception for glaucoma patients with profound vision loss. AI algorithms can pre-process visual input captured by the external camera, identifying and emphasizing critical features such as edges, contrast, object outlines, and motion—elements essential for spatial awareness and navigation. This data is then translated into optimized electrical stimulation patterns, improving the clarity and relevance of the visual signals delivered to the brain. Through computer vision, dynamic scene analysis (e.g., object recognition, facial detection, obstacle avoidance) can be incorporated, allowing the system to prioritize important stimuli in real-time [65]. Moreover, AI enables user-specific adaptation, learning from behavioural feedback to refine image simplification and stimulus delivery. In combination, these innovations can transform crude phosphene-based perception into functionally meaningful vision, significantly improving independence and quality of life for individuals with end-stage glaucoma (Table 9).

6. Challenges and Future Directions in AI-Enhanced Prosthetic Vision for Glaucoma

Even some of the best performing dependent AI-based prosthetic vision systems for glaucoma patients are not without limitations which restrict their efficacy as well as utility. The main barrier is the low-spatial resolution of currently available implants, which highly limits the information that can be transferred. Moreover, the low electrode number still limits the level of detail and clarity of the images perceived, and users still struggle to interpret complex environments properly even if processed with state-of-the-art AI-based preprocessing and object recognition algorithms. Real-world conditions are also highly varying, which further complicates the problem. Variations in lighting, occlusion, and messy background can degrade the efficacy of AI-based algorithms to accurately detect and classify objects. Even though the use of an adaptive pre-processing suppresses these effects to some extent, the development of robust models that can be used as is across a wide range of situations is a continuous research goal.

This idea of personalization is also important, and incredibly messy. AI systems will need to learn and adapt continually to the particular preferences, context, and operational objectives of specific users. A sub problem to achieve this and is developing efficient feedback and reinforcement learning which can customize the recognition output without increasing the user fatigue or the computational overhead. Ethical considerations are a major concern in the development of such systems, as they often use cloud computing and data sharing to provide model updates and improvement. Maintaining system responsiveness while handling sensitive visual information securely and privately is a difficult task both technically and legally [66, 67].

Where we're headed Vision into the future is increasingly focused on enhancing implant resolution via higher-density electrode arrays and better spatial selectivity to provide even richer visual inputs for AI to work with. Progress in neuromorphic computing and edge AI could allow for real-time processing on the device, decreasing latency and reliance on cloud computing. Furthermore, multimodal integration, for instance, integrating AI enhanced prosthetic vision with auditory or haptic perceptions, may also enhance the perception and interaction of users.

Table 9. Comparative Overview of AI Techniques for Diabetic Glaucoma Detection and the Emerging Role of Bionic Eye Technologies

Section	Key Aspect	Details	Examples/ Models	Advantages	Limitations	Future Directions
Diabetic Glaucoma	Definition & Pathophysiology	Combination of diabetic retinopathy (DR) and glaucomatous damage due to elevated IOP and microvascular changes		Understanding the overlap improves diagnosis - More complex disease management	Often asymptomatic in early stages - Requires multimodal imaging	Personalized medicine using AI biomarkers
Diagnostic Techniques	Traditional methods	Visual field testing, OCT, fundus photography, tonometry	- Humphrey Visual Field Analyzer - OCT Spectralis	Clinically validated High accuracy in clinical hands	Expensive Subjective interpretation - Not scalable	AI-assisted image reading for mass screening
AI Approaches for Detection	Machine Learning (ML)	Algorithms trained on imaging & clinical data	SVM, Random Forest, KNN	Good for small to medium datasets	Feature engineering needed Less robust for noisy data	Hybrid ML + DL models
	Deep Learning (DL)	End-to-end learning from images (fundus, OCT, etc.)	CNNs, ResNet, VGG16, U-Net	High accuracy Feature extraction automatic	Needs large datasets Black-box nature	Explainable AI Federated learning
Multimodal Imaging + AI	Integration of modalities	Combine OCT, fundus, and clinical data	Multistream CNNs, Attention-based models	Better accuracy Reduces false positives	High data complexity Inter-modality variation	Multimodal data harmonization
AI Tools & Datasets	Common datasets used	Public datasets for training/ validation	DRIONS-DB, RIM-ONE, REFUGE, APTOS	Benchmarking possible Enables reproducibility	Limited diabetic glaucoma-specific data	Need for diabetic glaucoma-specific datasets
Clinical Implementation	Deployment in practice	AI tools used in clinics and screening programs	IDx-DR, Google DeepMind, EyeArt	Scalable Remote screening possible	Regulatory and ethical hurdles Data bias issues	Real-world validation studies
Ethical and Regulatory Considerations	Bias, interpretability, privacy	Ensuring fairness and patient safety	GDPR, HIPAA, FDA-AI guidelines	Patient data protection - Clinical trust	Regulation lagging behind tech	Adaptive AI governance frameworks

Bionic Eye Technologies	Overview & goal	Restore vision via retinal implants or cortical interfaces	Argus II, PRIMA Bionic Eye, Gennaris System	Vision restoration Useful in advanced stages	Limited resolution - Requires surgery - High cost	Integration with AI for closed-loop feedback
	AI in Bionic Eye	Adaptive processing & scene recognition	Neuromorphic chips, DL-based scene analysis	Real-time adaptation Personalized image reconstruction	Power consumption Real-time processing constraints	Brain-AI interfaces Energy-efficient processors
Comparative Prospects	AI Detection vs Bionic Eye	Non-invasive early detection vs invasive restoration	-	Early intervention vs quality-of-life enhancement	Detection can't restore vision Bionics not suitable for early-stage	Convergence: Smart implants that detect & adapt
Future Trends	Integration & Innovation	AI-enhanced bionic vision, cloud-based diagnostics, bio-AI fusion	-	Personalized, accessible, and smart ophthalmic care	Interdisciplinary challenges	Digital twins AI-bionic synergy platforms

Ultimately, overcoming these challenges requires interdisciplinary collaboration among engineers, clinicians, AI researchers, and patients. Continued innovation will pave the way for more natural, functional, and personalized prosthetic vision systems, dramatically improving quality of life for glaucoma patients with profound vision loss [68-71] (Table 10).

6.1. Data and Regulatory Challenges in AI-Driven Glaucoma Diagnosis and Neuroprosthetics

The advancement of robust and clinically reliable AI systems in glaucoma diagnosis and neuroprosthetics devices, such as visual prostheses, critically depends on access to large, diverse, and well-annotated datasets. These datasets must encompass a wide range of glaucoma severity, demographic diversity, imaging modalities, and clinical contexts to ensure AI models generalize well across different patient populations and real-world environments. In glaucoma care, publicly available datasets like RIM-ONE, ORIGA, and DRIONS-DB have accelerated AI development by providing retinal images annotated with optic nerve head changes, RNFL thinning, and other glaucomatous markers. However, these datasets often lack comprehensive diversity in ethnicity, disease stages, or multimodal imaging inputs such as OCT combined with fundus photography. These restrictions could affect the medical reliability of AI algorithms in underrepresented groups through introducing bias and reducing their resilience [72]. Also, there is a serious absence of standardized datasets that capture dynamic visual environments, patient-device interactions, and implant-specific constraints in the field of glaucoma neuroproteins, where AI aids in real-time image preprocessing and neural stimulation to restore visual perception [73]. The creation and evaluation of AI models suited to the unique challenges of glaucoma-related vision loss and prosthetic vision restoration is restricted by this deficiency. Adoption of uniform label guidelines for glaucoma characteristics, cooperative data-sharing activities across institutions and regions, and adherence to ethical frameworks protecting patient privacy and data security are all necessary to close these data gaps. By improving dataset diversity and quality, such initiatives would allow for more precise, broadly applicable AI systems [74, 75].

At the same time, a major change in regulatory strategies is required to include AI into glaucoma diagnoses and neuroprosthetic devices. AI models that are constantly changing due to software upgrades and learning are difficult for traditional regulatory frameworks, which were created for static medical devices. Because AI technologies are iterative, regulatory bodies such as the European Medicines Agency (EMA) and the US Food and Drug Administration (FDA) are creating adaptive regulatory procedures [76]. Regulatory surveillance of glaucoma

Table 10. Comprehensive Overview of AI-Based Strategies for Early Detection of Diabetic Glaucoma and Technological Advances Toward Bionic Eye Integration

Section	Aspect	Detailed Description	Examples/ Studies	Implications for Diabetic Glaucoma	Limitations/ Challenges	Future Research Prospects
Disease Background	Pathophysiology of Diabetic Glaucoma	A complex interaction between diabetic retinopathy (vascular damage due to hyperglycemia) and glaucomatous optic neuropathy (elevated intraocular pressure and retinal ganglion cell death).	- N/A	Highlights the need for early multimodal screening due to overlapping disease profiles.	Late detection due to subtle symptoms and overlapping presentations.	Identification of shared biomarkers for AI targeting.
Clinical Diagnosis	Traditional Diagnostic Tools	Use of intraocular pressure testing, fundus examination, OCT, and visual field analysis to detect glaucomatous changes.	OCT Spectralis Humphrey Visual Field Analyzer	Still considered the gold standard in clinical settings.	Subjective interpretation, costly equipment, and limited accessibility in rural/low-income areas.	AI augmentation for mass screening and automation.
Imaging Modalities in Detection	Retinal Fundus Imaging	Non-invasive, 2D imaging of the retina useful for detecting optic disc cupping and diabetic changes.	APTOS Dataset DRIONS-DB	Easily integrated with AI image classifiers for automated screening.	Lacks depth information, can't capture subtle nerve fiber changes.	Integration with OCT and depth-learning architectures.
	Optical Coherence Tomography (OCT)	Provides 3D cross-sectional retinal images for measuring RNFL thickness and optic nerve integrity.	REFUGE Challenge RIM-ONE	Highly sensitive for early glaucomatous changes.	Expensive, limited data availability for diabetic glaucoma.	Data synthesis using generative AI to improve datasets.
AI Methodologies in Early Detection	Machine Learning (ML)	Supervised learning techniques using hand-engineered features (e.g., cup-to-disc ratio, vessel tortuosity).	Random Forests, SVMs applied on fundus/OCT data	Can yield good accuracy on small/moderate datasets.	Manual feature engineering limits scalability and generalizability.	Transition to semi-supervised ML using unlabeled datasets.
	Deep Learning (DL)	Neural networks that learn hierarchical features from large annotated datasets (fundus/OCT).	CNNs (e.g., ResNet50, VGG16, DenseNet121)	Automatically detects minute pathological changes with high accuracy.	Requires large, diverse datasets. "Black box" nature limits interpretability.	Explainable AI (XAI) frameworks to improve trust in medical use.

	Hybrid & Multimodal AI	Combines multiple imaging inputs and clinical metadata using ensemble or multistream models.	Attention-Guided CNNs for combining OCT and fundus data	Improves accuracy and reduces false positives in complex cases.	Data harmonization and processing challenges.	Development of AI fusion models for real-time diagnosis.
Diabetic-Specific AI Challenges	Dataset Limitations	Most public datasets lack annotated cases of diabetic glaucoma.	Lack of specificity in RIM-ONE, REFUGE, etc.	AI models trained on general glaucoma data may underperform.	Model generalization suffers; bias risk increases.	Creation of large-scale, diabetic-glaucoma-specific datasets.
	Clinical Overlap	Co-existing signs of diabetic retinopathy and glaucoma confuse model outputs.	Retinal hemorrhages vs optic nerve changes	Reduced specificity in AI predictions.	Need for fine-grained feature disentanglement.	Use of multi-task learning to identify overlapping disease cues.
Bionic Eye: Concept and Applications	Overview of Bionic Vision	Implantable systems designed to restore partial vision via electrical stimulation of retina or visual cortex.	Argus II (Second Sight) PRIMA Retina Implant	Offers hope for patients with end-stage vision loss from glaucoma or DR.	Only effective in advanced blindness; requires surgery.	Combining AI to optimize image translation into stimulation patterns.
	AI Integration in Bionic Eyes	AI helps interpret camera inputs into neural stimulation signals for enhanced spatial awareness and object recognition.	Gennaris Cortex System Neuromorphic vision chips	AI enables better adaptation to user environments and dynamic scenes.	Real-time processing and power consumption limitations.	Use of low-power AI hardware (e.g., edge AI, neuromorphic chips).
AI vs Bionic Restoration	Functional Objective	AI focuses on early detection and prevention, while bionic systems aim at vision restoration.	Screening tools vs implanted prosthetics	Complements clinical management across the disease spectrum.	Bionics do not prevent disease; AI does not restore vision.	Unified frameworks where AI guides bionic function (e.g., adaptive stimulation).
Ethical and Socioeconomic Considerations	Bias, Privacy, and Access	Ensuring equity in AI development, and ethical deployment of high-cost bionic technologies.	HIPAA, GDPR, AI MedTech regulation	Vital for widespread adoption and trust.	Technology access disparities; AI bias due to non-representative data.	Community-centered dataset building and equitable bionic eye trials.
Future Convergence	AI-Bionic Synergy	Vision of integrating AI-driven diagnostic tools with smart bionic interfaces that adapt in real time.	"Closed-loop" vision systems	Merges prevention and restoration paradigms.	High development cost; lack of interdisciplinary platforms.	Digital twins, real-time brain-AI interfaces, personalized visual prosthetics.

neuroprosthetics must guarantee their efficacy, safety, and transparency, with a focus on explainability and user-centered design. It has to cover cybersecurity threats, strong data governance, and responsibility for AI-driven choices that affect visual perception. Additionally, long-term safety monitoring, means of ongoing post-market review, and proof of AI efficiency across a range of populations should all be prerequisites for regulatory clearance. In summary, rich and diversified data infrastructure coupled with flexible regulatory environment will be required for successful deployment of AI for glaucoma diagnosis and neuroprosthetics. Ultimately, the approach will lead to improved diagnosis, greater facilitation, and smart prosthesis that can provide vision and independence to glaucoma patients, all whilst encouraging innovation and maintaining clinical trust [77].

6.1.1. Importance of Large-Scale, Diverse, and Well-Annotated Datasets for AI in Glaucoma Diagnosis and Neuroprosthetics

High-quality large datasets that are diverse, well-annotated, and clinically relevant are needed to develop and refine AI systems for diagnosing glaucoma and for neuroprosthetic devices (both prosthetic vision and non-visual prosthetic devices). To reach for a strong and generalizable performance, AI models have to be trained on full variability dataset for glaucoma, as glaucoma presents with clinically diverse course in different patients, most with subtle structure and functional changes [78].

Enormous datasets are necessary to enable training of deep learning models that can identify complicated patterns of glaucomatous optic neuropathy. These datasets should represent a wide range of disease severity from mild glaucoma with few clinical signs to those with large losses of retinal ganglion cells and visual field abnormalities. This spectrum allows AI systems to recognize glaucoma in its earliest forms (and thus as its most treatable stage) and perhaps before an individual experiences irreversible vision loss [79]. Moreover, longitudinal data can assist AI models in predicting the development of disease and in the planning of personalized therapeutic interventions.

Diversity is also key in the datasets. Age, race and other demographics may play a significant role in the prevalence and characteristics of glaucoma. For example, certain subtypes of glaucoma are more frequently found in certain types of people, such as those of Asian or African descent. If applied in the real-world clinical context, data that derivate from an underrepresentation of these populations may lead to AI models that provide biased or less accurate predictions. There is a requirement for datasets to contain a mix of patient demographics, including underrepresented races and age groups in order to resolve such disparities and to ensure that AI developments are unbiased and effective across the spectrum [80]. Requisite for successful AI training and validation in glaucoma management is high-quality annotation. In order to detect small GON changes, clinical images such as optic nerve head photos, OCT RNFL thickness maps as well as VF test results had to be adequately annotated. AI models are able to distinguish between glaucomatous damage and normal anatomic changes because of the accurate labelling of features such as optic disc cupping, neuroretinal rim thinning and localised RNFL irregularities. Similarly, the ability of a model to relate structural damage to functional loss would be enhanced by incorporating brain recordings or patient functional measurements, such as visual field sensitivity. Our multi-modal annotation approach allows comprehensive AI evaluations involving all structural and functional information to enhance the diagnostic accuracy [81]. Datasets for neuroprosthetics and prosthetic vision for glaucoma patients with serious vision loss must go beyond still photos to incorporate real-time patient actions, brain stimulation the preferences, and dynamic interactions with the surroundings. By capturing this precise data, computerized platforms can better restore functional vision by tailoring stimulation patterns and responding to the user's visual demands [82].

Finally, standardized data formats and ethical frameworks for data sharing are essential to enable collaboration across research institutions and healthcare providers. Ensuring patient privacy and compliance with regulations, while promoting open access to diverse and well-annotated datasets, will accelerate AI advancements in glaucoma diagnosis and treatment [83].

The availability of large-scale, diverse, and meticulously annotated datasets is vital for developing AI systems that can effectively support early glaucoma detection, monitor disease progression, and enhance neuroprosthetics function—ultimately improving patient outcomes in glaucoma care worldwide.

6.1.2. Evolving Regulatory Frameworks

The integration of AI into glaucoma diagnostic tools and neuroprosthetics devices presents novel regulatory challenges that traditional medical device frameworks are ill-prepared to address. Unlike conventional static devices, AI-driven systems used in glaucoma care—such as automated optic nerve head analysis, RNFL segmentation, and bionic vision prostheses—are often adaptive, capable of continuous learning and updating post-deployment. This dynamic capability, while enhancing clinical utility, complicates regulatory oversight because it requires monitoring not only the initial safety and efficacy but also the evolving behaviour of the algorithms over time [84].

A primary concern in glaucoma management is ensuring that AI algorithms maintain consistent diagnostic accuracy across diverse patient populations, including different ethnicities and stages of disease. As glaucoma is often asymptomatic until advanced stages, reliance on AI for early detection and monitoring demands rigorous validation that includes variability in optic nerve morphology, image quality, and coexisting ocular conditions. Regulatory bodies, such as the U.S. FDA, must therefore adopt flexible, risk-based approval pathways that consider the unique adaptive nature of these systems and their potential to learn from new clinical data continuously [85].

Transparency and explainability of AI algorithms are critical in glaucoma care, where clinical decisions regarding treatment initiation or progression monitoring hinge on AI-derived outputs. Regulatory frameworks increasingly emphasize the need for interpretable AI models, allowing ophthalmologists to understand the rationale behind algorithmic decisions, such as identifying suspicious optic disc changes or RNFL thinning. Explainability promotes clinician trust and facilitates auditability, which is essential for patient safety and medico-legal accountability.

Data privacy and security are also paramount, given the sensitive nature of patient ocular images, electronic health records, and neuroprosthetics device data streams. Compliance with regulations like the HIPAA and the GDPR requires secure handling, storage, and transmission of patient information used both for training AI models and in real-time clinical use [86, 87].

Post-market surveillance mechanisms are essential to detect performance drift, algorithmic bias, or adverse events associated with AI-driven glaucoma diagnostics and neuroprosthetics. Continuous monitoring protocols must be established to evaluate device performance in diverse clinical environments and over extended timeframes, ensuring sustained safety and efficacy. This necessitates new regulatory strategies to approve software updates and retraining cycles without compromising patient safety (Figure 4).

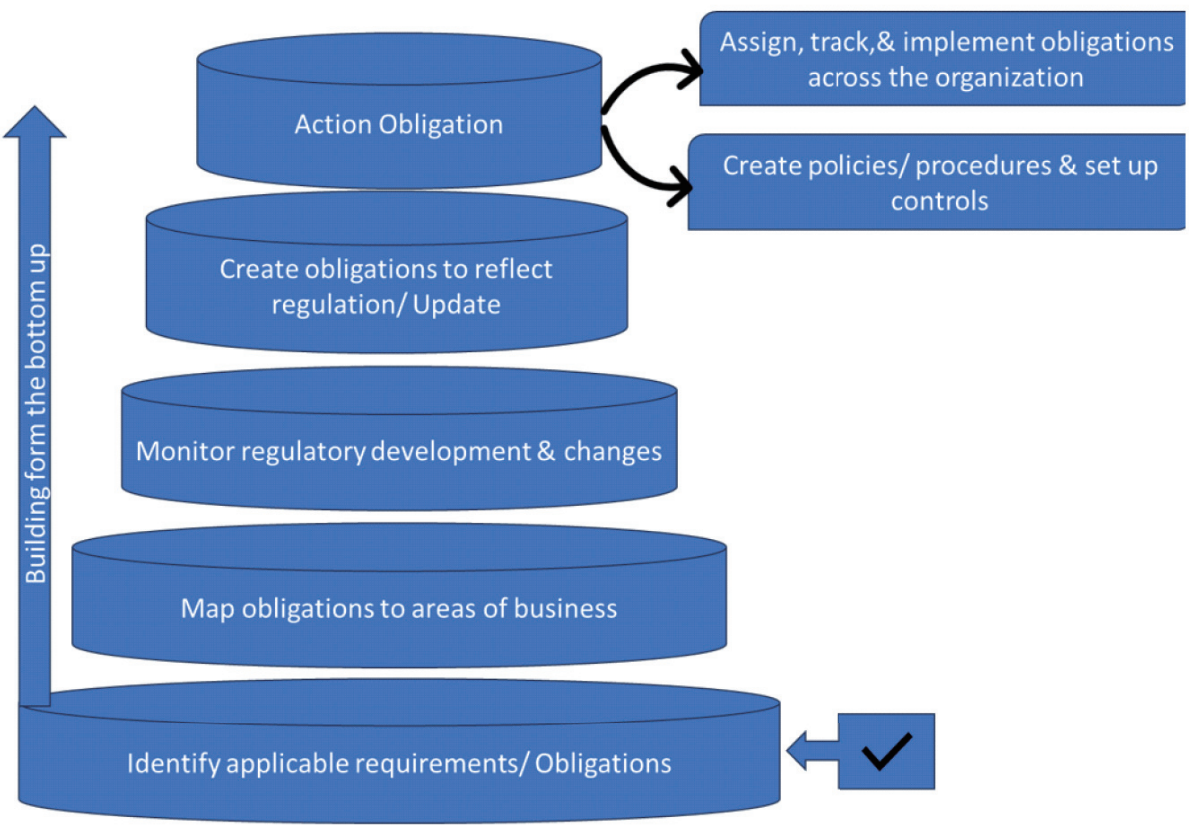

Figure 4. Steps to Manage and Implement Regulatory Obligations

The evolving landscape of AI in glaucoma diagnostics and neuroprosthetics demands regulatory frameworks that accommodate adaptive learning, enforce transparency, safeguard patient data, and ensure ongoing performance monitoring. Addressing these challenges is crucial to responsibly translate AI innovations into improved clinical outcomes for glaucoma patients worldwide [88-91].

6.2. Affordability and Accessibility

Cost represents one of the biggest hurdles for the broad use of modern glaucoma diagnostic and neuroprosthetic equipment in resource-constrained regions. These state-of-the-art technologies — which include OCT, AI-aided imaging platforms, and bionic eye systems — frequently require expensive equipment, specialized maintenance and a trained staff, making them beyond the reach of many health care systems in poor countries or underdeveloped rural areas. Economic constraints preclude the timely identification and proper treatment of glaucoma thereby people with a high risk of glaucoma present late and continue their sight losing without stop [92, 93].

Creative solutions that blend scalable technology deployment with financial sustainability are needed to address this problem. By combining resources, infrastructure, and knowledge from governments, non-profits, academic institutions, and industry players, public-private partnerships (PPPs) present a potential option. By supporting programs for training, improving distribution networks, and lowering the cost of technology, such collaborations can make advanced glaucoma care accessible to more people. PPPs, for instance, can assist primary care clinics in using AI-based screening technology, which can improve early detection rates and decrease the need for expensive specialist visits [94-97].

Another significant aspect of cost reduction is scalable production. Through economies of scale, mass manufacture of standardized, modular components—like portable OCT devices or tiny fundus cameras—can reduce unit costs. The viability of creating glaucoma diagnostic instruments at costs appropriate for low-income markets is further boosted by improvements in inexpensive materials and manufacturing operations, such as 3D printing and inexpensive electronics [98]. Furthermore, reach may be increased without a large infrastructure investment through developing AI algorithms that run effortlessly on low-cost hardware like cellphones.

Combining cost-effective technology design with strong PPP frameworks is essential to overcoming economic barriers and democratizing access to glaucoma diagnostics and neuroprosthetics vision restoration globally. Such efforts will help reduce the global burden of glaucoma-related blindness by enabling timely intervention and ongoing monitoring in resource-limited environments [99].

6.3. Challenges and Future Perspectives

Notwithstanding the aforementioned developments, there is a need to overcome several hurdles for optimal application of AI in glaucoma management. First, are large; diverse, and well- annotated datasets targeted to glaucoma and other optic neuropathies. Good quality data is important in training AI models that generalise beyond the 'white' population and in varying the presentation of disease by ethnic group and comorbidity. In addition, ethical aspects including patient privacy, data security, and algorithmic transparency need to be continuously addressed, with aim of generating trust and facilitating responsible innovation. Regulatory paradigms will need to be adjusted to address such adaptive artificial intelligence while ensuring glaucoma diagnostic and neuroprosthetic systems are very safe and effective [100].

Lastly, equitable availability is still an issue. Glaucoma is a disproportionately debilitating disease for the underserved and low-resource communities, in which advanced diagnostics and neuroprosthetic rehabilitation are usually unavailable secondary to cost and infrastructure. To overcome these discrepancies, there is a clear need for collaboration between scientists, clinicians, industry and policy makers to develop scalable manufacturing, cost-effective approaches and representative clinical trials [101]. With AI in glaucoma care, the approach toward glaucoma is expected to shift gears—from reactive therapeutic intervention to proactive, personalized attention that includes early detection, continuous surveillance, and functional recovery. By providing greater diagnostic accuracy, predictive risk scores, as well as improved performance of neuroprosthetics AI enables a more proactive response to the challenges of vision loss for clinicians and patients alike. As continued interdisciplinary teamwork, ethical oversight, and focus on accessibility persist among AI-driven technologies, hope remains for millions affected by this blinding global disease, that glaucoma care will be transformed [102-104].

7. Conclusion

The leading cause of irreversible blindness is glaucoma due to optic nerve injury and RGC loss. Although clinical care has improved, early diagnosis is still difficult because of the subtle presentation, coexistence with other ocular diseases, and resource limitations in many areas. Early detection is crucial to avoid vision loss, but conventional tools like OCT, perimetry, and IOP monitoring are typically inadequate, particularly for patients with comorbidities (e.g., diabetes-retinopathy). AI brings an era-shifting solution to glaucoma screen, monitor and personalize management. Deep learning models, primarily CNNs, are able to process complex imaging data combined with clinical and demographic information, and they achieved better sensitivity and specificity than human experts in subtle changes in structure. Furthermore, through longitudinal integrative health records (including, among others, data from ophthalmic telemedicine), AI can make early, risk-stratifying predictions of disease course, including severe vision loss, prompting tailored interventions. But beyond diagnosis, AI enhances the long-term disease management by automatically establishing standards, reducing variability and spotting real-time trends for personalized treatment adjustments. It also provides medication adherence via life tracking, patient reported outcomes and pretext alerts, increasing long-term results and ultimately quality of life.

In severe stages of glaucoma in which there is blur vision AI is important not only for visual rehabilitation with the help of bionic eyes, but also brain-machine interface. These implants apply electrical current to viable retinal neurons or the visual cortex. Optimized image preprocessing emphasizes important data in the visual input such as edges and faces driven by an AI and an adaptive algorithm tailors stimulation parameters for improved handling. In addition, AI-driven personalized neurofeedback enhances cortical plasticity, and facilitates the interpretation of artificial visual input. Although todays neuroprosthetics have not reached fully restored sight, the combined effect of the AI and prosthetic technologies promise useful recovery of vision, independence and better life quality for glaucoma patients.

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Conflict of Interest

Declared none.

Authors Contribution

GT: Conceptualization, Writing – Original Draft, Supervision; AW: Methodology, Literature Review; RSS: Data Curation, Visualization; RS: Resources, Formal Analysis; MK: Funding Acquisition; BKC: Visualization, Writing – Review & Editing.

Abbreviations

AI: Artificial intelligence
AMD: Age-related macular degeneration
AUC: Area under the curve
CDR: Cup-to-disc ratio
CNNs: Convolutional neural networks
CpRNFL: Peripapillary Retinal Nerve Fiber Layer
DL: Deep learning
DR: Diabetic retinopathy
EDI: Enhanced depth imaging
EMA: European Medicines Agency
FDA: Food and Drug Administration
GBS: Gradient Boosting Survival
GCC: Ganglion Cell Complex
GCIPL: Ganglion Cell-Inner Plexiform Layer
GON: Glaucomatous optic neuropathy
HER: Electronic health records
IOP: Intraocular pressure
IPL: Inner Plexiform Layer
LC: Lamina Cribrosa
MEA: Microelectrode array
ML: Machine learning
NVG: Neovascular glaucoma
OCT: Optical coherence tomography
OCT-A: OCT-Angiography
ONH: Optic nerve head
ORIGA: Online Retinal Fundus Image Database for Glaucoma Analysis
POAG: Primary open-angle glaucoma
PPA: Peripapillary Atrophy
PPPs: Public-private partnerships
RGC: Retinal ganglion cell
RIM-ONE: Retinal Images for Optic Nerve Evaluation
RNFL: Retinal nerve fiber layer (RNFL)
RP: Retinitis pigmentosa
RSF: Random survival forests
SLO: Scanning Laser Ophthalmoscopy
UBM: Ultrasound Biomicroscopy

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