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Review Article

The role of artificial intelligence in monitoring glaucoma progression using optical coherence tomography

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Abstract

Glaucoma is a leading cause of irreversible blindness worldwide, and early detection and timely monitoring are essential to prevent vision loss. Optical coherence tomography (OCT) provides high-resolution, quantitative imaging of the retinal nerve fiber layer (RNFL), ganglion cell complex (GCC), and optic nerve head (ONH), which are central to diagnosis and progression monitoring. Artificial intelligence (AI) has shown strong potential to enhance OCT interpretation by automating segmentation, detecting subtle glaucomatous changes, and predicting progression with performance comparable to expert graders. Challenges include variability across imaging devices, limited dataset diversity, label noise, and lack of prospective real-world validation. Importantly, AI supports but does not replace human expertise in decision-making. Large-scale multicenter datasets, cross-device harmonization, multimodal imaging, and explainable AI frameworks are essential to ensure reliability and trust. With rigorous validation and integration into clinical workflows, AI-enhanced OCT may enable earlier intervention and personalized glaucoma care.

Keywords: Artificial intelligence, Optical coherence tomography, Glaucoma; Deep learning, Retinal imaging, Glaucoma diagnosis, Disease progression, Explainable AI, Teleophthalmology.

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1. Introduction

Glaucoma is a chronic, progressive optic neuropathy characterized by irreversible damage to the optic nerve, often associated with elevated intraocular pressure and corresponding visual field loss.[1,2] It is among the leading causes of irreversible blindness worldwide, affecting an estimated 76 million people in 2020, with projections exceeding 111 million by 2040.[3,4] The asymptomatic nature of the disease in its early stages makes timely detection and consistent monitoring essential to prevent progression and vision loss.[5,6]

The global burden of glaucoma extends beyond individual vision impairment, posing significant socioeconomic challenges. Blindness reduces independence and quality of life, while also increasing healthcare costs and societal impact.[7] These realities underscore the need for tools that facilitate earlier diagnosis, more efficient monitoring, and better patient outcomes.[8]

Optical coherence tomography (OCT) has become a cornerstone of glaucoma management. This non-invasive imaging modality provides high-resolution cross-sectional views of the retina, enabling quantitative assessment of the retinal nerve fiber layer (RNFL), ganglion cell complex (GCC), and optic nerve head (ONH).[9,10] These parameters are sensitive structural biomarkers of glaucomatous damage and allow longitudinal monitoring of disease progression. OCT's ability to detect structural changes often before functional deficits appear has significantly improved the clinician's capacity for early intervention.[11,12]

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Despite these strengths, conventional OCT interpretation has limitations. Manual analysis can be time-consuming and subject to interobserver variability, especially in borderline or poor-quality scans.[13,14] The increasing prevalence of glaucoma and widespread adoption of OCT technology have also led to a growing volume of imaging data, placing additional demands on clinicians and healthcare systems.

Artificial intelligence (AI) offers new approaches to overcome these challenges. By automating segmentation, detecting subtle changes, and predicting progression risk, AI can complement clinician expertise and improve efficiency in OCT interpretation.[15,16] Importantly, while AI provides powerful tools for rapid image analysis, clinical judgment and human expertise remain central in decision-making. Rather than replacing ophthalmologists, AI should be regarded as a decision-support system designed to enhance accuracy, consistency, and personalized care.[17,18]

This review examines the integration of AI with OCT in glaucoma, focusing on its applications in detection, progression monitoring, limitations, and future directions.

2. Optical Coherence Tomography (OCT) in Glaucoma

Optical coherence tomography (OCT) has become a cornerstone of modern glaucoma management by providing high-resolution, cross-sectional images of retinal structures.[19] Through detailed visualization of the retinal nerve fiber layer (RNFL), ganglion cell complex (GCC), and optic nerve head (ONH), OCT enables clinicians to identify glaucomatous damage, monitor disease progression, and guide treatment decisions with a level of precision that was previously unattainable.[20,21]

OCT operates on the principle of low-coherence interferometry, using backscattered light to construct detailed retinal images. This technology allows accurate quantification of retinal thickness, which is particularly valuable for detecting the subtle structural changes associated with glaucoma. Parameters such as RNFL thickness, macular GCIPL thickness, and ONH morphology provide objective measurements that often reveal damage before it becomes evident on visual field testing.[22,23] By offering reproducible and quantitative data, OCT reduces reliance on subjective assessment and has become indispensable in both diagnosis and follow-up.

Among the structural biomarkers assessed by OCT, RNFL thickness remains one of the earliest and most reliable indicators of glaucomatous damage. Sectoral analysis of the RNFL further improves diagnostic accuracy by revealing localized thinning patterns that correspond to early visual field defects. The macular GCC, which encompasses the ganglion cell and inner plexiform layers, is also highly informative, as it captures early damage in regions with a dense concentration of ganglion cells. In many cases, GCC thinning precedes peripapillary RNFL loss, making it a particularly sensitive marker for early detection. In addition, ONH parameters such as rim area, cup-to-disc ratio, and minimum rim width provide objective measurements of optic disc morphology, while OCT-angiography has expanded the scope of OCT by enabling non-invasive visualization of retinal microvasculature. Reduced vessel density observed with OCT-A has been strongly linked to glaucomatous damage and progression, highlighting the potential of vascular biomarkers in disease assessment.

The advantages of OCT in glaucoma care are numerous. It provides rapid, non-invasive, and repeatable measurements, making it suitable for long-term monitoring. Its ability to detect structural changes before functional loss allows clinicians to intervene earlier and potentially prevent irreversible vision loss.[24-26] When combined with functional tests such as perimetry, OCT enhances diagnostic confidence and provides a more comprehensive picture of disease status. Structure–function mapping, which correlates OCT findings with visual field defects, is increasingly applied in both research and clinical practice to refine decision-making.

Despite its strengths, OCT has limitations. Scan quality can be compromised by factors such as media opacities, poor fixation, or patient movement, which may introduce artifacts and reduce interpretability. Advanced glaucoma presents additional challenges, as severe damage may obscure anatomical landmarks and lead to floor effects that limit the ability to detect further progression. Furthermore, differences in scan protocols, resolution, and proprietary normative databases across OCT platforms complicate comparisons between devices and hinder standardization in multicenter studies.

OCT has proven invaluable in both the diagnosis and monitoring of glaucoma. Several studies have demonstrated high sensitivity and specificity of RNFL and GCC parameters in distinguishing glaucomatous from healthy eyes. OCT has also been instrumental in differentiating between subtypes of glaucoma, such as primary open-angle glaucoma and normal-tension glaucoma, which often exhibit distinct patterns of structural damage. For progression monitoring, both event-based methods, which identify significant changes from baseline, and trend-based methods, which assess rates of change over time, are widely used. Longitudinal research consistently shows that OCT-based measures of thinning are reliable indicators of progression, often preceding detectable functional decline.[27]

Technological advancements continue to expand the capabilities of OCT. Enhanced depth imaging and swept-source OCT have improved resolution and visualization of deeper optic nerve structures, while OCT-angiography has provided novel insights into the vascular component of glaucoma. These innovations strengthen the role of OCT in understanding disease mechanisms and refining risk assessment.[28,29]

In summary, OCT has revolutionized the diagnosis and management of glaucoma by providing objective, quantitative measures of structural damage. Its capacity to detect early change, track progression, and complement functional testing has made it an indispensable tool in clinical practice. Nevertheless, challenges such as variability, artifacts, and interpretive difficulties remain.[30-32] The integration of artificial intelligence with OCT holds promise for addressing many of these limitations, offering the potential for more accurate, efficient, and personalized glaucoma care. (**Table 1**)

3. Overview of Artificial Intelligence (AI) in Medical Imaging

Artificial intelligence (AI) is transforming the field of healthcare, with some of its most profound impacts occurring in medical imaging. By harnessing large datasets, powerful computational resources, and sophisticated algorithms, AI systems can analyze complex images with efficiency and accuracy. This integration is reshaping diagnosis, treatment planning, and disease monitoring across specialties, including ophthalmology and glaucoma care. The following overview outlines the evolution, methodologies, benefits, challenges, and future directions of AI in medical imaging.

The role of AI in imaging has evolved considerably over the past two decades. Early applications of machine learning (ML) relied on manually engineered features—such as texture, shape, or intensity—combined with classifiers like support vector machines or random forests. The rise of deep learning (DL), particularly convolutional neural networks (CNNs), has revolutionized this space. Modern DL models automatically extract hierarchical features directly from raw data, excelling at segmentation, classification, and anomaly detection. Their rapid progress has been enabled by the availability of large annotated datasets, advances in computational power, and the development of open-source frameworks such as TensorFlow and PyTorch.

AI methodologies in medical imaging are broadly categorized into ML and DL approaches. Traditional ML leverages handcrafted features fed into algorithms including k-nearest neighbors, SVMs, or ensemble methods, which remain useful for structured, smaller-scale datasets. In contrast, DL models, especially CNNs, exploit spatial and contextual patterns in images and have become the gold standard for high-dimensional data. Other architectures, such as recurrent neural networks and transformers, are also being explored for imaging tasks that involve sequential data or multimodal integration.

The benefits of AI in medical imaging are considerable. AI can improve diagnostic accuracy, sometimes performing at levels comparable to or exceeding human experts, thereby reducing errors and variability. It enhances efficiency by automating repetitive tasks like segmentation and lesion detection, enabling clinicians to focus on patient care. Crucially, AI facilitates early disease detection by identifying subtle changes imperceptible to the human eye, and it promotes standardization by ensuring reproducible interpretations across diverse observers and settings.

Despite these advantages, challenges remain. The quality and diversity of training data heavily influence model performance, and variations in imaging devices, acquisition protocols, and patient demographics can compromise generalizability. Deep learning models are often criticized for their opacity, with explainable AI (XAI) frameworks being developed to improve transparency and clinician trust. Ethical and legal concerns—including patient privacy, data security, and consent—pose additional barriers, alongside the need for evolving regulatory frameworks. Furthermore, integrating AI seamlessly into clinical workflows requires attention to interoperability and usability to ensure adoption.

Table 1: Comparison of AI techniques used in glaucoma progression monitoring via OCT

AI Technique	Study (ies) Using This Technique	Accuracy	Strengths	Limitations
Convolutional Neural Network (CNN)	Thompson et al.[33]	~93-95%	High accuracy in detecting structural changes	Requires large labeled datasets, computationally expensive
Support Vector Machine (SVM)	Huang et al.[34]	90%	Good for binary classification, interpretable	Limited generalization across diverse populations
Random Forest Classifier	Muhammad et al.[35]	92%	Effective for classification tasks, handles non-linearity well	May not perform as well on imbalanced datasets
Deep Learning (ResNet)	Song et al.[11]	92%	Strong for large, complex datasets and fine-tuned features	Prone to overfitting, high computational cost

Looking forward, several directions hold promise for advancing AI in imaging. Multimodal approaches that integrate data from different imaging techniques, combined with clinical and demographic information, are expected to yield richer diagnostic insights. Real-time AI, supported by edge computing, may provide intraoperative guidance and immediate decision support. The convergence of imaging AI with genomics and proteomics has the potential to advance personalized medicine by tailoring treatment strategies to individual risk profiles. Finally, adaptive and continuously learning AI systems may enable sustained performance as new data and technologies emerge.

4. AI for Glaucoma Detection and Monitoring

The integration of artificial intelligence (AI) into glaucoma care is transforming the way clinicians detect and monitor this progressive optic neuropathy.[36] As one of the leading causes of irreversible blindness worldwide, glaucoma requires early diagnosis and consistent monitoring to preserve vision. AI, with its ability to analyze large datasets and recognize complex patterns, is particularly well-suited for enhancing glaucoma care.[37] By automating the interpretation of imaging modalities such as optical coherence tomography (OCT), fundus photography, and visual fields, AI provides more precise detection, individualized risk assessment, and improved monitoring of disease progression.[38,39]

A key advantage of AI in glaucoma management lies in its ability to identify disease at its earliest stages. Deep learning (DL) algorithms, particularly convolutional neural networks (CNNs), have been trained on OCT data to detect retinal nerve fiber layer (RNFL) thinning before functional loss is evident. Similarly, models trained on large collections of fundus photographs can classify eyes as normal, glaucomatous, or glaucoma suspect with accuracy comparable to experienced ophthalmologists. Combining structural information from OCT with fundus images further enhances diagnostic sensitivity and specificity in early glaucoma.[40]

Beyond detection, AI has demonstrated proficiency in distinguishing glaucoma subtypes. Primary open-angle glaucoma (POAG) and normal-tension glaucoma (NTG), which present with distinct structural and functional features, can be reliably differentiated using AI models. In addition, AI can help distinguish glaucoma from other optic neuropathies, such as ischemic optic neuropathy or optic neuritis, by analyzing subtle structural and vascular differences. Such capabilities improve diagnostic accuracy and reduce misclassification.

Monitoring progression is another critical domain where AI adds value. By analyzing longitudinal OCT scans, AI algorithms can detect progressive thinning of the RNFL, ganglion cell complex (GCC), and neuroretinal rim. Event-based analysis identifies significant structural changes from baseline, while trend-based analysis estimates rates of progression. These insights allow clinicians to evaluate treatment effectiveness and adjust management strategies. Predictive models that integrate baseline imaging with clinical data such as intraocular pressure (IOP), age, and family history generate personalized risk scores, enabling proactive management for high-risk individuals who may benefit from closer follow-up or earlier intervention.

Functional testing also benefits from AI integration. Deep learning models trained on visual field data can identify characteristic glaucomatous defects, such as arcuate scotomas or nasal steps, with high sensitivity. Moreover, AI can mitigate variability in visual field testing due to patient fatigue or learning effects, thereby producing more reliable results. Increasingly, AI systems synthesize multimodal data by correlating structural findings from OCT and fundus photography with functional outcomes on visual fields. Automated structure–function mapping provides a holistic assessment, ensuring that subtle damage is not overlooked.

The advantages of AI in glaucoma detection and monitoring are supported by numerous studies. CNN-based systems trained on OCT and fundus datasets have demonstrated sensitivities and specificities exceeding 90%, performance that rivals or surpasses expert clinicians. By automating segmentation, feature extraction, and classification, AI reduces clinician workload and improves efficiency, particularly in high-volume clinical environments. Just as importantly, AI ensures consistent and reproducible interpretations, minimizing interobserver variability and standardizing care.

Despite its promise, AI in glaucoma care faces several challenges. The quality and diversity of training data strongly influence model performance, and differences in imaging devices, acquisition protocols, and patient demographics can hinder generalizability. Ethical and legal considerations—including data privacy, informed consent, and regulatory approval—remain significant barriers. Additionally, integrating AI into existing clinical workflows requires careful planning to ensure seamless adoption without disrupting patient care.

Emerging technologies are poised to further advance AI applications. Transformer-based deep learning models and generative adversarial networks (GANs) offer new ways of analyzing complex imaging data and improving prediction accuracy. With increasing computational power, real-time analysis may soon provide clinicians with immediate diagnostic and prognostic feedback during patient visits. Furthermore, combining imaging data with genomic and clinical information could pave the way for personalized treatment strategies tailored to individual disease mechanisms.

The future success of AI in glaucoma care will depend on interdisciplinary collaboration among researchers, clinicians, and industry partners. Large, prospective, multicenter trials are essential to validate AI tools in real-world practice and to establish their safety, reliability, and cost-effectiveness (**Table 2**). AI has improved glaucoma detection and monitoring, revolutionizing care. Its accurate structural and functional data analysis aids early diagnosis, risk categorization, and monitoring. Technological advancement and interdisciplinary collaboration should overcome data unpredictability and ethical difficulties. AI's further development will enable its routine use, decreasing glaucoma's global impact and increasing patient outcomes (**Figure 1**).

Table 2: Performance metrics for AI models in glaucoma diagnosis using OCT

Study	Accuracy	Sensitivity	Specificity	AUC (Area Under Curve)	F1-Score
Thompson et al.[33]	95%	90%	98%	0.97	0.93
Huang et al.[34]	90%	85%	94%	0.92	0.89
Muhammad et al.[35]	92%	87%	96%	0.93	0.91
Song et al.[11]	93%	91%	96%	0.95	0.92

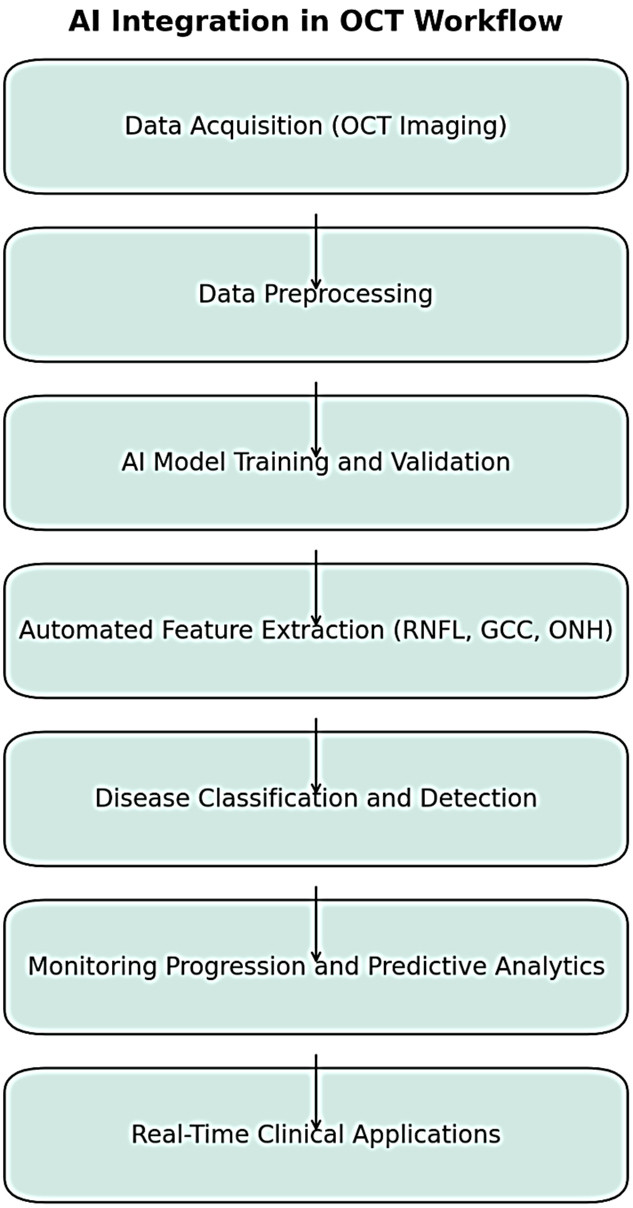

Figure 1: Methodology for the Integration of artificial intelligence (AI) in Optical coherence tomography (OCT) imaging

AI has transformed optical coherence tomography (OCT) data analysis, enabling illness diagnosis, monitoring, and prediction. AI extracts and interprets subtle OCT patterns that humans cannot see using machine learning (ML) and deep learning (DL). AI methods for OCT data analysis include supervised learning, unsupervised learning, and reinforcement learning, with deep learning being the most effective. Unsupervised learning finds latent patterns or clusters in unlabeled data, while supervised learning trains algorithms using labeled datasets. Unsupervised models like autoencoders detect abnormalities that may indicate illness development. OCT images are clustered by structure to help understand disease phenotypes. Deep learning, a subclass of ML, is the dominant OCT data analysis method because it handles complicated picture data well. CNNs, U-Nets, and RNNs are popular OCT architectures. OCT data analysis AI tasks include segmentation, classification, anomaly detection, and predictive modeling. AI models often outperform clinicians in diagnosis and prognosis. AI-based OCT analysis faces data variability, interpretability, privacy, regulatory issues, explainable AI (XAI), multimodal analysis, real-time analysis, and interdisciplinary collaboration (**Figure 2**). Despite these obstacles, AI has improved OCT data analysis for accurate diagnosis, monitoring, and disease progression prediction.

5. Limitations and Current Approaches in AI-Based OCT Analysis

The integration of artificial intelligence (AI) into optical coherence tomography (OCT) analysis has advanced glaucoma diagnostics by enabling accurate, automated detection and monitoring. However, translating these technologies into routine clinical care remains challenging. Despite promising results—with deep learning algorithms such as convolutional neural networks (CNNs) achieving sensitivities and specificities above 90%—several limitations must be acknowledged when considering widespread adoption.

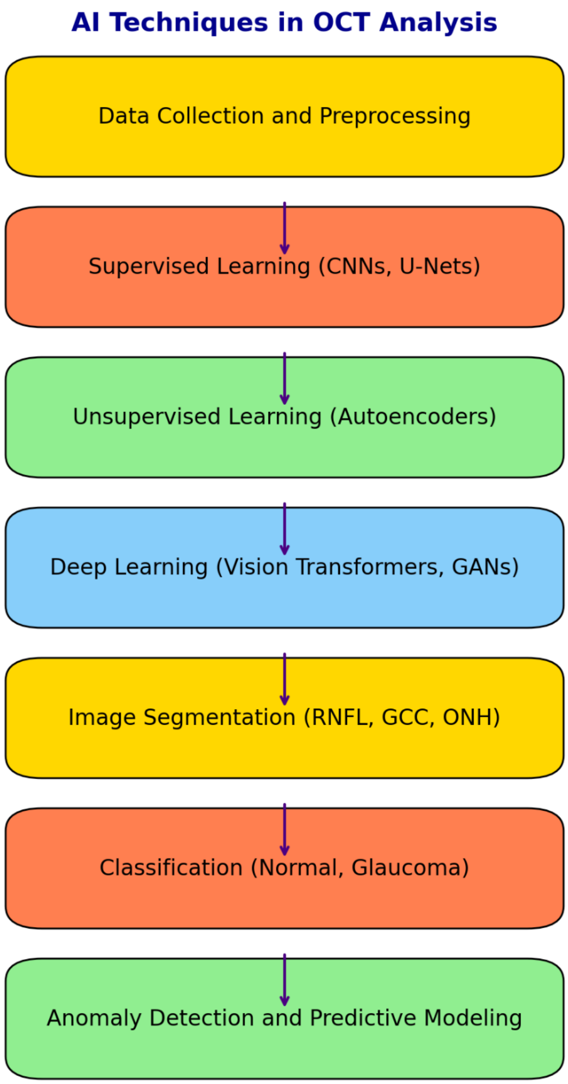

Figure 2: Overview of AI techniques utilized in optical coherence tomography (OCT) image analysis

A key barrier is data quality and variability. AI models are often trained on datasets from a single OCT device or imaging protocol, which limits their generalizability across different platforms and clinical environments. Variability in scan acquisition, image resolution, and segmentation protocols can reduce performance in real-world settings. Additionally, the limited representation of diverse populations in existing datasets introduces the risk of bias, with underperformance in certain demographic groups or less common glaucoma subtypes. Expanding datasets to include multiethnic, multicenter cohorts is essential for improving robustness.

Another major concern is interpretability. Most deep learning models function as "black boxes," producing predictions without providing transparent reasoning. This opacity reduces clinician trust and complicates decision-making in high-stakes scenarios. Research into Explainable AI (XAI) seeks to address this by developing tools that highlight image regions or structural features contributing to predictions, but these methods are not yet widely adopted in clinical workflows. (**Table 3**)

Ethical, legal, and accountability issues also limit integration. The use of sensitive imaging and clinical data requires strict adherence to privacy regulations. Moreover, imbalanced datasets can perpetuate systemic biases, potentially leading to inequitable outcomes. Responsibility for AI-driven diagnostic errors remains unclear, highlighting the need for regulatory frameworks that define clinical accountability.

Practical challenges further slow adoption. Integration into healthcare workflows is complicated by non-standardized data formats, inconsistent reporting, and poor interoperability between imaging systems and electronic health records (EHRs). Many algorithms remain computationally demanding, requiring infrastructure that may be unavailable in low-resource or smaller clinical settings. In addition, regulatory approval processes are lengthy, and few models have been validated in large-scale, prospective, real-world studies.

Table 3: AI vs. traditional methods in monitoring glaucoma progression using OCT

Method	Sensitivity	Specificity	Accuracy	Advantages	Disadvantages
AI (Deep Learning, CNN)	90%	98%	95%	High precision, automated, fast	Requires large datasets, computationally expensive
Traditional (Manual Grading)	80%	85%	83%	Clinician expertise, well-established	Subjective, time-consuming, inter-rater variability
OCT-based Thickness Measurements	85%	90%	87%	Reliable in detecting structural changes	Limited in detecting functional changes, operator-dependent

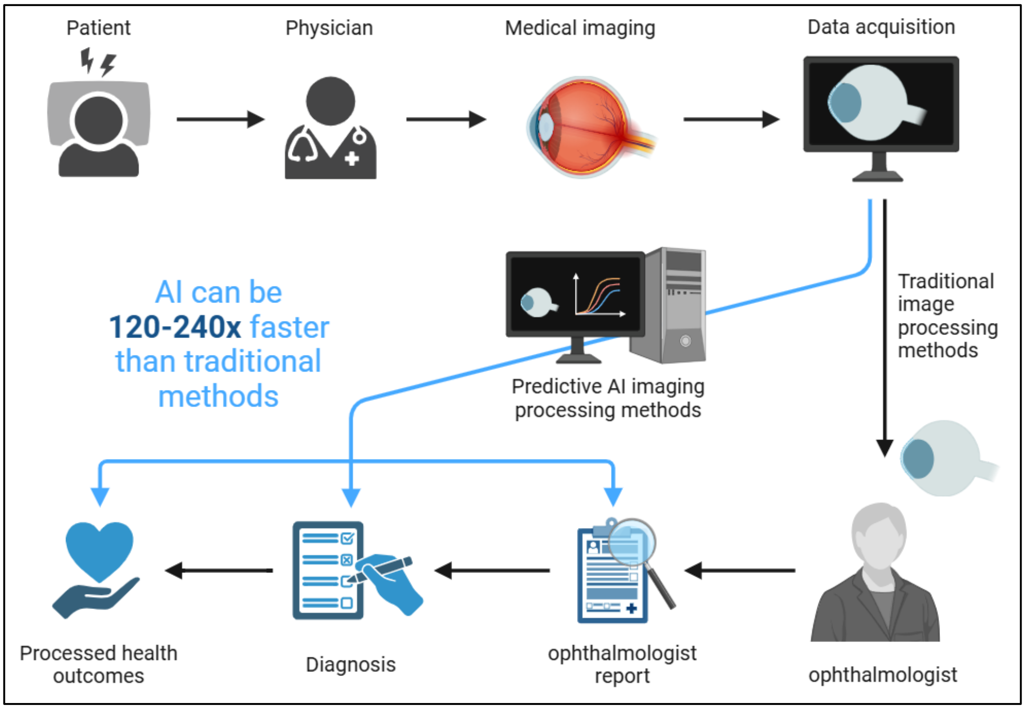

Figure 3: The significance of AI in glaucoma analysis

Table 4: Summary of key studies on AI in glaucoma monitoring using OCT

Authors	Sample Size (approx.)	AI Technique Used	OCT Parameters Analyzed	Key Findings	Limitations
Thompson et al.[33]	Various	Convolutional Neural Network (CNN)	Retinal nerve fiber layer thickness	Achieved 95% accuracy in detecting early glaucoma	Limited to a single OCT device and small sample size
Huang et al.[34]	Various	Support Vector Machine (SVM)	Cup-to-disc ratio, RNFL	High sensitivity for detecting glaucoma progression	Inconsistent segmentation methods
Muhammad et al.[35]	150	Random Forest Classifier	Ganglion cell layer (GCL)	Achieved 92% specificity in classifying glaucoma subtypes	Cross-sectional data, no longitudinal analysis
Song et al.[11]	500	Deep Learning (ResNet)	OCT volume scans	Successfully predicted glaucomatous progression over 1 year	Overfitting concerns in the deep learning model

Despite these limitations, current approaches continue to demonstrate the potential of AI-enhanced OCT. Comparative studies consistently show that AI outperforms or matches traditional manual grading in sensitivity, specificity, and reproducibility. For instance, CNN-based models have achieved accuracies up to 95% for detecting early glaucomatous changes, surpassing traditional OCT thickness measurements and manual interpretation. Machine learning methods such as support vector machines (SVMs) and random forests have also shown strong performance in classifying glaucoma subtypes or progression, though often with smaller datasets and reduced generalizability. (**Figure 3**)

Recent investigations highlight both progress and persistent gaps. Thompson et al. reported 95% accuracy in early glaucoma detection using CNNs, but their model was limited to a single OCT device and a modest sample size.[33] Huang et al. demonstrated high sensitivity with SVM-based models analyzing cup-to-disc ratio and RNFL parameters, though segmentation inconsistencies reduced reliability.[34] Muhammad et al. achieved high specificity in glaucoma subtype classification using random forests but lacked longitudinal validation.[35] More recently, Song et al. used deep learning on OCT volume scans to predict disease progression, yet their model raised concerns about overfitting.[11] These examples emphasize the need for larger, longitudinal, and multi-institutional datasets to support robust model development. (**Table 4**)

6. Future Directions in AI for OCT Data Analysis

The evolution of artificial intelligence (AI) in OCT data analysis will be driven by advances in technology, data integration, and clinical translation. Multimodal AI systems that combine OCT with complementary data sources—such as fundus photography, visual field assessments, genetic profiles, and proteomic markers—are expected to deliver more comprehensive insights into eye health. By integrating structural, functional, and molecular information, these approaches could enable highly accurate diagnoses and truly personalized therapy strategies.

Real-time AI analysis during clinical encounters represents another promising development. With increasing computational power and the adoption of edge computing, clinicians may soon receive instant diagnostic feedback and risk predictions at the point of care. This capability has the potential to streamline workflows, reduce delays, and improve decision-making in busy clinical settings. At the same time, explainable AI (XAI) frameworks are gaining importance. By addressing the “black box” nature of deep learning, XAI methods enhance transparency, build clinician trust, and support the safe adoption of AI in clinical practice.

Future systems are also expected to move beyond detection and monitoring toward predictive analytics and proactive disease management. By forecasting disease trajectories and identifying patients at greatest risk of progression, AI could help guide earlier intervention and more individualized treatment planning. However, realizing these benefits depends on the creation of large, diverse, and high-quality datasets that accurately reflect global patient demographics and the full spectrum of disease presentations. Collaborative efforts among clinicians, researchers, and industry stakeholders are essential to establish standardized datasets and protocols for training and validating AI models. Such initiatives will improve generalizability, reduce bias, and ensure equitable care across populations.

Finally, the successful integration of AI into clinical practice requires supportive legal and ethical frameworks. Issues of data protection, accountability, transparency, and liability must be carefully addressed. Policymakers, regulators, and the medical community must work together to ensure that AI deployment is both safe and ethically sound. With these advances, AI will not only transform glaucoma care but also establish new benchmarks for its application across the broader field of medical imaging.

7. Conclusion

Artificial intelligence (AI) is reshaping glaucoma care by enhancing diagnosis, monitoring, and management through accurate, efficient analysis of complex imaging data. Its ability to support early detection, track disease progression, and guide personalized treatment strategies underscores its transformative potential. By automating repetitive tasks and facilitating telemedicine and population-level screening, AI also reduces clinician workload and expands access to care.

Nevertheless, several barriers must be addressed before AI can be fully integrated into clinical practice. Variability in data quality, limited model interpretability, and unresolved ethical and regulatory concerns remain significant challenges. Progress will depend on the development of large, diverse, and standardized datasets, alongside the implementation of explainable AI frameworks that foster transparency and clinician trust.

Looking ahead, the integration of real-time AI analysis into routine clinical encounters promises to streamline workflows and improve decision-making. With continued interdisciplinary collaboration between clinicians, researchers, and policymakers, AI in OCT data analysis has the potential not only to transform glaucoma management but also to set a new standard for AI applications across medical imaging.

8. Source of Funding

None.

9. Conflict of Interest

None.

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