Glaucoma Detection Using Machine Learning: A Review

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Abstract. One of the main causes of permanent blindness in the globe is glaucoma, and successful treatment depends on early detection. Automated glaucoma identification utilising fundus and optical coherence tomography (OCT) images has been made possible by recent developments in machine learning (ML) and deep learning (DL), which have demonstrated promising diagnostic potential. This review critically examines techniques, datasets, performance outcomes, and limitations in order to synthesise findings from current studies. Although a lot of models claim to be highly accurate at binary classification, their dependence on tiny, unbalanced, or single-center datasets limits their ability to be applied to a variety of populations. Furthermore, the majority of methods ignore progression prediction and severity rating, which are critical for clinical decision-making. In ophthalmology, DL's black-box status further restricts acceptance and confidence. In addition to outlining potential possibilities towards reliable, explicable, and clinically validated AI frameworks for real-world glaucoma detection and care, this review identifies present research gaps.

Keywords: Glaucoma detection, Machine learning (ML), Deep learning (DL), Fundus imaging, Optical coherence tomography (OCT).

1 Introduction

Glaucoma is a chronic degenerative disease of the optic nerve head that affects millions of people annually and is a leading cause of blindness worldwide. To avoid major vision loss, early diagnosis and treatment is necessary; however, clinical treatment is often based on the tedious manual assessment of fundus and optical coherence tomography (OCT) images which is subject to inter-observer variability [1]. The introduction of new technologies such as artificial intelligence (AI), in particular machine learning (ML) and deep learning (DL), has been rapidly advancing in the field of ophthalmology to address these challenges offering scalable and automated solutions for the management and detection of glaucoma [2]-[3].

Convolution neural networks (CNNs), hybrid deep learning-based frameworks and machine learning assisted image analysis have also demonstrated promising results in classifying glaucoma using retinal fundus and OCT images [4]-[8]. These methodologies may prove useful to ophthalmologists in therapeutic decisions as they showed promising diagnostic accuracy, often outperforming traditional diagnostic methods [9]-[10].

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Also, hybrid models that integrate clinical and imaging data have emerged as the most robust predictive models, suggesting the importance of multimodal approaches [11]-[12].

However, these advances still have significant limitations. We raise concerns about generalizability amongst diverse populations given that numerous models are developed based on minuscule, imbalanced, or single institution datasets. In addition, the majority of existing work dismisses severity evaluation and disease progression prediction, which are crucial for long-term patient care, in favor of concentrating on the two-class categorization of glaucomatous and healthy eyes. In addition, the majority of existing work dismisses severity evaluation and disease progression prediction, which are crucial for longterm patient care, for the sake of concentrating on the two-class categorization of glaucoma vs healthy eyes. The “black-box” nature of DL architecture also introduces another challenge as it limits explainability and impairs physician trust [16]. While these problems are starting to be addressed with recent approaches (e.g., XAI), federated learning, and GAN-based systems, they still are computationally intensive, and more testing is required for widespread adoption

2 Literature Survey

Table 1. Literature Survey based on Glaucoma based different methods and ai model to make an accurate result

Sr. No.	Title	Year	Method	Dataset	Results/Outcomes	Limitations
1	A hybrid framework for glaucoma detection through federated machine learning and deep learning models [1]	2024	Federated ML + DL	Fundus images (multi-center)	Improved privacy-preserving training; high accuracy (≈94%)	Computationally intensive; limited clinical validation
2	Advanced Glaucoma Detection by Integrating ANFIS with CNN Models [2]	2024	ANFIS + CNN hybrid	Custom dataset (fundus)	Accuracy ~92%	Small dataset; lack of external validation

3	An efficient glaucoma prediction and classification integrating retinal fundus images and clinical data using DnCNN [3]	2025	DnCNN + ML	Fundus + clinical data	Accuracy ~95%	Dataset imbalance; limited scalability
4	Clinical Applicability and Cross-Dataset Validation of ML Models for Binary Glaucoma Detection [4]	2025	ML models (SVM, RF, DL)	Multiple fundus datasets	Demonstrated cross-dataset validation; accuracy >90%	Binary only; severity/progression ignored
5	Eye disease detection using machine learning [5]	2021	ML classifiers (SVM, KNN)	Fundus dataset	Detected multiple eye diseases with ~88% accuracy	General eye disease; limited glaucoma-specific analysis
6	Glaucoma detection: Binocular approach and clinical data in ML [6]	2025	ML + binocular data	Clinical + fundus	Improved detection vs monocular	Needs large-scale validation
7	Glaucoma detection by AI: GlauNet framework [7]	2021	Deep CNN (GlauNet)	Fundus dataset	Accuracy ~91%	Small sample size; no progression analysis
8	Glaucoma Detection Using CNN [8]	2024	CNN	Fundus dataset	Accuracy ~90%	Limited dataset size; only binary classification
9	Glaucoma Detection Using Deep Learning [9]	2023	DL (CNN variants)	Fundus images	Accuracy ~92%	Imbalanced dataset; limited interpretability
10	Glaucoma detection using fundus images with DL [10]	2023	CNN-based DL	Fundus images	Accuracy ~89%	Overfitting risk; lack of generalization
11	Glaucoma Disease Detection Using Hybrid Deep Learning [11]	2023	Hybrid DL	Fundus dataset	Accuracy ~93%	Limited dataset diversity
12	Hybrid Deep Learning Techniques for	2023	Hybrid CNN + ML	Fundus dataset	Accuracy ~94%	No progression/severity prediction

	Glaucoma Detection [12]					
13	OCT-based diagnosis of glaucoma using explainable ML [13]	2025	Explainable ML (XAI + OCT)	OCT dataset	High accuracy (~95%); explainable predictions	Validation needed on large-scale datasets
14	Predicting glaucoma progression using ML [14]	2023	ML (SVM, RF)	Longitudinal clinical data	Progression prediction ~85%	Limited dataset size; short follow-up duration

3 Research Methodology

So as to make sure that the body of research on glaucoma detection in ML and DL is well covered and critically assessed, this survey adopts a structured methodology. This review adopts a structured methodology. A complete literature search was conducted focusing on the period from 2021 to 2025 in the academic databases of IEEE Xplore, PubMed, SpringerLink, ScienceDirect, and MDPI. "Glaucoma detection," "machine learning," "deep learning," "fundus imaging," "OCT," and "artificial intelligence in ophthalmology" were the used key terms. A total of 14 relevant works, including review articles, conference proceedings, and journal articles mainly original research papers were selected. (i) Studies Employing ML or DL models to diagnose, classify, or predict the progression of glaucoma had to satisfy the following inclusion criteria: (ii) Performance metrics, such as accuracy, AUC, sensitivity or specificity were reported; and (iii) The models were built based on the use of fundus images, OCT, or multimodal datasets. Papers concerning unrelated eye diseases or that had no empirical validation were excluded.

The methods, datasets, results, and limitations of each work were extracted and tabulated. Subsequently, patterns in model performance, dataset usage, methodological heterogeneity, and persistent challenges were assessed via comparison. This systematic approach ensures that the review focuses on clinical utility and explainability as well as technical contribution.

The flowchart illustrates the systematic review process implemented in your study. It ensures transparency and clarity in the processes of collecting, screening and reviewing the literature:

1. Searching a Database

   - We performed a comprehensive search of academic databases, such as MDPI, IEEE Xplore, PubMed, SpringerLink, and ScienceDirect.

- "Glaucoma detection," "machine learning," "deep learning," "fundus imaging," "OCT," and "AI in ophthalmology" were some of the keywords at the beginning of the search.

2. Criteria for Screening

   - Papers utilising ML/DL for glaucoma detection, classification, or progression prediction that were published between 2021 and 2025 were included.
   - The works devoid of scientific evidence or those dealing with the topic unrelated to the glaucoma are not included.

3. 14 Papers Selected

   - Following the application of the criteria, a final 14 pertinent studies were selected.
   - These comprised conference proceedings, reviews, and research articles.

4. Methods/Datasets/Results Extraction

   - Information on the approaches, datasets, evaluation metrics and results of methodologies in terms of predictive performance were extracted in an overview form. The methods, data sets, evaluation metrics, and results used in each of the selected papers were systematically extracted.

5. Analysis by Comparison

   - In order to identify trends, good and bad practices, and gaps in research, the data were analyzed comparatively.
   - Particular attention was also paid to the accuracy, diversity of the dataset, generalizability and clinical applicability.

4 Discussion

Present analyses in AI for glaucoma detection suffers from multiple important limitations. Models built on small, homogeneous, or single-center data sets are known to not generalize well to different devices, centers or populations, and therefore to significantly underperform when deployed in the real world[3]-[4]-[6]. Also, a large number of studies do not perform sufficient external or cross-dataset validation, but rather heavily rely on internal testing, which might lead to overestimated accuracy values and less reliability when brought into practical use [3]-[4]. The comment the writer wants to make: the prior art focuses too much on binary detection and misses the critical clinical tasks of severity (=stage) and progression prediction [4]. Also, the explainability of deep models is Inadequate since existing XAI approaches fail to produce clear and reliable explanations that can be naturally utilized by clinicians [6]. Finally, although multimodal models combining fundus images, OCT and clinical data are promising, these often are computationally intensive, inadequately validated and not robust to noise, artefacts, or other issues faced in real-world application [3]-[6].

5 Conclusion and Future Scope

This study, which summarizes the findings of 14 recent works on glaucoma detection based on ML and DL algorithms, indicates both promising results and research challenges. In spite of the reports of excellent accuracy of diagnosis, the generalizability of the models are still challenged due to the dependency of the small and unbalanced datasets. At present, most systems only focus on detection, thus ignoring two problems that would be essential to clinical usefulness: estimation of severity and prediction of progression. Furthermore, the absence of explainable frameworks hinders the adoption in clinical practice as it decreases trust of ophthalmologists in AI-based decisions.

To enhance the generalization, the future research should be directed towards

(i) large-scale, multi-center datasets;
(ii) integrating multimodal data for thorough analysis;
(iii) developing interpretable AI models that boost clinical trust; and
(iv) validating lightweight, scalable architectures for use in practical ophthalmology.

By moving further in these ways, we can close the gap between experimental AI models and useful, clinically verified technologies that can help ophthalmologists reduce blindness caused by glaucoma globally.

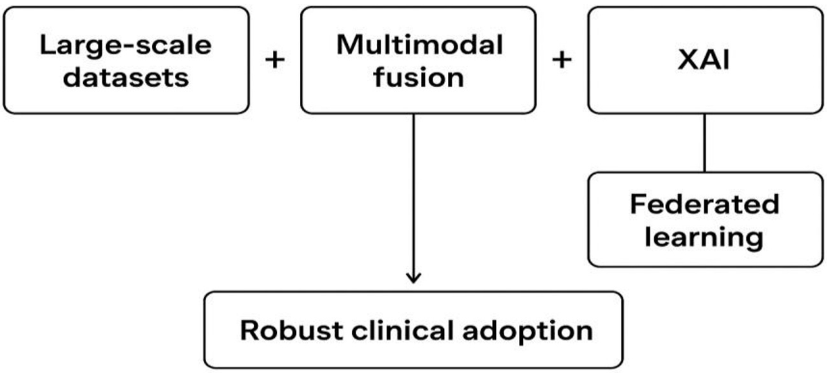

Fig.1. Proposed future Research Framework

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