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A Systematic Survey on the Glaucoma Eye Disease Detection using Enhanced DL and Modified Classification Techniques

Lokesha K[1] and A. Muruganandham[2]
[1]Part-Time Research Scholar (USN-1RR21PEC01), VTU Research Centre, Dept. of ECE, Rajarajeswari College of Engineering & Assistant Professor, Department of Electronics & Communication Engineering, Rajarajeswari College of Engineering, Bangalore, Karnataka
Email: lokeshk555@gmail.com
[2]Supervisor & Professor, Department of Electronics & Communication Engineering, Rajarajeswari College of Engineering, Bangalore, Karnataka

***Abstract*— This survey study presents a concise literature review on glaucoma eye disease detection using enhanced deep learning and modified classification techniques. The selected works highlight the evolution of automated glaucoma diagnosis from traditional methods to advanced deep learning models utilizing fundus images, optical coherence tomography (OCT), and hybrid approaches. The reviewed studies demonstrate significant improvements in detection accuracy, early-stage diagnosis, segmentation of optic disc and cup regions, and model interpretability. Key advantages include high diagnostic performance, availability of public datasets for benchmarking, and the development of lightweight and real-time applicable models. However, common limitations such as lack of dataset diversity, high dependency on costly imaging devices, limited generalization across populations, and challenges in explainability are still evident. Overall, the survey emphasizes the need for robust, cost-effective, and interpretable deep learning frameworks to achieve reliable glaucoma detection in real-world clinical environments.**

***Index Terms*— Glaucoma, Eye, RNFL, Retina, OC, OD, OCT, Fundus, AI, ML, DL.**

I. Introduction

A lot of researchers have worked on the proposed topic in various platforms & conditions from clinical to the implementation & detection point of view. Here, follows a brief survey of the works done by various authors [1]-[50] in the chosen field.

II. Survey / Review

Ashtari-Majlan et.al. [1] aimed to present a comprehensive survey of deep learning methods for glaucoma diagnosis across different imaging modalities. The authors reviewed fundus image analysis, OCT-based approaches, visual-field-based models, and multimodal systems. A major advantage of this work is that it gives a broad understanding of how glaucoma detection has evolved from feature-engineered methods to end-to-end deep models.

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Another strength is that it discusses practical barriers such as interpretability, data imbalance, and domain shift. The main lacuna is that, being a survey, it does not experimentally validate a unified framework and leaves open the issue of how to standardize comparisons across datasets.

Camara et.al. [2] focused on reviewing artificial intelligence methods for glaucoma screening, segmentation, and classification. The study summarized state-of-the-art methods dealing with optic disc, optic cup, and papilla-centered image analysis. Its main advantage is that it clearly separates the tasks of segmentation and classification, which helps researchers understand pipeline design. Another merit is that it emphasizes methodological trends and the importance of clinical validation. The weakness is that many reviewed studies used heterogeneous datasets and evaluation protocols, making direct comparison difficult.

Zedan et.al. [3] aimed to analyze recently used deep learning techniques for automated glaucoma screening and diagnosis. The authors examined classification, segmentation, and hybrid diagnosis pipelines, especially for fundus and OCT images. A clear advantage is that the paper highlights the diagnostic relevance of optic nerve head features and image preprocessing. It also helps identify why deep learning has become attractive for large-scale screening. The demerit is that it still reflects the limitations of the underlying studies, especially small datasets, weak generalization, and limited explainability.

Meedeniya et.al. [4] systematically reviewed deep-learning approaches for glaucoma identification from retinal fundus images between 2018 and 2024. The authors synthesized major architectures, datasets, and performance trends in fundus-based glaucoma research. The advantage of this review is that it is recent and specifically centered on fundus imaging, which is highly relevant for low-cost screening. Another strength is that it identifies the progression from CNN-based methods to transformer-influenced models and ensemble strategies. Its limitation is that it is restricted mainly to fundus-based literature and therefore does not fully represent OCT-dominant or multimodal diagnosis pipelines.

Thompson et.al. [5] critically reviewed deep learning for glaucoma screening, diagnosis, and progression detection. The work discussed not only classification from images but also the possible role of deep models in longitudinal monitoring. The major advantage is that it places technical findings in a clinical context and points out the translational potential of AI in ophthalmology. It also underscores issues such as labeling quality, disease definition, and external validity. The weakness is that many of the studies available at that time were early-stage and lacked large prospective validation.

Murtagh et.al. [6] reviewed machine learning applications in the screening and diagnosis of glaucoma. The authors examined several algorithms used for retinal image processing and glaucoma decision support. The advantage of this work is that it provides a useful bridge between classical machine learning and later deep learning systems. It also shows how structured ophthalmic measurements and imaging can be jointly exploited. However, the review points to a recurring demerit in the field, namely inconsistent reference standards and a lack of broad real-world validation.

Barros et.al. [7] conducted a systematic review on machine learning applied to retinal image processing for glaucoma diagnosis. The authors investigated algorithms for disc/cup segmentation, feature extraction, and classification. The main advantage is that the paper offers a structured overview of how retinal image analysis has been automated over time. It also helps clarify the role of handcrafted features before the rise of deep learning. The limitation is that many earlier methods depended strongly on image quality and manual preprocessing, which restricts robustness in clinical practice.

Wu et.al. [8] evaluated the performance of machine learning in detecting glaucoma using fundus and retinal OCT images. The authors assessed how well AI systems perform across imaging modalities and datasets. A key advantage is that the work provides a modality-aware perspective rather than focusing on only one image source. Another merit is that it helps quantify where machine learning performs better and where uncertainty remains. The limitation is that performance variability across datasets suggests that generalization is still a major unresolved challenge.

Li et.al. [9] aimed to assess the efficacy of a deep learning system for detecting referable glaucomatous optic neuropathy from color fundus photographs. The authors trained and validated a large-scale deep model for practical glaucoma screening. The major advantage of this study is that it demonstrated the feasibility of AI-assisted, fundus-based screening on a clinically relevant scale. Another strength is that it helped establish confidence in deep learning as a screening support tool. Its demerit is that detecting referable disease is easier than identifying very early or borderline glaucoma, so subtle-stage discrimination remained limited.

Phene et.al. [10] aimed to determine the relative importance of optic disc features predicted by deep learning for referable glaucoma. The authors built a model that not only predicted disease status but also related its decisions to disc features. An important advantage is the move toward interpretable glaucoma AI rather than pure black-box prediction. It also helped show that clinically meaningful optic nerve head characteristics can be learned from fundus photographs. The limitation is that explainability at the feature level does not fully solve the clinical trust problem, especially in atypical cases.

Keel et.al. [11] sought to visualize validated deep learning models for detecting referable glaucomatous optic neuropathy. The authors used visualization tools to identify image regions that influenced model decisions. The main advantage is that it improved transparency and showed that the networks focused on relevant optic disc regions. Another benefit is that it supported the clinical plausibility of fundus-based AI decisions. The demerit is that visualization methods still provide indirect explanations and can sometimes oversimplify what the model has actually learned.

Al-Aswad et.al. [12] evaluated a deep learning system for identifying glaucomatous optic neuropathy. The authors tested the model in a realistic diagnostic context rather than merely reporting internal accuracy. A strong advantage is that the work contributes to translational validation of glaucoma AI. It also highlights how AI can support screening in settings with limited subspecialty expertise. The weakness is that deployment performance may still vary with camera type, ethnicity, disease prevalence, and referral criteria.

Phan et.al. [13] evaluated deep convolutional neural networks for glaucoma detection using color fundus images. The authors compared model behavior under different preprocessing and training conditions. One advantage is that the study demonstrated the practical value of image preprocessing for improving discrimination. It also showed that DCNNs can identify glaucoma-suspected eyes from routine fundus images. The limitation is that fundus-image-only models may miss structural details that OCT can capture better, especially in ambiguous or early cases.

Hemelings et.al. [14] aimed at accurate prediction of glaucoma from colour fundus photographs using deep learning. The authors used optic disc-centered fundus images and demonstrated strong automated classification performance. The advantage of the work is that it supports low-cost, image-based screening without requiring expensive OCT acquisition. Another merit is the emphasis on image-centered automation with minimal handcrafted intervention. The lacuna is that strong performance on curated disc-centered images may not directly translate to uncontrolled clinical or community screening images.

Ajitha et.al. [15] proposed a CNN-based method for automatic glaucoma diagnosis from fundus images. The authors aimed to create a powerful and accurate algorithm for classification with limited manual feature design. The major advantage is the simplicity of the framework and its direct application to fundus photographs. It also shows how end-to-end CNN learning can reduce reliance on handcrafted optic disc features. The demerit is that performance may depend heavily on dataset composition and may not fully address cross-domain robustness.

Singh et.al. [16] developed an enhanced deep image model for glaucoma diagnosis from retinal fundus data. The authors emphasized early diagnosis through improved image-driven feature learning. A key advantage is that the proposed model reported strong discrimination and supported automated diagnosis. Another benefit is that it reinforced the usefulness of enhanced deep architectures over simple baseline CNNs. The limitation is that highly tuned architectures can perform well on benchmark datasets but still struggle with noisy or demographically diverse images.

Hemelings et.al. [17] investigated whether deep learning could detect glaucoma from fundus image regions beyond the optic nerve head. The authors showed that informative disease cues may exist outside the conventionally used ONH region. This is a significant advantage because it broadens the understanding of disease-relevant visual biomarkers. It also cautions against overly narrow preprocessing pipelines that crop only the optic disc. The demerit is that such distributed evidence can make clinical interpretation more difficult and may increase the risk of learning dataset-specific shortcuts.

Cho et.al. [18] proposed a deep learning ensemble method for classifying glaucoma stages from fundus photographs. The authors combined multiple CNN models to improve grading beyond simple normal-versus-glaucoma classification. The main advantage is that ensemble learning can stabilize performance and better capture disease severity patterns. Another strength is its relevance for stage-wise clinical decision making. The limitation is that ensemble systems are computationally heavier and often harder to interpret than a single compact model.

Chang et.al. [19] attempted to explain the rationale of deep learning glaucoma decisions. The authors explored explanation strategies beyond conventional heatmaps to improve interpretability. The advantage is that the study directly addresses clinician trust, which is crucial for AI adoption in ophthalmology. It also illustrates that explanation quality can vary significantly depending on the chosen visualization method. The demerit is that explainability methods still do not guarantee causal correctness, so clinicians must interpret them cautiously.

Medeiros et.al. [20] trained a deep learning algorithm using quantitative SD-OCT data to detect glaucomatous structural damage. The authors focused on optic disc and retinal structural measurements rather than only fundus photographs. The major advantage is the strong structural sensitivity of OCT for early glaucomatous damage.

Another merit is that OCT-based learning can be more clinically aligned with progression-related tissue loss. The main limitation is that OCT acquisition is costlier and less widely available than fundus photography, which affects scalability.

Muhammad et.al. [21] proposed a hybrid deep learning method on single wide-field OCT scans for glaucoma detection. The authors used OCT-derived representations to separate healthy, suspect, and early glaucomatous eyes. The advantage is that wide-field OCT contains rich structural information relevant to glaucoma. Another strength is the promising performance for subtle or early disease categories. The demerit is that hybrid OCT systems can become technically complex and may depend on device-specific scan characteristics.

Maetschke et.al. [22] introduced a feature-agnostic approach for glaucoma detection directly from raw OCT volumes. The authors avoided handcrafted segmentation-derived features and used a 3D CNN on unsegmented data. The major advantage is that the model can learn informative volumetric patterns that may be missed by manually designed features. It also reduces dependence on error-prone intermediate segmentation steps. The weakness is that 3D CNNs demand greater computational resources and large training datasets for stable generalization.

Russakoff et.al. [23] developed a 3D deep learning system for detecting referable glaucoma using full OCT macular cube scans. The authors trained a volumetric CNN and also analyzed the impact of preprocessing and external validation. An important advantage is that the work moved beyond simple internal testing and explored cross-site generalization. It also demonstrated that retinal segmentation-based homogenization can improve model performance. The demerit is that dataset characteristics and referral definitions still influenced outcomes, showing that portability remains incomplete.

Sun et.al. [24] proposed a dual-input convolutional neural network for glaucoma diagnosis using SD-OCT. The authors combined complementary inputs to improve disease discrimination. The main advantage is that multi-branch designs can capture different structural aspects of the glaucomatous eye. Another benefit is that such architectures can enhance sensitivity for early abnormalities. The lacuna is that more complex input strategies may complicate deployment and require carefully standardized imaging protocols.

Bowd et.al. [25] studied deep learning analysis of OCT en face images for glaucoma classification. The authors compared image-based deep learning against feature-based gradient boosting classifiers. The advantage is that the deep model improved upon feature-engineered baselines, highlighting the value of direct image learning. It also showed that en face OCT representations can be useful for disease recognition. The demerit is that en face analysis still depends on OCT image quality and may not fully capture all clinically relevant volumetric cues.

Mariottoni et.al. [26] developed a deep learning model to detect glaucoma progression using SD-OCT retinal nerve fiber layer measurements. The authors targeted progression assessment rather than only cross-sectional diagnosis. The advantage is its direct clinical importance, since progression detection is essential for treatment planning. It also demonstrates that AI can extract longitudinal structural change patterns beyond simple threshold rules. The limitation is that progression labels are difficult to define reliably, and longitudinal ground truth can be noisy.

Hussain et.al. [27] proposed a multimodal deep learning model combining CNN and LSTM structures for predicting glaucoma progression. The authors incorporated temporal information to handle sequential disease evolution. The main advantage is that the approach recognizes glaucoma as a dynamic condition rather than a static image-label problem. Another strength is that multimodal temporal learning can improve risk forecasting. The weakness is that such systems require richer longitudinal data, which is harder to collect and curate at scale.

Mandal et.al. [28] investigated whether deep learning could differentiate glaucomatous progression from normal aging in OCT B-scans. The authors addressed a clinically relevant challenge because aging itself causes structural change. The advantage is that the study tackles a subtle diagnostic confounder that many previous models ignored. It also indicates the potential of deep learning for nuanced longitudinal interpretation. The limitation is that surrogate reference standards and limited follow-up diversity may still affect the robustness of conclusions.

Chiang et.al. [29] evaluated deep learning for glaucoma detection in highly myopic eyes using fundus photographs. The authors aimed to separate glaucoma from normal eyes in a population where diagnosis is particularly difficult. The major advantage is that the work addresses a challenging subgroup often excluded from earlier studies. It also improves the clinical relevance of AI by focusing on a difficult real-world population. The demerit is that high-myopia-specific models may not generalize equally well to routine non-myopic screening populations.

Fan et.al. [30] compared the diagnostic performance and explainability of a Vision Transformer approach for glaucoma detection from fundus images. The authors contrasted transformer-based learning with more conventional deep architectures. The key advantage is that transformer models can capture broader contextual relations in retinal images. Another merit is that the study explicitly considered explainability along with performance. The limitation is that transformer models often require large datasets and careful tuning, which may limit adoption in small clinical datasets.

Bragança et.al. [31] presented a public dataset and deep learning-based glaucoma detection study on fundus images. The authors contributed both data resources and classification experiments for glaucoma pattern recognition. The advantage is that public datasets improve reproducibility and make fair benchmarking easier. Another strength is that dataset publication helps reduce dependence on inaccessible private collections. The demerit is that even public datasets may still be limited in population diversity, image acquisition conditions, and disease spectrum.

Shoukat et.al. [32] proposed an automatic deep learning method for early-stage glaucoma diagnosis from retinal images. The authors aimed specifically at identifying disease earlier, where clinical intervention is most valuable. A major advantage is the focus on early glaucoma rather than only advanced disease. It also highlights the benefit of deep learning in extracting subtle retinal cues that might be missed manually. The limitation is that early-stage labels are often the most subjective, which may introduce uncertainty into training and evaluation.

Sudhan et.al. [33] developed a glaucoma detection framework using U-Net for segmentation and CNN-based classification. The authors followed a pipeline in which structural regions were segmented before final disease categorization. The main advantage is that the explicit segmentation stage improves anatomical focus and makes the workflow more interpretable. Another strength is that combining segmentation with classification can improve cup-disc related analysis. The demerit is that error propagation from imperfect segmentation can reduce final classification robustness.

Kim et.al. [34] proposed a deep learning approach for optic disc and cup segmentation and their boundary analysis to identify glaucoma risk. The authors aimed to create a clinically meaningful anatomical framework rather than only a black-box classifier. The advantage is that boundary-aware segmentation directly supports cup-to-disc related assessment. It also increases interpretability because the system produces structures familiar to ophthalmologists. The limitation is that boundary estimation becomes difficult in low-quality images, peripapillary atrophy, and pathological variations.

Alawad et.al. [35] reviewed machine learning and deep learning techniques for optic disc and optic cup segmentation. The authors critically assessed segmentation methods relevant to glaucoma screening. The main advantage is that the review isolates one of the most important pre-diagnostic tasks in glaucoma CAD systems. Another benefit is that it clarifies how segmentation quality influences downstream classification. The weakness is that segmentation-only improvements do not automatically translate into strong clinical diagnosis unless classification and validation are also robust.

Yu et.al. [36] developed a robust optic disc and cup segmentation method using a modified U-Net architecture. The authors specifically targeted accurate OD/OC delineation for glaucoma screening. A key advantage is the strong segmentation focus on structures central to glaucoma diagnosis. It also showed that modified encoder-decoder designs can outperform simpler segmentation baselines. The demerit is that even strong segmentation accuracy may still be sensitive to imaging artifacts and variations in field of view.

Fu et.al. [37] proposed M-Net for joint optic disc and cup segmentation in a one-stage multi-label deep architecture. The authors aimed to solve OD and OC segmentation simultaneously instead of treating them as separate problems. The major advantage is the joint learning of correlated anatomical structures, which improves efficiency and consistency. Another strength is that this work became a foundational reference for segmentation-driven glaucoma systems. The limitation is that segmentation-centric frameworks still rely on the assumption that cup-disc morphology alone sufficiently captures glaucoma severity.

Bajwa et.al. [38] proposed a two-stage framework for optic disc localization and glaucoma classification from retinal fundus images. The authors first localized the disc region and then performed disease prediction. The advantage is that targeted localization reduces irrelevant background information and improves computational focus. Another merit is that a staged architecture can be easier to interpret and debug. The demerit is that localization errors at the first stage can negatively affect final classification accuracy.

Liu et.al. [39] introduced a densely connected depthwise separable network for joint optic disc and cup segmentation. The authors sought more efficient yet accurate segmentation for glaucoma assistance. The advantage is that the architecture reduces parameter burden while preserving segmentation quality. It also supports practical deployment where computational resources are limited. The limitation is that segmentation efficiency alone does not guarantee best end-to-end glaucoma diagnosis without strong classification integration.

Joshi et.al. [40] proposed a graph deep network for optic disc and optic cup segmentation in glaucoma screening. The authors incorporated graph-based reasoning to better model structural relationships. The main advantage is that graph learning can capture shape and relational dependencies that ordinary CNN kernels may miss. Another strength is the improved structural coherence in OD/OC predictions. The demerit is that graph-based systems can be harder to train and may not be as straightforward to deploy as conventional CNNs.

Song et.al. [41] proposed a lightweight deep learning architecture for simultaneous optic disc and cup segmentation using fuzzy learning ideas. The authors targeted accurate segmentation with lower computational complexity. The advantage is that a lightweight model is more suitable for portable screening systems and edge deployment. It also preserves the clinical value of anatomical segmentation while reducing model size. The limitation is that lightweight networks may sacrifice some fine-detail accuracy in complex retinal images.

Govindharaj et.al. [42] proposed an advanced glaucoma disease segmentation and classification system. The authors combined optimized segmentation solutions with classification strategies for automated diagnosis. The strength of this work is the integrated pipeline that attempts to improve both localization and decision making. Another advantage is the emphasis on automation for practical diagnostic support. The demerit is that highly integrated pipelines can become sensitive to the cumulative error of multiple stages and require extensive validation.

Islam et.al. [43] proposed a multimodal deep learning model combining fundus photographs and OCT for glaucoma detection. The authors aimed to improve early diagnosis by exploiting complementary structural information from both modalities. The major advantage is that multimodal fusion can capture disease evidence more comprehensively than either modality alone. It also improves the chance of detecting subtle glaucoma changes missed by a single imaging source. The limitation is that multimodal data collection is resource-intensive and may reduce applicability in low-cost screening environments.

Lin et.al. [44] explored code-free machine learning for glaucoma detection. The authors aimed to enable clinicians without programming expertise to create ML models for glaucoma assessment. The advantage is the democratization of AI development and easier clinical experimentation. It also encourages clinician engagement with model-building workflows. The demerit is that code-free platforms may offer limited control over architecture design, bias analysis, and rigorous optimization.

Milad et.al. [45] studied code-free deep learning for glaucoma detection on color fundus images and compared it with expert-designed models. The authors used a very large labeled fundus dataset to test the feasibility of no-code AI development. The advantage is that the work shows how accessible DL toolchains can lower the barrier for clinical AI research. Another benefit is the large-scale evaluation setting. The limitation is that convenience-oriented systems may still underperform carefully designed expert models in highly nuanced diagnostic tasks.

Xu et.al. [46] proposed a deep learning model integrating domain-specific features with image-driven learning. The authors attempted to combine structured ophthalmic knowledge with unstructured deep representations. The major advantage is that domain-guided modeling can improve clinical relevance and reduce purely data-driven ambiguity. It also reflects a move toward hybrid intelligent classifiers rather than standalone black-box CNNs. The weakness is that selecting and integrating domain features appropriately remains nontrivial and may reduce portability across institutions.

Vieira et.al. [47] carried out a comparative analysis of explainable AI techniques applied to CNN-based glaucoma classification. The authors examined how different explanation methods behave on glaucoma prediction tasks. The main advantage is the direct focus on interpretability, which is essential for clinician acceptance. Another strength is that it shows that not all XAI methods provide equally meaningful explanations in ophthalmic imaging. The limitation is that explainability comparisons do not in themselves solve performance generalization or dataset bias.

Song et.al. [48] discussed deep learning-based glaucoma detection using CNN approaches. The authors aimed to develop an AI method for more precise glaucoma diagnosis. The advantage is that the work reinforces the ongoing relevance of CNN frameworks in practical glaucoma classification. It also provides additional evidence that retinal imaging can support automated disease identification. The demerit is that CNN-based methods, when used alone, may still face difficulty with cross-device variability and subtle early disease patterns.

Upadhyaya et.al. [49] evaluated the offline Medios AI glaucoma software in a primary eye-care setting. The authors assessed real-world diagnostic efficacy rather than only retrospective benchmark performance. The main advantage is its practical relevance for screening deployment in resource-constrained environments. It also contributes evidence about how AI behaves at the point of care. The limitation is that performance lower than human experts in some settings shows that current systems still need refinement before fully dependable standalone use.

He et.al. [50] studied the cross-camera performance of deep learning algorithms for glaucoma diagnosis from fundus images. The authors compared diagnostic consistency when images came from different cameras. The advantage is that the paper directly addresses a crucial real-world challenge: device shift. Another strength is that it highlights that good internal accuracy does not automatically imply cross-device reliability. The demerit is that camera-dependent variability remains a major obstacle for scalable glaucoma AI deployment across institutions. Like this, a large no. of authors have worked on the proposed topic, here, we have considered only the important ones [1]-[50]. This survey forms as the ready reckoner for those who want to pursue research in the field of glaucoma eye disease detection so that the problem statement could be coined since a variety of case studies done by various researchers have been considered.

III. Conclusions

A exhaustive review or survey was conducted on the proposed topic & finally, we conclude the following. From the above literature studies, it is clear that glaucoma detection research has moved from handcrafted image features and classical machine learning toward enhanced deep learning, segmentation-guided diagnosis, multimodal fusion, progression modeling, and explainable AI. Fundus-image-based methods are attractive for low-cost screening, whereas OCT-based and multimodal methods usually offer stronger structural sensitivity. Segmentation of the optic disc and optic cup remains an important intermediate task, but several recent studies show that end-to-end and multimodal systems can capture richer disease cues. At the same time, common lacunas continue to appear across the literature, especially small or curated datasets, inconsistent labels, lack of external validation, poor cross-camera generalization, limited interpretability, and reduced reliability in early or atypical glaucoma cases. Hence, there is strong motivation for a new systematic review centered on enhanced deep learning and modified classification techniques that explicitly examines robustness, generalization, explainability, and clinical usability. The drawbacks of the various authors were used to coin or define the problem statement & hence fine tuned the proposed research work as "Glaucoma eye disease detection using enhanced DL & modified classification technique implementations".

References

[1] M. Ashtari-Majlan et al., "Glaucoma diagnosis in the era of deep learning: A survey," Expert Systems with Applications, 2024.
[2] J. Camara et al., "Literature Review on Artificial Intelligence Methods for Glaucoma Screening, Segmentation, and Classification," 2022.
[3] M. J. M. Zedan et al., "Automated Glaucoma Screening and Diagnosis Based on Deep Learning: A Review," Diagnostics, 2023.
[4] D. Meedeniya et al., "Glaucoma identification with retinal fundus images using deep learning: A systematic review," Intelligent Systems with Applications, 2025.
[5] A. C. Thompson et al., "A Review of Deep Learning for Screening, Diagnosis, and Detection of Glaucoma Progression," Translational Vision Science & Technology, 2020.
[6] P. Murtagh et al., "Current applications of machine learning in the screening and diagnosis of glaucoma," 2020.
[7] D. M. S. Barros et al., "Machine learning applied to retinal image processing for glaucoma diagnosis: Review and perspectives," 2020.
[8] J. H. Wu et al., "Performances of Machine Learning in Detecting Glaucoma Using Fundus and Retinal Optical Coherence Tomography Images: A Meta-Analysis," 2022.
[9] Z. Li et al., "Efficacy of a Deep Learning System for Detecting Glaucomatous Optic Neuropathy Based on Color Fundus Photographs," Ophthalmology, 2018.
[10] S. Phene et al., "The Relative Importance of Optic Disc Features to Predict Referable Glaucoma Using Deep Learning on Fundus Photographs," 2019.
[11] S. Keel et al., "Visualizing Deep Learning Models for the Detection of Referable Glaucomatous Optic Neuropathy," 2019.
[12] L. A. Al-Aswad et al., "Evaluation of a Deep Learning System for Identifying Glaucomatous Optic Neuropathy Based on Color Fundus Photographs," 2019.
[13] S. Phan et al., "Evaluation of Deep Convolutional Neural Networks for Glaucoma Detection," 2019.
[14] R. Hemelings et al., "Accurate prediction of glaucoma from colour fundus photographs with deep learning," 2020.
[15] S. Ajitha et al., "Identification of glaucoma from fundus images using deep learning," 2021.
[16] L. K. Singh et al., "An enhanced deep image model for glaucoma diagnosis using retinal fundus image," 2021.
[17] R. Hemelings et al., "Deep learning on fundus images detects glaucoma beyond the optic disc," 2021.
[18] H. Cho et al., "Deep Learning Ensemble Method for Classifying Glaucoma Stages from Fundus Photographs," 2021.
[19] J. Chang et al., "Explaining the Rationale of Deep Learning Glaucoma Decisions with Visual Explanations," 2021.
[20] F. A. Medeiros et al., "An OCT-Trained Deep Learning Algorithm for Detecting Glaucomatous Damage from Optic Disc Photographs," 2019.
[21] H. Muhammad et al., "Hybrid Deep Learning on Single Wide-field Optical Coherence Tomography Scans Accurately Classifies Glaucoma Suspects," 2017.

[22] S. Maetschke et al., “A feature agnostic approach for glaucoma detection in OCT volumes,” 2018.
[23] D. B. Russakoff et al., “A 3D Deep Learning System for Detecting Referable Glaucoma Using Full OCT Macular Cube Scans,” Translational Vision Science & Technology, vol. 9, no. 2, p. 12, 2020.
[24] S. Sun et al., “Dual-input convolutional neural network for glaucoma diagnosis using spectral-domain optical coherence tomography,” 2021.
[25] C. Bowd et al., “Deep Learning Image Analysis of Optical Coherence Tomography for Glaucoma Classification,” 2022.
[26] E. B. Mariottoni et al., “Deep Learning-Assisted Detection of Glaucoma Progression Using Spectral-Domain OCT,” 2023.
[27] S. Hussain et al., “Predicting glaucoma progression using deep learning of longitudinal visual fields and clinical data,” 2023.
[28] S. Mandal et al., “Progression or Aging? A Deep Learning Approach for Identifying Longitudinal Glaucomatous Change in OCT B-Scans,” 2024.
[29] Y. Y. Chiang et al., “Deep Learning Evaluation of Glaucoma Detection Using Fundus Photographs in Highly Myopic Eyes,” 2024.
[30] R. Fan et al., “Detecting Glaucoma from Fundus Photographs Using Deep Learning with Vision Transformer,” 2022.
[31] C. P. Bragança et al., “Detection of Glaucoma on Fundus Images Using Deep Learning and a New Public Database,” 2022.
[32] A. Shoukat et al., “Automatic Diagnosis of Glaucoma from Retinal Images Using Deep Learning,” 2023.
[33] M. B. Sudhan et al., “Segmentation and Classification of Glaucoma Using U-Net with Deep Learning Model,” 2022.
[34] J. Kim et al., “Identifying Those at Risk of Glaucoma: A Deep Learning Approach for Optic Disc and Cup Segmentation and Their Boundary Analysis,” Diagnostics, 2022.
[35] M. Alawad et al., “Machine Learning and Deep Learning Techniques for Optic Disc and Cup Segmentation for Glaucoma Screening,” 2022.
[36] S. Yu et al., “Robust optic disc and cup segmentation with deep learning for glaucoma detection,” 2019.
[37] H. Fu et al., “Joint Optic Disc and Cup Segmentation Based on Multi-Label Deep Network and Polar Transformation,” 2018.
[38] M. N. Bajwa et al., “Two-stage framework for optic disc localization and glaucoma classification in retinal fundus images using deep learning,” 2019.
[39] B. Liu et al., “Joint optic disc and cup segmentation based on densely connected depthwise separable network for glaucoma screening,” 2021.
[40] A. Joshi et al., “Graph deep network for optic disc and optic cup segmentation for glaucoma screening,” 2022.
[41] Y. Song et al., “A novel lightweight deep learning approach for simultaneous optic disc and optic cup segmentation,” 2024.
[42] I. Govindharaj et al., “Advanced glaucoma disease segmentation and classification using optimized deep learning methods,” 2025.
[43] S. Islam et al., “Novel Deep Learning Model for Glaucoma Detection Using Fundus and OCT Images,” 2025.
[44] T. Lin et al., “Code-Free Machine Learning for the Detection of Glaucoma,” 2025.
[45] D. Milad et al., “Code-Free Deep Learning Glaucoma Detection on Color Fundus Images,” 2025.
[46] J. Xu et al., “A deep learning model integrating domain-specific features for glaucoma diagnosis,” 2025.
[47] C. Vieira et al., “A comparative analysis of explainable artificial intelligence techniques for glaucoma classification,” 2025.
[48] R. Song et al., “Deep Learning-based Glaucoma Detection Using CNN Approaches,” 2024.
[49] S. Upadhyaya et al., “Diagnostic Performance of the Offline Medios Artificial Intelligence Glaucoma Software in Primary Eye Care,” 2025.
[50] S. He et al., “Cross-camera Performance of Deep Learning Algorithms for Glaucoma Diagnosis from Fundus