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Article

An Extensive Comparative Study on Early Glaucoma Classification Using Fundus Images

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Abstract: Glaucoma is a chronic, progressive optic neuropathy that is among the leading causes of irreversible blindness worldwide. Because it remains largely asymptomatic until an advanced stage, a large proportion of cases are detected only after substantial and permanent vision loss. Conventional diagnostic procedures are time-consuming, resource-intensive and dependent on specialist expertise, which limits large-scale screening. Deep learning and machine learning applied to retinal fundus images have therefore emerged as promising tools for automated, low-cost and early glaucoma detection. This paper presents an extensive comparative study of recent artificial-intelligence-based glaucoma classification methods. It reviews the deep-learning architectures, classifier models, benchmark fundus datasets and performance metrics that underpin this field, and organises the surveyed literature into five methodological categories: convolutional and transfer-learning networks, vision-transformer and attention-based models, hybrid deep-learning–machine-learning and feature-fusion pipelines, classical machine learning with handcrafted features, and segmentation-assisted and multimodal frameworks. Reported accuracies range from about 76% for early single-network baselines to over 99% for ensemble, hybrid and segmentation-guided pipelines. The study consolidates the current state of the art, highlights recurring limitations such as class imbalance, limited generalisation and low sensitivity, and identifies open research directions including explainable and privacy-preserving distributed learning.
Keywords: Glaucoma; Fundus Images; Deep Learning; Image Classification; Cup-to-Disc Ratio (CDR); Vision Transformer.

I. INTRODUCTION

Glaucoma silently damages the optic nerve and is one of the principal causes of irreversible blindness across the globe [1]. Patients who experience prolonged episodes of elevated blood-glucose level and high blood pressure frequently show damage to the inner retina on examination, yet many report no symptoms of visual loss in the early phase. Because glaucoma is largely asymptomatic until the disease is well advanced, a substantial fraction of those affected remain undiagnosed, and the true prevalence is considerably higher than the number of confirmed cases [2].

The head of the optic nerve, commonly called the optic disc, is composed of neural, vascular and connective tissue and lies within the retina. A central depression known as the optic cup is located inside it. In glaucoma, damage to the optic nerve produces structural and functional alterations in this region: the optic cup enlarges, nerve cells degenerate and microcirculation is disturbed, ultimately leading to vision loss. Fundus imaging and retinography are highly valuable for diagnosis because they can reveal these alterations, which makes retinal fundus images crucial for the analysis of glaucoma.

Ophthalmologists evaluate a variety of features from these images to detect glaucoma accurately, but manual assessment is time-consuming, expensive and subject to inter-observer variability. Consequently, the automatic detection and prediction of glaucoma using machine learning and deep learning has gained considerable popularity for effective early screening [3]. Deep-learning models applied directly to colour fundus photographs have been shown to detect glaucomatous damage even beyond the optic disc [4], to generalise across imaging devices and populations

[5], and, more recently, to be deployable through code-free platforms that widen clinical accessibility [6]. This research scrutinises and compiles previous studies that have employed deep-learning algorithms and classifier models for glaucoma detection, focusing on the algorithms, classifier models, datasets and performance metrics that quantify detection quality, and aims to provide a detailed understanding of the current landscape of classifier models for glaucoma detection.

II. GLAUCOMA

Glaucoma is a cluster of eye disorders whose characteristic feature is progressive damage to the optic nerve, which transfers visual information from the eye to the brain. It is commonly associated with raised intra-ocular pressure, although it can also occur at normal pressure. The primary mechanism involves impaired drainage of the aqueous humour, the fluid present in the eye; this leads to elevated pressure that impairs the optic nerve and induces the structural changes visible on fundus examination [7], [8].

The key causes and risk factors include:

- Increased intra-ocular pressure (IOP) due to blocked drainage channels;
- Genetic predisposition or family history;
- Age-related changes, especially above 40 years;
- Systemic conditions such as diabetes and hypertension;
- Eye injuries or trauma;
- Long-term corticosteroid use;
- Limited blood flow to the optic nerve, particularly in normal-tension glaucoma.

The typical progression of glaucoma is as follows:

1. Early stage: no noticeable symptoms;
2. Peripheral vision loss: side vision becomes reduced, often unnoticed initially;
3. Tunnel vision: advanced stages restrict vision to a narrow central field;
4. Complete blindness: if untreated, total vision loss may occur.

In some forms, such as acute angle-closure glaucoma, symptoms can appear suddenly and include severe eye pain, blurred vision, halos around lights, nausea and vomiting.

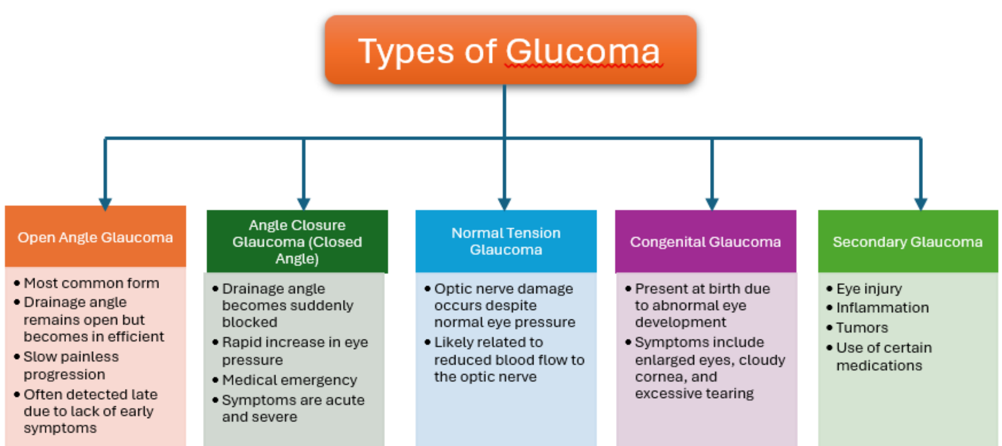

Fig. 1. Classification of glaucoma into its major types.

Figure 1 shows the classification of glaucoma into its major types. Clinicians use fundus images (retinal photographs) and optical coherence tomography (OCT) scans to evaluate the eye. The key factors examined are optic-nerve damage, the shape of the optic disc, the cup-to-disc ratio and nerve-fibre loss. These images are then analysed by artificial-intelligence models that automatically detect glaucoma and classify the eye as healthy or glaucomatous.

The cup-to-disc ratio (CDR) plays a major role in identifying glaucoma and acts as a primary structural biomarker [9], [10]. It is defined as:

CDR = (Size of optic cup) / (Size of optic disc)

A normal eye has values between 0.3 and 0.4 (a small cup), whereas a glaucomatous eye typically has a value greater than 0.6 (a large cup). Table 1 summarises the differences between a healthy eye and a glaucomatous eye with respect to the cup-to-disc ratio and other structural changes.

Table 1. Comparison of the features of a healthy eye and a glaucomatous eye

Normal (Healthy) Eye	Glaucomatous Eye
Small optic cup	Enlarged optic cup (cupping)
Healthy, thick optic-nerve rim	Thin optic-nerve rim
Balanced neuro-retinal rim thickness	Nerve-fibre loss
Low or normal CDR (0.3–0.4)	High CDR (> 0.6)
Preserved retinal structure	Progressive structural changes in the retina

The impact of glaucoma is a gradual loss of peripheral vision, the onset of tunnel vision and, if not detected in time, permanent loss of sight.

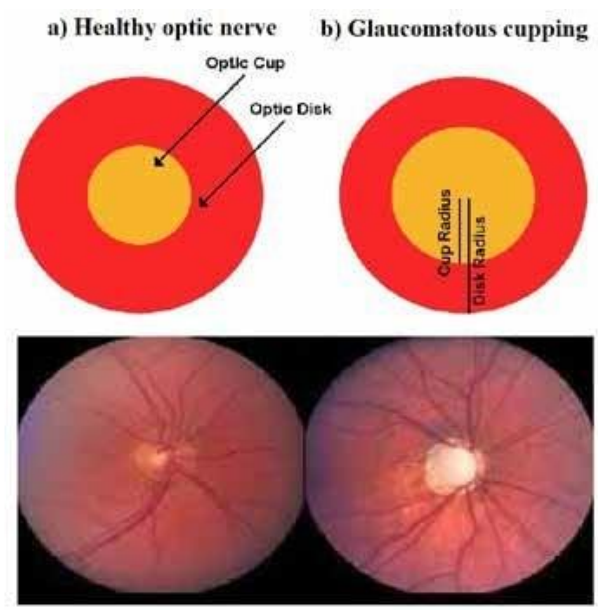

Fig. 2. Variation between a healthy optic nerve and an eye showing cupping due to glaucoma.

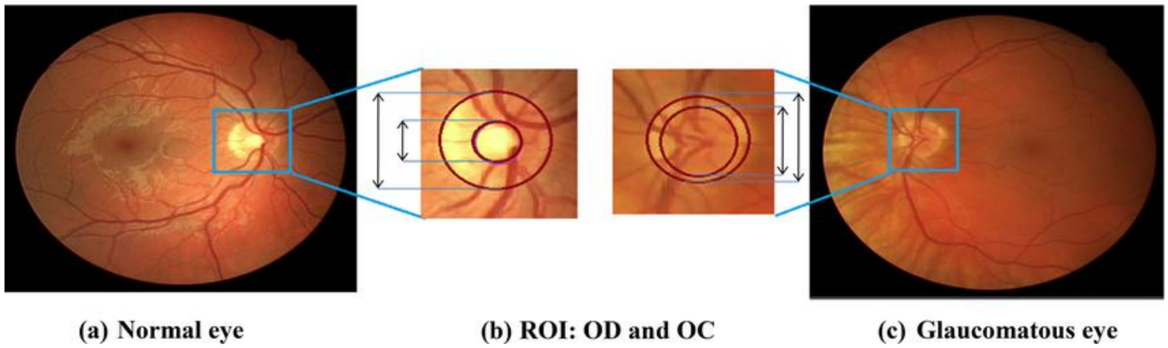

Fig. 3. Glaucomatous eye versus healthy eye.

Figure 3(a) shows a healthy eye. The nerve head can be pictured as a doughnut: the neuro-retinal rim is healthy living tissue, pink and thick, forming the doughnut shape. In Figure 3(b) the region of interest is enlarged, clearly showing the optic disc (OD) and optic cup (OC); the pale central hole (the cup) is small and the surrounding layer of nerves is dense and healthy. Figure 3(c) shows a glaucomatous eye in which the pale central hole is large—this is termed cupping. Here the nerve fibres have died out and, because of the cupping, the blood vessels bend sharply over the rim edge. Glaucoma has effectively hollowed out the nerve, destroying the healthy fibres necessary to transmit visual information to the brain.

III. ALGORITHMS, TECHNIQUES AND CLASSIFIER MODELS

A wide range of classifier models has been applied to glaucoma detection, spanning classical machine learning, deep learning and hybrid combinations of the two. Table 2 lists the most widely used models together with their reported accuracy and salient characteristics.

Table 2. Most widely used classifier models for glaucoma detection

Model / Classifier	Type	Accuracy	Details
EfficientNetB4 (Snapshot Ensemble CNN)	Deep Learning	99.35%	High precision, recall and AUC (≈0.99)
EfficientNetB4 (Transfer Learning)	Deep Learning	99.38%	High sensitivity and specificity
Hybrid CNN (ResNet50 + InceptionV3)	Deep Learning	99.1–99.4%	Best across multiple datasets
AdaBoost (LBP + Chip Histogram)	Machine Learning	99.29%	Best feature-based ML model
Ensemble ML + DL (GLCM + Voting)	Hybrid	95.41%	High precision (99.37%)
Custom Deep CNN	Deep Learning	93.75%	High sensitivity (100%)
ViT + Capsule Network	Deep Learning	93%	Explainable AI (Grad-CAM)
Ensemble CNN + ML (CCA + RF/SVM/KNN)	Hybrid	93.39%	Feature fusion improves accuracy

Deep-learning models dominate the top ranks in glaucoma detection, particularly EfficientNet and hybrid CNN architectures. At the same time, traditional feature-based methods such as Local Binary Patterns (LBP) and the Gray-Level Co-occurrence Matrix (GLCM) still perform very well when combined with boosting techniques such as AdaBoost [11], [12]. Hybrid approaches that combine deep learning and machine learning provide a more balanced performance [13]. Accuracy alone, however, is not sufficient: some models with slightly lower accuracy offer better clinical reliability owing to higher sensitivity. Overall, EfficientNet-based deep learning gives the best performance [14], LBP with boosting is the strongest traditional method, and hybrid models offer a good balance between the two.

IV. FUNDUS DATASETS

The performance of any classifier model depends strongly on the dataset used for training and evaluation. Table 3 lists the benchmark fundus-image datasets most frequently used in the surveyed literature, together with the number of images, typical resolution, image type and the availability of optic-disc annotations. Several recent studies combine multiple public datasets to improve generalisation across imaging conditions [15].

Table 3. Benchmark fundus-image datasets and their characteristics

Dataset	No. of Images	Resolution	Image Type	Optic-Disc Annotation
DRISHTI-GS	101	≈ 2896 × 1944	Retinal fundus	Annotated (available)
RIM-ONE	455	≈ 2144 × 1424 (varies)	Retinal fundus	Annotated (available)
ORIGA	650	≈ 3072 × 2048	Retinal fundus	Annotated (available)
REFUGE	1200	2124 × 2056	Retinal fundus	Annotated (available)
HRF (High-Resolution Fundus)	45	3504 × 2336	Retinal fundus	Not mentioned
ACRIMA	705–7705	≈ 1444 × 1444 (varies)	Retinal fundus	Not mentioned

Table 3 highlights the wide variation in dataset size, resolution and annotation availability. Small, high-resolution sets such as DRISHTI-GS and HRF are well suited to segmentation studies, whereas larger sets such as REFUGE and ACRIMA support the training of data-hungry deep networks.

V. PERFORMANCE METRICS

A consistent set of performance metrics is essential for the fair comparison of classifier models. Table 4 lists the metrics most commonly reported in the surveyed studies, what each measures and why it matters for glaucoma screening.

Table 4. Metrics used in the performance analysis of a classifier model

Metric	What it Measures	Importance
Accuracy	Overall correctness of classification	Evaluates the overall effectiveness of the combined features
Sensitivity (Recall)	Ability to correctly detect glaucoma cases	Most critical metric; avoids missing glaucoma cases
Specificity	Ability to correctly detect healthy cases	Prevents false alarms and balances sensitivity
Precision	Correctness of predicted glaucoma cases	Ensures reliability of predictions and reduces false positives
F1-Score	Harmonic balance between precision and recall	Important for imbalanced datasets
ROC-AUC	Overall class separability	Evaluates performance across a complex feature space

Metric	What it Measures	Importance
Confusion Matrix	TP, TN, FP and FN counts	Helps analyse errors and debug the system
MCC (Matthews Correlation Coefficient)	Balanced measure using all confusion-matrix values	Reliable for imbalanced datasets

It can be inferred from Table 4 that the most important performance metrics are sensitivity, AUC and F1-score; the secondary supporting metrics are specificity and precision; while accuracy, MCC and the confusion matrix provide additional support. Given the clinical cost of a missed diagnosis, sensitivity is generally prioritised over raw accuracy.

VI. LITERATURE SURVEY

This section reviews recent research on glaucoma detection using artificial intelligence. To make the comparison meaningful, the studies are grouped into five methodological categories: (A) convolutional and transfer-learning networks; (B) vision-transformer and attention-based models; (C) hybrid deep-learning–machine-learning and feature-fusion pipelines; (D) classical machine learning with handcrafted features; and (E) segmentation-assisted and multimodal frameworks. For each category a short narrative is followed by a compact comparison table. Across all categories, reported accuracy ranges from about 76% to over 99%, with hybrid, ensemble and segmentation-guided models generally performing best, while some methods still suffer from low recall and higher false-negative rates.

A. Convolutional and Transfer-Learning Networks

Convolutional neural networks (CNNs), often initialised with transfer learning from ImageNet, form the backbone of most glaucoma-detection systems. Kaur [16] applied a VGG16 transfer-learning model to a large Kaggle dataset and achieved 76% accuracy; although precision for glaucoma was high (0.89), recall was low (0.43), reflecting a high false-negative rate that is clinically undesirable. Govindan et al. [17] combined ResNet50 and InceptionV3 into a hybrid CNN and reported accuracies of 99.1–99.4% across ORIGA, STARE and REFUGE. Thanapaisal et al. [18] used EfficientNetB7 with fine-tuning to grade severity (normal, mild-moderate, severe), reaching 87.1% test accuracy with strong AUC for the normal class and Grad-CAM localisation of the optic disc. Geetha et al. [19] proposed DEEP GD, a snapshot-ensemble EfficientNetB4 coupled with a V-Net segmentation stage, attaining 99.35% accuracy and outperforming ResNet, MobileNet, U-Net and RNN baselines. Jisy et al. [20] designed a compact deep CNN with feature-map visualisation focused on the optic-nerve head and retinal-nerve-fibre-layer regions, obtaining 93.75% accuracy with 100% sensitivity.

Table 5. Convolutional and transfer-learning approaches for glaucoma detection

Author (Year) [Ref]	Model / Approach	Dataset	Best Performance	Key Insight
Kaur (2024) [16]	CNN – VGG16 with transfer learning	Kaggle (16,642 images)	Acc 76%	High precision but low glaucoma recall (high false negatives)
Govindan et al. (2024) [17]	Hybrid CNN (ResNet50 + InceptionV3), transfer learning	ORIGA, STARE, REFUGE	Acc 99.1–99.4%	Hybrid ensemble best across all datasets
Thanapaisal et al. (2025) [18]	EfficientNetB7, fine-tuning, Grad-CAM	2,940 hospital fundus images	Acc 87.1%; AUC 0.988 (normal)	Multi-class severity grading (normal/mild-moderate/severe)
Geetha et al. (2025) [19]	DEEP GD – Snapshot-Ensemble EfficientNetB4 + V-Net	GFI + hospital	Acc 99.35%; AUC ≈ 0.99	Joint classification and segmentation; beats ResNet/MobileNet/U-Net

Author (Year) [Ref]	Model / Approach	Dataset	Best Performance	Key Insight
		(1,609 images)		
Jisy et al. (2024) [20]	Custom deep CNN (4 conv + 2 dense) + feature visualisation	L.V. Prasad (415 images)	Acc 93.75%; Sens 100%	ONH + RNFL focus; outperforms VGG16/ResNet50/MobileNetV2

B. Vision-Transformer and Attention-Based Models

Vision transformers (ViTs) and attention mechanisms have recently been adopted to capture long-range dependencies in fundus images. Vigneshwaran et al. [21] combined a Vision Transformer with a Capsule Network and Grad-CAM explainability, achieving 93% accuracy on RIM-ONE while improving interpretability relative to conventional CNNs. Yurdakul et al. [22] introduced MaxGlaViT, a lightweight model that augments the MaxViT backbone with modern CNN blocks and ECA, CBAM and SE attention modules; it reached 87.93% accuracy and an F1-score of 87.96% for early-stage staging on the HDV1 dataset while using only 6.2M parameters (versus 31M for the baseline) and outperforming 40 CNN and 40 ViT baselines. These works show that attention-based models can match or exceed CNNs while remaining computationally efficient and more explainable.

Table 6. Vision-transformer and attention-based approaches for glaucoma detection

Author (Year) [Ref]	Model / Approach	Dataset	Best Performance	Key Insight
Vigneshwaran et al. (2025) [21]	Vision Transformer + Capsule Network + Grad-CAM	RIM-ONE	Acc 93%	Explainable; outperforms traditional methods
Yurdakul et al. (2025) [22]	MaxGlaViT (MaxViT + ECA/CBAM/SE attention)	HDV1 (1,542 images)	Acc 87.93%; F1 87.96%	Only 6.2M vs 31M params; beats 40 CNN + 40 ViT baselines; early-stage staging

C. Hybrid Deep-Learning–Machine-Learning and Feature-Fusion Pipelines

A third group of studies fuses deep and classical learning to combine the representational power of CNNs with the robustness of traditional classifiers. Aljohani and Aburasain [23] built an ensemble of Random Forest, ResNet50 and VGG16 with a two-out-of-three majority-voting rule, trained within a federated framework across the ACRIMA, G1020, ORIGA and REFUGE datasets; the ensemble reached 95.41% accuracy and 99.37% precision, exceeding each individual model. Ejaz et al. [24] extracted features from two CNNs of different depth, fused them using Canonical Correlation Analysis (CCA) and fed the result to classical classifiers, achieving 93.39% accuracy for multi-class retinal-disease classification on the RFMiD dataset. These pipelines demonstrate that feature fusion and ensembling can raise both accuracy and stability.

Table 7. Hybrid deep-learning–machine-learning and feature-fusion approaches

Author (Year) [Ref]	Model / Approach	Dataset	Best Performance	Key Insight
Aljohani & Aburasain (2024) [23]	RF + ResNet50 + VGG16 ensemble (majority voting), federated	ACRIMA, G1020, ORIGA, REFUGE (2,775 images)	Acc 95.41%; Prec 99.37%	Ensemble with GLCM texture features beats individual models
Ejaz et al. (2025) [24]	Dual CNN (12 + 20 layers) + CCA feature fusion + ML classifiers	RFMiD + RFMiD 2.0 (1,908 images)	Acc 93.39% (ensemble)	Multi-class retinal disease (DR, MH, ODC, Normal)

D. Classical Machine Learning with Handcrafted Features

Before end-to-end deep learning became dominant, glaucoma detection relied on handcrafted features fed to classical classifiers, and this approach remains competitive on small datasets. Kalita and Borgohain [9] combined structural biomarkers (CDR, neuro-retinal rim, rim-to-disc ratio, nerve-rim thickness) with non-structural statistical, spectral, geometric and textural features (GLCM, GLRLM, LBP), and used an Extra-Trees classifier with SMOTE balancing to reach 85.42% accuracy on the SMDG-19 dataset, reducing the feature set from 96 to 60. Velpula et al. [25] evaluated combinations of HOG, LBP, GLCM and chip-histogram features with SVM and AdaBoost classifiers on the ACRIMA dataset, obtaining a best accuracy of 99.29% with LBP plus chip histogram under AdaBoost, and showed that AdaBoost outperforms SVM for complex feature combinations. Classical pipelines therefore remain attractive when data are scarce and interpretability is required, though they depend heavily on the quality of engineered features.

Table 8. Classical machine-learning approaches with handcrafted features

Author (Year) [Ref]	Model / Approach	Dataset	Best Performance	Key Insight
Kalita & Borgohain (2024) [9]	Extra Trees + structural (CDR/NRR/RDR) & textural (GLCM/GLRLM/LBP) features, SMOTE	SMDG-19 (2,873 images)	Acc 85.42%	ONH-based biomarker; feature set reduced 96 → 60
Velpula et al. (2024) [25]	HOG + LBP + GLCM + chip histogram; SVM / AdaBoost; CLAHE	ACRIMA (705 images)	Acc 99.29% (AdaBoost, LBP + chip histogram)	Feature combinations matter; AdaBoost > SVM for complex features

E. Segmentation-Assisted and Multimodal Frameworks

The most accurate and clinically robust systems often add optic-disc/optic-cup segmentation or fuse multiple imaging modalities. Alkhaldi and Alabdulathim [26] coupled a U-Net (ResNet34 backbone) for optic-disc and optic-cup segmentation with an EfficientNetB0 classifier, reaching a segmentation mIoU of 0.9826 and test accuracies of 90–100% across ORIGA, RIM-ONE DL, HRF and REFUGE, showing that segmentation improves accuracy under limited data. Islam et al. [27] proposed a dual-branch network that fuses ResNet-18 features from fundus images with custom-CNN features from paired OCT scans; the fusion model reached 92% accuracy and 0.95 AUC and reduced false negatives by roughly 50% relative to the fundus-only branch. Al-Fahdawi et al. [28] developed Fundus-DeepNet, an HRNet-based system with SENet channel attention and a discriminative restricted Boltzmann machine, using dual-eye data fusion to detect eight ocular diseases (including glaucoma) on the OIA-ODIR dataset with an F1-score of 89.13% and AUC of 99.86%. These results confirm that structural localisation and multimodal fusion materially improve glaucoma detection.

Table 9. Segmentation-assisted and multimodal approaches for glaucoma detection

Author (Year) [Ref]	Model / Approach	Dataset	Best Performance	Key Insight
Alkhaldi & Alabdulathim (2024) [26]	U-Net (ResNet34) segmentation + EfficientNetB0 classification	ORIGA, RIM-ONE DL, HRF, REFUGE	mIoU 0.9826; Acc 90–100%	OD/OC segmentation improves accuracy under limited data
Islam et al. (2025) [27]	Dual-branch ResNet-18 (fundus) + custom CNN (OCT) feature fusion	Bangladesh Eye Hospital (416 paired images)	Acc 92%; AUC 0.95	Paired fundus–OCT fusion cuts false negatives ~50%

Author (Year) [Ref]	Model / Approach	Dataset	Best Performance	Key Insight
Al-Fahdawi et al. (2024) [28]	Fundus-DeepNet: HRNet + SENet attention + DRBM, dual-eye fusion	OIA-ODIR (10,000 images)	F1 89.13%; AUC 99.86%	Multi-label detection of 8 ocular diseases

VII. KEY FINDINGS OF THE LITERATURE SURVEY

The categorised review in Tables 5–9 shows that deep-learning methodologies such as CNNs and vision transformers dominate current practice, achieving accuracies of roughly 93–99% in many works. The best-performing systems combine optic-disc and optic-cup segmentation with subsequent cup-to-disc region extraction, or fuse deep features with handcrafted descriptors. By feature-based machine learning, authors typically extract meaningful information such as LBP for texture, GLCM for spatial texture relationships, wavelet features for frequency and multi-resolution analysis, and CDR as a clinical biomarker.

From this survey a clear performance hierarchy emerges: feature-based machine learning achieves approximately 85% accuracy; hybrid deep-learning–machine-learning pipelines reach approximately 95%; and pure deep-learning techniques such as EfficientNet and its ensembles achieve the highest accuracy, exceeding 99%. Attention-based and lightweight transformer models add explainability and efficiency at comparable accuracy. The recommended workflow that consolidates these findings is shown in Figure 4.

Fig. 4. Workflow for early glaucoma detection using deep-learning-based classifier models.

VIII. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite high reported accuracies, several challenges limit clinical translation. First, class imbalance and small, single-centre datasets inflate accuracy while depressing sensitivity, as seen in the high false-negative rate of early CNN baselines; larger, multi-centre and well-balanced datasets are needed. Second, generalisation across imaging devices, populations and acquisition conditions remains difficult, motivating cross-dataset validation and domain-adaptation techniques. Third, clinical adoption demands explainability: Grad-CAM, capsule and attention-based models are promising steps, but standardised interpretability protocols are still lacking.

A further barrier is data privacy. Fundus and OCT images are sensitive medical data, and centralising them for training raises regulatory and ethical concerns. Federated learning, in which models are trained across institutions without sharing raw images, offers a practical solution and has already been applied to glaucoma detection [23].

However, federated training over bandwidth-constrained healthcare networks incurs heavy communication costs. Communication-efficient federated-learning strategies that combine gradient sparsification and quantisation have been shown to reduce this overhead substantially for medical imaging [29], and related work demonstrates efficient federated CT-image classification in bandwidth-limited wireless healthcare settings [30]. Integrating such privacy-preserving, communication-efficient distributed learning with the explainable segmentation-guided architectures identified in this survey is a promising direction for scalable, real-world glaucoma screening.

IX. CONCLUSION

This survey examined thirty publications on glaucoma detection and analysed fourteen primary studies in detail, grouping them into five methodological categories. The analysis shows that deep learning is better suited to glaucoma detection than classical machine learning because it automatically extracts features from images, whereas classical methods depend on manually engineered features that may overlook significant trends. Deep-learning models, particularly EfficientNet-based and hybrid architectures, consistently deliver the highest accuracy when sufficient data are available, while segmentation-assisted and multimodal frameworks add clinical robustness and attention-based transformers add efficiency and explainability.

In summary, deep learning improves predictive performance and reduces manual effort, but its clinical deployment will depend on addressing class imbalance, cross-population generalisation, interpretability and data privacy. Combining explainable, segmentation-guided deep networks with communication-efficient, privacy-preserving federated learning represents a compelling path towards accurate, trustworthy and scalable early glaucoma screening.

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