

A Comprehensive Review of AI-Based Glaucoma Detection and Monitoring: From Deep Learning to Real-Time Hardware-Integrated Systems

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Abstract - Glaucoma is one of the main causes of irreversible blindness worldwide, impacting nearly 80 million people globally. This number is expected to reach 111 million by 2040. Early diagnosis is essential, but traditional techniques, such as measuring intraocular pressure, visual field tests, and Optical Coherence Tomography (OCT), face challenges like high costs, limited access, and the need for specialized clinicians. Retinal fundus imaging offers a useful non-invasive alternative.

Recently, artificial intelligence (AI), especially deep learning, has become an effective solution for automated glaucoma detection. This paper reviews fifteen recent studies (2020–2025) from IEEE, Scopus, and other respected journals, examining the development of glaucoma detection models. These models range from Convolutional Neural Networks (CNNs) and Capsule Networks to Vision Transformers and hybrid fusion architectures.

While these methods show accuracies greater than 95% on datasets such as REFUGE, DRISHTI-GS, ACRIMA, and ORIGA, they are mostly limited to offline testing and do not support real-time use. Our project addresses this gap by combining ResNet for classifying the optic disc and cup, UNet for segmenting vessels, and a fusion decision layer. This layer integrates Cup-to-Disc Ratio (CDR), vessel density, and structural asymmetry. Additionally, our system uses a 20D lens linked with an iPhone camera for real-time fundus imaging, which feeds directly into the model for evaluation. This blend of AI and portable hardware creates new opportunities for affordable, real-time glaucoma screening and monitoring.

Index Terms - *Glaucoma Detection, Deep Learning, Convolutional Neural Networks (CNN), Fundus Imaging, Optical Coherence Tomography (OCT), Computer-Aided Diagnosis, Medical Image Analysis, Early Disease Prediction*

I. INTRODUCTION

Glaucoma is a progressive condition that damages the optic nerve and leads to vision loss. It is often called the "silent thief of sight" because symptoms only show up after irreversible damage has occurred.

Worldwide, glaucoma causes nearly 10

Traditional diagnostic methods, such as tonometry, perimetry, and OCT, are reliable but require costly, bulky equipment and trained staff. In contrast, fundus photography offers a more affordable and scalable option. It captures 2D images of the retina, optic disc, and blood vessels. The Cup-to-Disc Ratio (CDR) is an important marker. A CDR above 0.6 or an interocular difference greater than 0.2 strongly suggests glaucoma.

Manual evaluation of fundus images has issues with subjectivity and differences in interpretation among observers. This has led to the use of deep learning (DL) for automatic glaucoma detection. CNNs, Vision Transformers, and Capsule Networks have shown promising results on public datasets. However, these models mostly serve as proofs of concept and have limited real-world application.

Our project aims to bridge this gap by creating a real-time system for detecting and monitoring glaucoma. It combines deep learning with low-cost, smartphone-based fundus imaging hardware, making diagnosis portable and clinically relevant.

II. LITERATURE LANDSCAPE

The literature reveals the transition from mechanical to intelligent systems. Early solutions were limited to obstacle detection, while modern systems leverage AI for contextual scene understanding.

A. Foundational Stage

Early works established CNNs as the basis for automated glaucoma detection.

- VGG19-based CNN models (2020) achieved up to 98.6% accuracy on small local datasets, showing strong potential but limited generalization.
- Hybrid CNN and Random Forest models improved classification accuracy to 95.4% on the ACRIMA dataset by combining deep and handcrafted features.

- CNN and RNN (LSTM) architectures introduced temporal modeling, achieving an F1-score of 96.2%, but were heavy on computation.
- Capsule Networks (CapsNets) showed better spatial feature retention, achieving 93% accuracy on the RIM-ONE dataset, though they faced training instability.

These studies set the stage for future hybrid and transformer-based approaches, but they focused only on data without considering real-time or hardware aspects.

B. Integration and Explainability Phase

In this phase, researchers began combining pre-trained models and enhancing explainability.

- ResNet50 Transfer Learning (2022) achieved 94% accuracy on ORIGA but faced criticism as a “black box” model.
- DeiT (Vision Transformer) reached 95% accuracy on the OHTS dataset, outperforming CNNs due to global attention mechanisms.
- ViT + CapsNet Hybrids (2023) on ACRIMA improved robustness and achieved 94% accuracy.
- Certainty Theory Expert Systems (2023) introduced interpretability by assigning confidence scores to predictions but did not test for deployment.

This integration era marked a shift from pure CNNs to hybrid and explainable architectures, yet the models were still limited to offline evaluation.

C. Advanced Methods

Recent years have seen significant architectural innovations and performance improvements.

- UNet++ + CapsNet hybrids (2024) achieved 97% accuracy on DRISHTI-GS by integrating segmentation and classification into a unified pipeline.
- DeepEyeNet (2025) used ConvNeXtTiny and Adaptive Genetic Bayesian Optimization (AGBO) to reach 95.8% accuracy on ACRIMA, showing leading results.
- DETR (Detection Transformer) localized optic discs and cups directly with 90.5% accuracy on REFUGE.
- Federated CNNs (2024) trained models collaboratively across institutions while protecting data privacy, achieving 93% accuracy.
- Graph Neural Networks (GNNs) with DBSCAN (2025) improved the clustering of glaucomatous features, reaching 92% accuracy on private datasets.

Smartphone-based imaging studies (2025) demonstrated low-cost fundus image capture but lacked end-to-end AI integration.

This evolution shows a clear trend toward designs that combine different methods, focus on explainability, and consider hardware, setting the stage for real-world use.

III. SUMMARY OF INSIGHTS AND IDENTIFIED RESEARCH GAPS

From the reviewed literature, three ongoing limitations stand out:

- Absence of real-time deployment: All reviewed systems operate offline and analyze pre-collected datasets.
- No hardware integration: None of the reviewed works connect image acquisition directly to inference models.
- Lack of interpretability: Only a few methods, such as Certainty Theory and LIME, provide explanations for AI predictions.

These limitations hold back clinical adoption, even with high accuracy reported.

Our project directly tackles these gaps by introducing a real-time pipeline. This system integrates AI models with a 20D lens and iPhone setup for image capture, preprocessing using OpenCV, inference with ResNet, UNet, and a Fusion Layer, and visualization through a user-friendly interface for clinicians.

IV. METHODOLOGY OF THIS REVIEW

The review followed a systematic and structured approach to ensure comprehensive coverage and consistency in analysis.

- Data Sources: IEEE Xplore, SpringerLink, Elsevier, PubMed, and Scopus-indexed repositories were used as primary databases.
- Timeframe: Research works published between 2020 and 2025 were considered.
- Inclusion Criteria:
 - Studies utilizing AI or deep learning for glaucoma detection.
 - Publications appearing in peer-reviewed and indexed venues.
 - Papers reporting key performance metrics such as accuracy, sensitivity, and specificity.

- Categorization: Selected papers were organized into three developmental phases—*Foundational*, *Integration*, and *Advanced*—to represent the chronological and technological evolution of the field.

Each paper was examined in terms of architecture type, dataset employed, accuracy metrics, interpretability mechanisms, and readiness for real-world deployment.

V. DISCUSSION AND CRITICAL ANALYSIS

The reviewed works show three main algorithmic trends:

- CNN dominance (2020–2021): Provided strong baseline accuracy but limited understanding of contextual features.
- Transformer transition (2022–2023): Improved global feature extraction and generalization performance.
- Hybrid fusion models (2024–2025): Combined multiple networks for segmentation and classification tasks.

However, most studies focus primarily on accuracy rather than usability. None include real-time feedback or affordable image acquisition systems.

Our project stands out by addressing this gap through an integrated design combining AI, hardware, and user experience:

- AI Models: ResNet for optic disc and cup detection, UNet for vessel segmentation, and a Fusion Layer for decision integration.
- Hardware Integration: Utilizes a 20D lens and iPhone setup for capturing fundus images in real-time.
- Software Stack: Employs OpenCV for preprocessing, PyTorch for training, and TensorFlow Lite/CoreML for on-device inference.
- User Interface: Displays segmentation overlays, cup-to-disc ratio (CDR), and glaucoma predictions dynamically for clinician review.

This design transforms glaucoma screening from a laboratory experiment into a practical, real-time diagnostic tool ready for clinical application.

VI. ACCURACY MATRIX

Table I summarizes the performance of major glaucoma detection models from 2020–2025, comparing their datasets, accuracy metrics, and major limitations.

TABLE I
ACCURACY COMPARISON OF REVIEWED GLAUCOMA DETECTION MODELS (2020–2025)

Paper	Model	Dataset	Accuracy	Sensitivity	Specificity	Limitation
Krishnaveni et al. (2025)	GNN + DBSCAN	Private	92%	89%	90%	No hardware
Vigneshwaran et al. (2024)	ViT + CapsNet	ACRIMA	94%	91%	92%	Offline only
Verma et al. (2023)	Hybrid CNN	REFUGE	99%	97%	98%	Dataset-limited
Hajiarbabi (2023)	DL + Certainty	ORIGA	90%	88%	89%	Theoretical model
UNet++ + CapsNet (2024)	Hybrid	DRISHTI-GS	97%	95%	96%	Non-real-time
DeepEyeNet (2025)	ConvNeXtTiny + AGBO	ACRIMA	95.8%	93%	94%	Prototype stage
DETR (2024)	Transformer	REFUGE	90.5%	89%	91%	Limited validation
Federated CNN (2024)	Ensemble	Multi-center	93%	91%	92%	Needs collaboration
ResNet50 (2022)	Transfer Learning	ORIGA	94%	92%	93%	Black-box
DeiT (2022)	Vision Transformer	OHTS	95%	93%	94%	Dataset-limited
CNN + RNN (2021)	CNN + LSTM	Private	F1=96.2%	–	–	Non-real-time
CapsNet (2021)	Capsule Network	RIM-ONE	93%	90%	91%	Poor generalization
VGG19 (2020)	CNN	Local	98.6%	–	–	Small dataset
CNN + RF (2020)	CNN + Random Forest	ACRIMA	95.4%	93%	94%	Dataset-limited
Explainable AI (2022)	Transfer + LIME	REFUGE	94.7%	92%	93%	Limited deployment

VII. KEY TECHNICAL COMPONENTS OF THE GLAUCOMA DETECTION SYSTEM

This section outlines the major hardware, software, and algorithmic components that constitute the proposed glaucoma detection framework.

A. Optical Hardware Setup

Components:

- **20D Condensing Lens (Volk 20D Lens):** Captures a wide-field image of the retina through indirect ophthalmoscopy. Provides approximately $3\times$ magnification and a field of view of 46° – 60° . It is essential for visualizing the optic disc and cup, which are key for glaucoma diagnosis.
- **iPhone Camera:** Serves as the imaging sensor, offering high-resolution capture (12 MP or higher). It can record fundus images when aligned properly with the 20D lens, either hand-held or through a 3D-printed mounting frame for stability and correct alignment.
- **Illumination Source:** A white LED or smartphone torch is used for retinal illumination. The light reflects through the 20D lens to clearly visualize the fundus.

B. Image Acquisition Process

The subject's eye may be dilated to improve clarity. The 20D lens is positioned approximately 50 mm in front of the eye, with the iPhone camera placed behind the lens at the correct focal distance. The camera captures real-time images or videos of the optic disc region, which are saved locally or uploaded directly to a cloud-based analysis application.

C. Image Processing and Analysis

Processing Steps:

- 1) **Preprocessing:** Crop the optic disc region and apply CLAHE (Contrast Limited Adaptive Histogram Equalization) to enhance visibility. Normalize and resize images to 224×224 pixels.
- 2) **Feature Extraction:** Segment the optic disc and cup using U-Net or Mask R-CNN models. Compute the Cup-to-Disc Ratio (CDR), a critical indicator for glaucoma, and check for inter-eye asymmetry if data from both eyes is available.
- 3) **Classification:** A deep learning model such as ResNet50 or MobileNetV2 classifies the image as *Normal* or *Glaucomatous*. The model is trained on public datasets and further fine-tuned using images from the portable setup.

D. Software and Communication Framework

- **Mobile Application:** Built using React Native or Flutter, the app allows users to capture, upload, and view AI-generated diagnostic results in real time.
- **Backend Server:** Developed using Flask or FastAPI, it handles image uploads, invokes AI inference, and communicates results through APIs. Cloud platforms such as AWS, Google Cloud, or Cloudinary manage image storage and processing.
- **AI Model:** A pretrained convolutional neural network fine-tuned on fundus datasets. The model outputs a risk probability score indicating the likelihood of glaucoma.

E. Evaluation and Validation

Model performance is evaluated using metrics such as Accuracy, Sensitivity, Specificity, and AUC-ROC. Results from the portable system are compared against those from standard fundus cameras to validate diagnostic consistency. Testing is performed under varying lighting and distance conditions to ensure robustness and repeatability.

VIII. CHALLENGES AND RESEARCH GAPS

1) Image Quality and Illumination Control

The quality of fundus images captured using smartphone cameras and 20D lenses depends heavily on ambient lighting, user handling, and lens alignment. Uneven illumination, reflections, and motion blur can obscure optic disc boundaries, leading to inaccurate estimation of the cup-to-disc ratio (CDR). There is a need for standardized imaging protocols or enhancement algorithms to maintain consistent image quality across different devices and environments.

2) Limited Field of View (FOV) and Optical Constraints

A 20D condensing lens offers a narrower field of view compared to professional fundus cameras. This restricts visibility of peripheral retinal regions, leading to incomplete diagnostic information. Research gaps exist in improving optical alignment and developing compact lens attachments that expand the FOV without compromising clarity.

3) Dataset Limitations for Model Training

Most existing deep learning models are trained on clinical-grade datasets such as RIM-ONE, DRISHTIGS, and REFUGE, which are collected using high-end fundus cameras. These models often perform poorly on smartphone-acquired images due to variations in resolution, lighting, and noise. There is a strong need for new datasets collected using portable imaging setups, as well as domain adaptation methods that bridge the gap between clinical and real-world data.

4) Optic Disc and Cup Segmentation Challenges

Accurate segmentation remains difficult due to low contrast, irregular disc shapes, and vessel occlusions. Convolutional Neural Networks (CNNs) struggle to distinguish the optic disc from surrounding tissues in low-quality images. Emerging attention-based and transformer architectures show promise in enhancing segmentation precision but require further optimization for portable applications.

5) Hardware and Alignment Variability

Manual alignment of the 20D lens and smartphone camera requires user expertise and is prone to error. Even slight misalignments introduce geometric distortion, affecting diagnostic reliability. Future work should explore automated alignment tools, gyroscopic stabilization, or optical calibration systems to minimize variability.

6) Real-Time Processing and On-Device AI Limitations

Running deep learning inference directly on mobile devices demands significant computational power. Cloud-based solutions can introduce latency and data privacy concerns. The challenge lies in developing lightweight AI models—such as MobileNet, TinyML, or quantized CNNs—that enable efficient on-device inference without major accuracy trade-offs.

7) Clinical Validation and Regulatory Approval

Few low-cost systems have undergone rigorous, large-scale clinical validation. Without evaluation across diverse patient populations, false positives and negatives can hinder adoption. Bridging this gap requires collaboration with ophthalmologists, multi-center trials, and standardized benchmarking methods aligned with regulatory standards.

IX. IMPLICATIONS AND FUTURE OPPORTUNITIES

This review emphasizes the need for:

- Hardware-embedded AI systems for real-time glaucoma detection.
- Fusion-based decision support that combines multiple biomarkers beyond the cup-to-disc ratio (CDR).
- Explainable AI frameworks to enhance transparency and build clinician trust.
- Affordable, portable setups leveraging smartphones and optical lenses for large-scale mass screening.
- Global data collaboration through federated learning to minimize dataset bias and improve model diversity.

Our project directly addresses points (1), (2), and (4) by providing a deployable, real-time system designed for accessibility and integration into practical screening workflows.

X. CONCLUSION

The past five years have shown remarkable progress in AI-driven glaucoma detection, achieving nearperfect accuracy on controlled datasets. However, most models fail to translate effectively into clinical environments due to challenges in hardware integration, real-time analysis, and interpretability.

This work addresses these limitations by integrating artificial intelligence models (ResNet, U-Net, and a Fusion Layer) with a real-time optical setup using a 20D lens and iPhone, supported by an intuitive user interface for live diagnostic analysis. The resulting framework demonstrates a scalable, low-cost solution for real-time glaucoma monitoring, particularly beneficial for early detection in underserved regions.

By merging deep learning, medical imaging, and portable hardware, this system exemplifies how AI can bridge the gap between research innovation and clinical application—marking a significant step toward accessible and practical ophthalmic diagnostics for all.

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