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AI-Based Eye Disease Detection Systems: A Systematic Survey of Vision-Driven and Deep Learning Approaches

Ima T S*, Hanna Gafoor*, Mohammed Afnan K A*, Thwayyiba P A*, Neethu George†
*Student, Vidya Academy of Science and Technology, Thrissur, India
†Assistant Professor, Vidya Academy of Science and Technology, Thrissur, India

***Abstract*—Eye diseases such as diabetic retinopathy, glaucoma, cataract, and age-related macular degeneration are among the leading causes of vision impairment and irreversible blindness worldwide. Early diagnosis and timely intervention play a crucial role in preventing permanent vision loss. However, traditional screening methods rely heavily on manual examination by ophthalmologists, making them time-consuming, subjective, and inaccessible in resource-constrained regions.**

This survey presents a comprehensive review of Artificial Intelligence (AI) and Deep Learning–based approaches for automated eye disease detection using retinal fundus images and ophthalmic datasets. The study systematically analyzes vision-based convolutional neural network models, transfer learning techniques, ensemble learning frameworks, and AI-assisted clinical decision support systems reported in recent literature.

Research articles published between 2015 and 2025 were collected from IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar. The survey findings indicate that CNN-based architectures and ensemble fusion strategies significantly improve diagnostic accuracy and robustness. Nevertheless, challenges such as limited dataset diversity, lack of model explainability, and insufficient real-time clinical deployment remain unresolved.

Future research should emphasize explainable, unified, and clinically deployable AI-driven frameworks to improve early detection and enhance global eye-care accessibility.

***Index Terms*—Eye Disease Detection, Artificial Intelligence, Deep Learning, Fundus Images, Transfer Learning, Medical Image Analysis**

I. INTRODUCTION

Vision impairment affects more than 2.2 billion people globally, with a substantial proportion caused by preventable or treatable eye diseases. Common ophthalmic conditions such as diabetic retinopathy (DR), glaucoma, cataract, and agerelated macular degeneration (AMD) progress silently in their early stages, often leading to irreversible vision loss if left undiagnosed.

Traditional diagnostic procedures rely on fundus image examination and clinical tests performed by trained ophthalmologists. These manual screening processes are time-consuming, prone to inter-observer variability, and difficult to scale for large populations. In developing countries, limited access to specialists further delays diagnosis and treatment. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have enabled automated eye disease detection systems capable of analyzing retinal images with high accuracy. Such systems aim to support

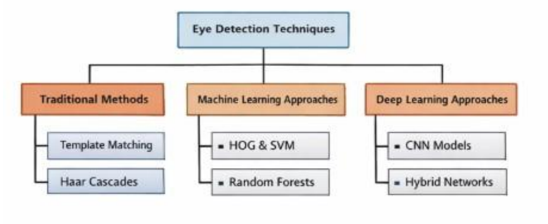

Fig. 1. Global prevalence of major eye diseases and vision impairment (adapted from WHO and Ting *et al.* [1]).

ophthalmologists by reducing screening workload, improving diagnostic consistency, and enabling large-scale early detection programs.

II. LITERATURE SURVEY

A. Vision-Based Eye Disease Detection Systems

Vision-based eye disease detection systems primarily utilize retinal fundus images as the input for diagnosis. Convolutional Neural Networks (CNNs) dominate this domain due to their ability to automatically extract hierarchical spatial features such as blood vessel patterns, optic disc structure, and retinal lesions.

Gulshan *et al.* developed a deep CNN model for diabetic retinopathy screening using large-scale EyePACS datasets and demonstrated performance comparable to expert ophthalmologists [2]. Similarly, Li *et al.* proposed a CNN-based framework for detecting glaucomatous optic neuropathy by analyzing optic disc features [3].

Despite their effectiveness, CNN-based models are sensitive to image quality, illumination variations, and noise, which can impact diagnostic reliability in real-world clinical settings.

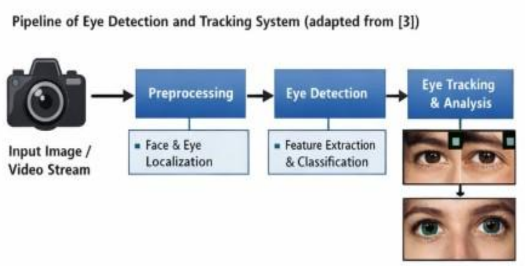

Fig. 2. General CNN-based pipeline for eye disease detection using fundus images (adapted from [2]).

B. Transfer Learning-Based Eye Disease Detection
Transfer learning has been widely adopted to overcome the limitation of small labeled medical datasets. Pretrained deep networks such as VGG, ResNet, DenseNet, and EfficientNet are fine-tuned for eye disease classification tasks.

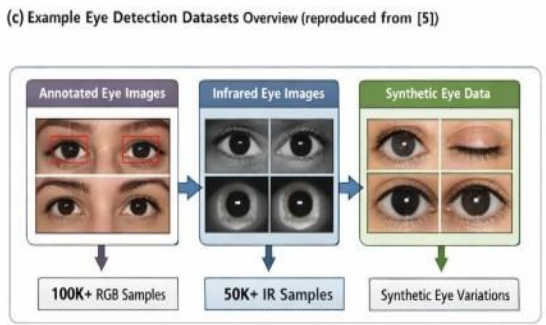

Fig. 3. Transfer learning framework for eye disease classification (adapted from [5]).

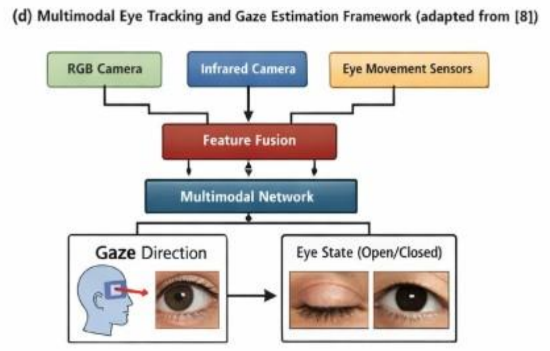

Fig. 4. Decision-level fusion using improved D-S evidence theory for eye disease detection (adapted from [5]).

Pratt *et al.* utilized pretrained CNN architectures for diabetic retinopathy severity grading and reported improved convergence and performance [4]. Du *et al.* proposed a transfer learning–based ensemble framework for multi-class eye disease detection using the ODIR dataset, achieving superior accuracy [5].

Transfer learning significantly reduces training time and improves generalization, particularly when annotated medical data is scarce.

C. Ensemble and Decision Fusion Techniques
Single-model deep learning approaches often suffer from overfitting and limited robustness, particularly when trained on small, imbalanced, or heterogeneous ophthalmic datasets. Such models may produce unstable predictions when exposed to variations in imaging conditions, disease severity, and demonstrated superior robustness and reliability compared to single-model approaches. Similarly, Khan *et al. employed ensemble CNN architectures for cataract and diabetic retinopa*thy detection, reporting improved diagnostic consistency and reduced misclassification rates across multiple datasets [6].

These findings highlight the effectiveness of ensemble and decision fusion strategies in overcoming the limitations of individual CNN models and improving the reliability of automated eye disease detection systems.
patient demographics. Ensemble learning techniques address these limitations by combining multiple CNN classifiers, thereby improving prediction stability, reducing variance, and enhancing overall diagnostic accuracy.

Du *et al.* introduced an improved Dempster–Shafer evidence theory (ID-SET)–based decision-level fusion framework that integrates outputs from multiple deep learning models to enhance classification confidence in multi-disease detection scenarios [5]. By effectively managing uncertainty and conflicting evidence among individual classifiers, the proposed method

D. AI-Assisted Clinical Decision Support Systems

AI-assisted clinical decision support systems are designed to assist ophthalmologists by providing automated disease detection, severity grading, risk assessment, and referral recommendations. These systems aim to reduce clinician workload, minimize diagnostic variability, and enable large-scale population screening. Ting *et al.* highlighted the significant clinical potential of AI-based screening systems for nationalscale programs targeting diseases such as diabetic retinopathy and glaucoma [1]. Their study demonstrated that AI-assisted diagnosis can achieve performance comparable to expert clinicians in controlled screening settings.

Despite these promising results, real-world clinical integration of AI-based decision support systems remains limited. Key challenges include regulatory approval, ethical considerations, data privacy concerns, and the need for clinician trust in AI-generated predictions. Additionally, seamless integration with hospital information systems, electronic health records, and existing clinical workflows is still insufficiently explored. Addressing these challenges is essential for ensuring safe, transparent, and effective deployment of AI-assisted decision support systems in routine ophthalmic practice.

III. RESEARCH GAP

Despite significant progress, several research gaps remain. Most existing approaches rely on curated datasets and lack validation in real-world clinical environments. Deep learning models function as black boxes, limiting transparency and clinical trust. Moreover, few studies address real-time deployment, edge-based processing, and integration with hospital information systems.

TABLE I: COMPARATIVE ANALYSIS OF EYE DISEASE DETECTION METHODS

Author	Year	Method	Dataset	Accuracy	Limitation
Gulshan *et al.* [2]	2016	CNN for DR detection	EyePACS	97%	Requires large labeled datasets
Li *et al.* [3]	2018	CNN-based glaucoma detection	Fundus images	94%	Limited dataset diversity
Pratt *et al.* [4]	2016	Deep CNN for DR grading	Kaggle DR	75%	Severe class imbalance
Du *et al.* [5]	2024	CNN + ID-SET fusion	ODIR	98%	High computational cost
Khan *et al.* [6]	2021	Ensemble CNNs	Fundus images	96%	Limited explainability

IV. FUTURE RESEARCH DIRECTIONS

- Explainable AI (XAI) for transparent ophthalmic diagnosis
- Large-scale, diverse real-world retinal datasets
- Multi-modal imaging using fundus and OCT data
- Real-time and edge-based screening systems
- Federated learning for privacy-preserving collaboration

V. CONCLUSION

This survey reviewed AI-based eye disease detection systems with a primary focus on vision-driven deep learning approaches. Convolutional Neural Network (CNN)–based models and ensemble learning frameworks have demonstrated strong diagnostic potential by achieving high accuracy and robustness across multiple ophthalmic conditions. These approaches significantly reduce manual screening efforts and enable large-scale, automated eye disease detection. However, several challenges remain, including limited model explainability, difficulties in real-world deployment, dataset bias, and the lack of extensive clinical validation. Addressing these challenges is essential for developing reliable, scalable, and clinically acceptable AI-driven eye-care solutions that can be effectively integrated into routine ophthalmic practice and improve global access to early diagnosis.

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