



A Review on Deep Learning-Based Multi-Disease Eye Detection and Classification Using Fundus Images

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Abstract. Eye diseases such as diabetic retinopathy, glaucoma, and cataract are among the leading causes of visual impairment worldwide. Early diagnosis is crucial to prevent irreversible vision loss, particularly in areas with limited access to specialized ophthalmic care. Recent progress in deep learning (DL) has enabled automated analysis of retinal fundus images, facilitating faster and more accurate detection of eye-related disorders. This paper presents a comprehensive review of deep learning-based approaches for multi-disease eye detection and classification using fundus images. Various techniques, including convolutional neural networks (CNNs), transfer learning methods, transformer-based architectures, and hybrid models, are examined. The study also reviews commonly used retinal datasets, evaluation metrics, and comparative performance of different approaches. In addition, key challenges such as dataset imbalance, limited generalization, and lack of model interpretability are discussed. Future research directions, including the use of explainable AI, lightweight models for edge deployment, and privacy-preserving techniques, are highlighted. The findings of this review provide valuable insights into current developments and support the advancement of reliable and clinically applicable AI-based ophthalmic diagnostic systems.

Keywords: — Deep Learning, Retinal Fundus Images, Eye Disease Detection, Diabetic Retinopathy, Glaucoma, Cataract, Transfer Learning, Explainable AI, Medical Image Analysis.

I. Introduction

Vision is an essential component of human life, enabling individuals to perform daily activities and interact effectively with their environment. Early detection of ocular diseases is therefore critical to prevent irreversible vision impairment. According to reports by the World Health Organization (WHO), billions of people worldwide experience some form of visual impairment, many of which could be avoided through timely diagnosis and appropriate treatment [1]. Major contributors to preventable blindness include diabetic retinopathy, glaucoma, and cataract, which continue to pose serious global health challenges [2].

Conventional approaches to eye disease diagnosis involve the manual assessment of retinal fundus images and optical coherence tomography (OCT) scans by trained specialists. Although these methods provide accurate clinical insights, they are time-intensive and may not be suitable for largescale screening, particularly in regions with limited medical expertise and resources [5]. Recent progress in artificial intelligence



has made it possible to develop automated systems for analysing retinal images. In particular, deep learning approaches based on convolutional neural networks (CNNs) have shown strong capability in extracting meaningful features from medical images and achieving high classification performance [3], [4]. Modern architectures such as ResNet, Inception, and EfficientNet have demonstrated effectiveness in identifying various retinal diseases from fundus images [10]. Transfer learning has further enhanced model performance by allowing pretrained networks to adapt to medical imaging tasks where labeled datasets are limited [11]. Furthermore, ensemble learning approaches aggregate outputs from multiple models to improve system reliability and reduce prediction bias. Another notable development is the adoption of explainable artificial intelligence methods. Methods such as Gradient weighted Class Activation Mapping (Grad-CAM) provide visual interpretations of model decisions by highlighting relevant regions in the input image, thereby improving transparency and supporting clinical decision-making [6].

Despite these advancements, many existing studies focus on single-disease detection and lack the scalability and interpretability required for real-world deployment [7]. Therefore, there is a growing need for unified frameworks capable of detecting multiple eye diseases simultaneously while maintaining high accuracy and clinical reliability. In response to these challenges, this paper presents a comprehensive review of deep learning approaches for multi-disease eye detection using retinal fundus images. The study examines current methodologies, identifies existing research gaps, and discusses potential future directions for building reliable and clinically applicable diagnostic systems.

II. Literature Survey

A. Deep Learning Models for Retinal Disease Detection

Advancements in artificial intelligence have significantly enhanced the capability of automated systems to analyze retinal fundus images for disease detection. Early approaches primarily employed conventional convolutional neural networks (CNNs) to classify retinal images into normal and abnormal categories. Although these models achieved encouraging performance, their effectiveness was often limited by overfitting and poor generalization due to small and imbalanced datasets [3]. To mitigate these challenges, transfer learning techniques have been widely adopted, allowing pretrained architectures such as ResNet, Inception, and EfficientNet to extract meaningful features even from limited medical datasets [10].

Multiple studies have validated the effectiveness of deep learning-based approaches for the classification of specific retinal diseases. For instance, Rao et al. [4] proposed an ensemble-based CNN framework that integrates predictions from multiple networks to improve classification accuracy. The proposed approach achieved a classification accuracy of 97.9% on benchmark datasets such as EyePACS and APTOS, emphasizing the effectiveness of ensemble learning in medical image analysis.

Interpretability has become an essential requirement in AI based healthcare applications. Selvaraju et al. [6] introduced the Grad-CAM technique, which generates visual explanations by highlighting the regions of input images that contribute most to model predictions. This approach has been widely utilized in ophthalmic systems to en-



hance transparency and assist clinicians in understanding automated diagnostic outputs.

Recent research has explored transformer-based architectures for retinal image analysis. Yang et al. [7] developed a transformer-based model combined with multiple instance learning for diabetic retinopathy classification. The method efficiently captures global contextual features in fundus images and demonstrates enhanced performance relative to traditional CNN-based models.

Hybrid deep learning models that combine convolutional and transformer-based components have also gained attention. Rieck et al. [8] proposed a CNN–transformer hybrid architecture that integrates local feature extraction with global attention mechanisms, resulting in improved performance for multi-disease classification tasks.

Beyond conventional classification methods, advanced training strategies have been explored for multi-label disease detection. Hu et al. [9] introduced a co-pseudo labelling approach that leverages unlabelled data and active sample selection to improve learning efficiency in complex retinal datasets.

In addition, Ju et al. [10] proposed a hierarchical knowledge-guided learning framework that incorporates domain-specific medical knowledge into the training process, enhancing both classification accuracy and interpretability in real-world applications. Furthermore, integrated frameworks combining segmentation and classification have been developed to improve diagnostic precision. Vadduri and Kuppusamy [11] presented a deep learning-based approach that jointly performs segmentation and classification for diabetic eye disease detection, improving both localization and diagnostic accuracy.

Survey studies such as that by Zhu et al. [12] emphasize the rapid progress of deep learning techniques in retinal disease detection and highlight the importance of large-scale annotated datasets for effective model training.

The literature highlights a transition from conventional CNN-based models to advanced architectures that leverage transfer learning, ensemble techniques, explainable AI, and transformer-based approaches, thereby improving the accuracy, interpretability, and scalability of automated ophthalmic diagnostic systems.

B. Comparative Analysis of Eye Disease Detection Approaches

Table I highlights selected deep learning approaches for retinal disease detection and offers a comparison based on architecture type, datasets utilized, performance metrics, and key contributions.

Figure 1 illustrates the distribution of different deep learning approaches used in existing eye disease detection studies.

CNN-Based Models

Transfer Learning

Transformer Models

Hybrid Architectures

Explainable AI

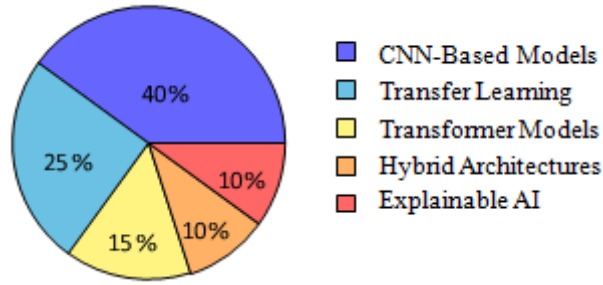


Fig. 1. Distribution of deep learning approaches used in eye disease detection studies.

C. Summary of Observations

Based on the analysis of existing studies, several important observations can be drawn:

Transfer learning with pretrained architectures, including ResNet and EfficientNet, contributes significantly to improved classification accuracy, particularly when limited retinal datasets are available.

Ensemble-based approaches contribute to enhanced model stability and reliability by aggregating predictions from multiple deep learning models.

Explainable artificial intelligence methods, including Grad-CAM, enable visualization of decision-making regions, thereby improving interpretability and increasing clinical confidence.

Transformer-based and hybrid architectures effectively model global contextual relationships within retinal images and demonstrate strong potential for multi-disease classification.

Despite these advancements, issues such as class imbalance, insufficient dataset diversity, and the absence of standardized evaluation frameworks continue to hinder real-world deployment. Recent studies highlight a movement away from traditional feature-based techniques toward modern deep learning approaches aimed at enhancing accuracy, interpretability, and scalability. These advancements support the development of reliable automated ophthalmic diagnostic systems suitable for large-scale screening and teleophthalmology applications.

Table I Comparative Analysis Of Deep Learning Methods For Eye Disease Detection

Author / Year	Model / Approach	Dataset	Disease	Acc. (%)	Contribution
Sarki et al. (2020) [2]	CNN-based DR detection (Survey)	EyePACS	DR	N/A	Analysis of deep learning approaches for identifying diabetic eye diseases.
Atwany et al. (2022) [3]	DL Techniques (Survey)	Fundus Images	DR	N/A	Overview of deep learning architectures for DR classification.
Goutam et al. (2022)	DL Retinal Diagnosis (Re-	Multiple datasets	Multi-disease	N/A	Review of DL strategies for



[4]	view)				retinal disease detection.
Massie et al. (2024) [5]	ResNet50(Transfer Learning)	Fundus dataset	Multi-disease	90.1	Transfer learning framework for eye disease classification.
Yang et al. (2024) [7]	Transformer + MIL	Kaggle DR	DR	93.1	Transformer model capturing global retinal features.
Rieck et al. (2025) [8]	CNN-Transformer Hybrid	Fundus images	Multi-disease	91.8	Combines CNN feature extraction with transformer attention.
Hu et al. (2025) [9]	Co-Pseudo Labeling	Fundus dataset	Multi-label	92.3	Semi-supervised multilabel retinal disease classification.
Ju et al. (2024) [10]	Knowledge-Guided DL	Retinal dataset	Multi-disease	94.5	Integrates medical knowledge into DL models.
Vadduri et al. (2023) [11]	CNN + Segmentation	Fundus images	DR	98.3	Combined segmentation and classification framework.
Zhu et al. (2024) [12]	DL Survey	EyePACS	DR	N/A	Review summarizing deep learning methods used for diabetic retinopathy detection.
Zhang et al. (2021) [13]	DeepUWF System	UWF fundus images	Retinal diseases	92.5	Automated DL screening system for retinal diseases.
Rodrigues et al. (2020) [14]	Vessel Segmentation Model	Fundus images	Vessel detection	96.7	Multi-modal retinal vessel segmentation method.
Albelaihi et al. (2024) [15]	DeepDiabetic CNN	Fundus images	DR	94.7	Deep neural network for automated DR detection.

III. Public Datasets For Retinal Disease Detection

The availability of high-quality retinal image datasets is crucial for developing and evaluating deep learning-based systems for automated eye disease detection. Public datasets facilitate training, validation, and benchmarking of algorithms for identifying retinal abnormalities such as diabetic retinopathy, glaucoma, and cataract, and several large-scale datasets are widely used in the literature.



- **EyePACS Dataset**
EyePACS is considered one of the most commonly utilized datasets for diabetic retinopathy detection. It contains thousands of retinal fundus images collected from different clinical centres. The dataset was introduced during the Kaggle Diabetic Retinopathy Detection Challenge and provides labelled images across multiple severity stages of diabetic retinopathy. Because of its large size and diverse image quality, EyePACS is frequently used for training deep learning models.
- **APTOS Dataset**
Another important dataset for diabetic retinopathy detection is APTOS, developed by the Asia Pacific Tele-Ophthalmology Society. It contains high-quality retinal fundus images labelled across various severity levels. Unlike EyePACS, APTOS has a relatively balanced dataset distribution, making it more effective for performance evaluation.
- **HRF Dataset**
The High-Resolution Fundus (HRF) dataset is commonly used for retinal vessel segmentation and glaucoma-related studies. It contains high-resolution retinal images with manually annotated vessel structures, enabling researchers to evaluate segmentation-based deep learning models.
- **Ultra-Wide Field (UWF) Dataset**
Compared to standard fundus images, ultra-wide field retinal datasets capture a larger area of the retina. The DeepUWF dataset [13] has been used to develop automated screening systems for identifying retinal diseases using deep learning techniques. These datasets facilitate the detection of peripheral retinal abnormalities that are not easily captured using conventional fundus images.
- **Dataset Challenges**
Despite the availability of these datasets, several challenges still exist. Many datasets suffer from class imbalance, limited demographic diversity, and variations in imaging devices. These limitations can influence model generalization when applied to real-world clinical environments. Therefore, future research efforts should concentrate on developing large and diverse retinal imaging datasets through multi-institutional data collection.

IV. Research Gaps And Future Directions

Although deep learning-based techniques for eye disease detection using retinal fundus images have shown significant progress, several challenges still limit their practical clinical deployment.

- **Dataset Availability and Diversity**
Many existing datasets such as EyePACS and APTOS are limited in diversity and often suffer from class imbalance and variations in imaging devices [12]. These limitations reduce the generalization ability of trained models. To improve model performance, future work should aim to build extensive and diverse datasets by combining data from multiple healthcare sources and applying techniques like data augmentation and semi supervised learning.

- **Multi-Disease Classification**
Most current models are designed to detect a single disease, while patients may present multiple eye conditions simultaneously. Developing multi-label and multi-disease classification frameworks remains an important research direction [9].
- **Interpretability and Clinical Trust**
Since deep learning models lack transparency in their decision-making, they are often viewed as black boxes, which affects clinician confidence. Explainable AI methods such as Grad-CAM can highlight disease-relevant regions and improve model transparency [6]. Future systems should integrate stronger explainability mechanisms to support clinical decision-making.
- **Model Generalisation and Deployment**
Models trained on a specific dataset may perform poorly on images from different devices or clinical environments. Techniques such as domain adaptation, self-supervised learning, and cross-dataset validation can improve robustness [10]. In addition, lightweight models such as EfficientNet and MobileNet can support deployment on mobile and teleophthalmology platforms [11].
- **Privacy and Standardisation**
- The sharing of medical imaging data is often constrained by privacy concerns. Federated learning addresses this challenge by allowing collaborative model development while ensuring that patient data remains protected. Furthermore, standardised evaluation protocols and benchmarking datasets are required for reliable comparison and clinical validation.
- **Summary**
Future studies should focus on designing diverse datasets, lightweight and interpretable models, improved cross-dataset generalisation, and standardized evaluation frameworks to support reliable AI-based ophthalmic screening systems.

V. Taxonomy of Deep Learning Approaches For Eye Disease Detection

Approaches based on deep learning for retinal disease detection can be divided into multiple categories depending on their model architecture and training strategies. Figure 2 presents



Fig. 2. Taxonomy of deep learning approaches for automated eye disease detection using retinal fundus images.

the taxonomy of deep learning approaches used for retinal disease detection. The methods can be categorized into CNN based models, transfer learning approaches,



transformer-based models, hybrid architectures, and explainable AI techniques. These categories represent the major research directions in automated ophthalmic diagnosis using retinal fundus images.

- **CNN-Based Methods**

For fundus image analysis, convolutional neural networks are extensively used because of their ability to learn complex features. Models such as VGGNet, ResNet, Inception, and EfficientNet have shown strong performance in detecting diseases like diabetic retinopathy, glaucoma, and cataract.

- **Transfer Learning Approaches**

The limited availability of labelled medical images has led to the widespread use of transfer learning in this domain. In this approach, models trained on large datasets such as ImageNet are further refined using retinal data to achieve better classification results.

- **Transformer-Based Models**

Recently, transformer architectures have attracted considerable attention in medical image analysis. These models capture global contextual relationships within retinal images and have demonstrated promising performance in diabetic retinopathy detection.

- **Hybrid CNN–Transformer Architectures**

Hybrid models integrate the strengths of convolutional neural networks for extracting local features with the global attention capabilities of transformer-based architectures. By combining these complementary properties, such models achieve improved performance and are increasingly applied in multi disease classification tasks.

- **Explainable AI Approaches**

Explainable artificial intelligence techniques, including Grad-CAM and attention-based visualization methods, are used to highlight important regions in retinal images that influence model predictions. These approaches enhance the transparency of deep learning systems and assist clinicians in understanding and validating diagnostic results.

- **Evaluation Metrics for Eye Disease Detection**

Performance evaluation is a critical aspect of developing deep learning models for retinal disease detection. Various quantitative metrics are commonly used to assess classification accuracy and the reliability of diagnostic systems.

Accuracy: Accuracy represents the ratio of correctly classified samples to the total number of observations. It can be expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP and TN denote true positives and true negatives, while FP and FN represent false positives and false negatives, respectively.

Sensitivity and Specificity: Sensitivity refers to the model's ability to correctly detect diseased cases, whereas specificity indicates its ability to correctly identify healthy instances.



Area Under the Curve (AUC): The Area Under the Receiver Operating Characteristic (ROC) Curve, commonly known as AUC, is widely used in medical diagnosis to evaluate model performance across varying classification thresholds.

F1-score: The F1-score is a harmonic mean of precision and recall, providing a balanced measure of performance, particularly useful when dealing with imbalanced datasets.

VI. Challenges In Deep Learning-Based Eye Disease Detection

Despite notable progress in deep learning-based retinal disease detection, several challenges still limit real-world clinical deployment.

- **Dataset Imbalance**
Many retinal datasets contain significantly more normal images than diseased samples. This imbalance can bias models toward majority classes and reduce detection accuracy for rare diseases.
- **Limited Dataset Diversity**
Public datasets often lack diversity in imaging devices, patient demographics, and clinical conditions, which reduces the generalization capability of trained models.
- **Image Quality Variations**
Fundus images may suffer from noise, poor illumination, blur, or occlusions, which can negatively affect feature extraction and classification performance.
- **Computational Complexity**
The high computational requirements of deep learning models pose challenges for their implementation on mobile devices and in healthcare environments with limited resources.
- **Limited Clinical Validation**
Many models are evaluated only on benchmark datasets. Large-scale clinical validation is necessary to ensure reliability and practical adoption.

VII. Workflow of Deep Learning-Based Eye Disease Detection System

Figure 3 illustrates the workflow of a deep learning-based eye disease detection system using retinal fundus images, including stages such as data acquisition, preprocessing, feature extraction with deep learning models, disease classification, and explainability mechanisms to aid clinical interpretation.

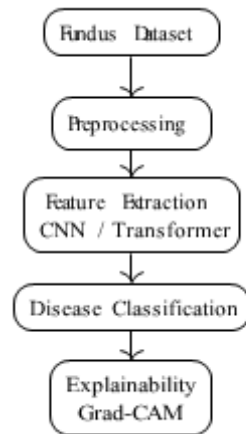


Fig. 3. Workflow of deep learning-based eye disease detection.

VIII. Future Research Directions

Future research in deep learning-based ophthalmic diagnosis should focus on enhancing model robustness, interpretability, and practical clinical applicability. Developing large-scale and multimodal datasets that integrate fundus images with OCT scans can significantly improve diagnostic performance.

The integration of explainable AI techniques, such as GradCAM and SHAP, can increase model transparency and build greater trust among clinicians in automated diagnostic systems.

Furthermore, there is a need to design lightweight deep learning models that can be efficiently deployed on mobile and edge devices, enabling real-time screening in remote and resource-constrained environments. Privacy-aware approaches, including federated learning, can facilitate collaborative model development across institutions while ensuring the protection of sensitive patient data.

Additionally, closer collaboration between AI researchers and ophthalmologists is essential for thorough validation and successful translation of AI-based diagnostic systems into real-world clinical practice.

IX. Conclusion

This review presents a detailed summary of recent advancements in deep learning techniques for automated eye disease detection using retinal fundus images. It examines various model architectures, including convolutional neural networks, transformer-based approaches, and hybrid models, which are applied to detect conditions such as diabetic retinopathy, glaucoma, and cataract. In addition, the study covers commonly used datasets, evaluation metrics, and key challenges in this field.



Despite the strong diagnostic capabilities demonstrated by deep learning models, several limitations still exist, including dataset imbalance, reduced generalization across different clinical settings, and limited model interpretability. Future research should focus on developing lightweight and explainable models, creating large and diverse datasets, and enabling reliable deployment in real-world clinical environments. These efforts will support the development of more effective and accessible AI-driven ophthalmic screening systems.

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