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A Comprehensive Study of Deep Learning Techniques for Retinal Disorders Screening Using Fundus Images

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Abstract

Retinal diseases such as age-related macular disorders, diabetic retinopathy [1], and glaucoma are progressive eye conditions that remain among the leading causes of preventable blindness worldwide. Initial detection and correct classification of these disorders are essential for timely treatment and vision preservation. Now a days, deep learning has emerged as a transformative approach for analysing retinal fundus images, offering high accuracy and efficiency in automated diagnosis and grading [1, 6]. This survey explores the latest advancements in DL-based classification of multiple retinal diseases, focusing on key architectures such as CNNs, RNNs, DBNs, and autoencoders [4, 15]. It also reviews widely used public datasets such as EyePACS, APTOS 2019, and MESSIDOR [16], and discusses pre-processing techniques including image enhancement, de-noising, and data augmentation [12, 13]. Furthermore, the paper highlights the role of transfer learning and hybrid models in improving performance when labelled medical data is limited [5, 7]. Challenges such as data imbalance, lack of image quality, and ethical factor in clinical adoption are addressed. Finally, future directions are outlined, including the development of lightweight models for mobile deployment [1], improved dataset diversity [13, 16], and stronger collaboration between AI researchers and healthcare professionals to reduce the gap between research and real-world healthcare applications.

Keywords: Retinal Disease, Multi-Disease Classification, Fundus Images, Convolutional Neural Networks (CNN), Transfer Learning, Image Pre-processing, Medical Image Analysis, Public Datasets (EyePACS, APTOS, MESSIDOR), Artificial Intelligence in Healthcare, Retinal Disease Screening Systems, Model Interpretability.

1. Introduction

One of the main causes of blindness and vision impairment in the world is retinal disorders. Early detection and precise classification are crucial for prompt prevention and management against permanent vision loss because these disorders frequently develop silently. The burden of retinal illnesses is on the rise due to the global incidence of diabetes and aging populations, especially in areas with limited access to specialized ophthalmic treatment.

Historically, trained ophthalmologists have manually interpreted fundus images to diagnose retinal disorders. Although this method works well, it is subjective, time-consuming, and challenging to scale for big screening programs. With its excellent accuracy and efficiency in identifying and grading retinal diseases, deep learning (DL) has become a game-changing technology for automated medical image analysis in recent years [3, 6, 7]. In recognizing disease-specific features, DL models—particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—have shown impressive performance, frequently matching or outperforming human experts [4, 5].

This survey provides a comprehensive analysis of DL-based methods for fundus image classification of various retinal disorders. It covers essential components such as publicly available datasets [16], preprocessing techniques, and diverse DL architectures, including CNNs, AEs, RNNs, and deep belief networks (DBNs) [9]. The paper also discusses binary and multi-class classification strategies, performance metrics, and challenges in clinical implementation. Finally, it outlines future directions, including improving model interpretability [13], enhancing dataset diversity [17], and developing lightweight solutions for deployment in resource-constrained environments [1].

2. Analysis of Existing Studies

Table I: Analysis of Existing Studies

Sr. No	Paper Name and Year	Techniques Used	Advantages	Gaps
1	A Hybrid Convolutional Neural Network Model for Automatic Diabetic Retinopathy Classification From Fundus Images, 2023 [6].	Hybrid CNN for DR Classification	Automatic feature extraction, good accuracy	Limited generalization on diverse datasets
2	DeepDiabetic: An Identification System of Diabetic Eye Diseases Using Deep Neural Networks, 2024 [3].	Deep Neural Networks	Effective identification of diabetic eye diseases	May not be optimized for fundus image variability
3	A Universal Field-of-View Mask Segmentation Method on Retinal Images From Fundus Cameras, 2024 [2].	FOV Mask Segmentation	Universal applicability to various cameras	Limited performance analysis on low-quality images
4	Efficient Deep Retinal Fundus Image-Based Network for Alzheimer's Disease Diagnosis Using Mobile Device Applications, 2024 [1].	Mobile Deep Fundus Network	Efficient for mobile devices	Unclear robustness for diverse conditions

5	Deep Transfer Learning Strategy to Diagnose Eye-Related Conditions and Diseases: An Approach Based on Low-Quality Fundus Images, 2023 [11].	Transfer Learning on Low-Quality Images	Handles low-resolution images well	Generalizability needs more validation
6	Multi-Label Retinal Disease Classification Using Transformers, 2023 [7].	Transformer-based Multi-Label Classification	Handles multiple diseases simultaneously	Transformers can be computationally intensive
7	Multi-Class Retinal Diseases Detection Using Deep CNN With Minimal Memory Consumption, 2023	Deep CNN with Low Memory	Memory-efficient design	Possible trade-off with lower accuracy
8	Enhancing Ocular Healthcare: Deep Learning-Based Multi-Class Diabetic Eye Disease Segmentation and Classification, 2023 [5].	Segmentation + Classification	Improves detection accuracy	May need better validation on real-world images
9	MTRA-CNN: A Multi-Scale Transfer Learning Framework for Glaucoma Classification in Retinal Fundus Images, 2023 [4].	MTRA-CNN, Transfer Learning	Multi-scale features help glaucoma detection	May not generalize to other diseases
10	Hybrid Retinal Image Enhancement Algorithm for Diabetic Retinopathy Diagnostic Using Deep Learning Model, 2022 [12].	Hybrid Image Enhancement + Deep Model	Better image quality leads to improved diagnosis	Performance may vary by enhancement method

3. Comparative Analysis of Retinal Disease Classification Algorithms

A. Convolutional Neural Networks (CNNs) in Retinal Disease Classification

Diabetic retinopathy identification is one of the many medical imaging tasks that Convolutional Neural Networks (CNNs) are used for [3, 4, 6]. They do not require human feature engineering because they automatically extract hierarchical features from pixel data. This makes them effective for disease detection and severity grading. However, CNNs require large annotated datasets, significant computational resources, and can overfit when data is limited [5]. Despite these challenges, CNNs remain central to automated retinal diagnostics [1, 6].

Popular CNN Models

- AlexNet: early breakthrough using ReLU activation and dropout.
- VGGNet (VGG16, VGG19): deeper networks with high accuracy, small filters but computationally heavy.
- GoogLeNet (Inception V1): inception modules for multi-scale feature extraction.
- ResNet: residual connections enabling very deep networks [4, 6]..

B. Autoencoders (AE) in Retinal Disease Classification

Autoencoders (AEs) are unsupervised models used for feature extraction and dimensionality reduction [14]. They consist of an encoder that compresses input images and a decoder that reconstructs them. Variants such as sparse autoencoders reduce overfitting, while denoising autoencoders improve robustness against noisy data. Stacked autoencoders (SAEs) extend this by combining multiple layers, often fine-tuned for classification tasks. In retinal disease applications, AEs are frequently integrated with CNNs to form hybrid models that combine spatial and compressed features, improving detection accuracy even with limited labeled data [14, 12]

C. Deep Belief Networks (DBNs)

Multiple Restricted Boltzmann Machine (RBM) layers make up Deep Belief Networks (DBNs), which are generative models. Through unsupervised pre-training and supervised fine-tuning, they acquire hierarchical representations [9, 10]. DBNs are useful when labeled data is scarce, as they can capture complex image patterns. However, their slower training and higher computational cost compared to CNNs limit practical adoption. They remain relevant in hybrid approaches and research on unsupervised learning [10, 14].

D. Recurrent Neural Networks (RNNs) in Retinal Disease Classification

Recurrent Neural Networks (RNNs) are made for sequential data, however they have been changed to classify retinal diseases in order to capture contextual dependencies in fundus images [4, 7]. Long Short-Term Memory (LSTM) networks enable long-term dependency modeling and solve vanishing gradient problems. In practice, RNNs are often combined with CNNs (CNN-LSTM) where CNNs extract spatial features and LSTMs process them sequentially for severity grading [4]. While effective for tasks requiring contextual understanding, RNNs are computationally intensive and less commonly used than CNNs alone.

4. Data Extraction and Categorization

A. Dataset Considerations

The success of deep learning models in retinal disease classification is closely tied to the quality and diversity of the datasets used. Accurate annotations are critical, as fundus images are typically labeled by expert ophthalmologists. However, variations in grading standards can introduce inconsistencies that affect model reliability [17, 20]. Class imbalance is another major challenge, where normal cases often dominate datasets, leading to biased predictions. To mitigate this, approaches such as data augmentation, synthetic image generation, and weighted loss functions are commonly applied [13, 14].

Diversity in datasets is equally important. Images should represent different age groups, ethnicities, and imaging devices to ensure generalization in real-world clinical settings [13, 19]. Variability in resolution and device type also impacts performance, requiring preprocessing steps such as normalization and enhancement for standardization [12, 14]. Publicly available datasets like EyePACS, APTOS, and MESSIDOR provide benchmarks that enable reproducibility and fair comparison across studies, fostering collaborative progress in automated retinal disease detection [16].

B. Image Preprocessing

Preprocessing improves the consistency and diagnostic value of fundus images. Common techniques include:

- **Histogram Equalization**: Enhances image contrast by redistributing intensity values, making retinal features such as microaneurysms and hemorrhages more visible [12].
- **Intensity Normalization**: Standardizes pixel intensity across images, reducing the impact of lighting variations and noise. This improves feature extraction and accelerates training [12, 14].

C. Datasets Used for Research

Table II: Analysis of Existing Datasets

Dataset Name	Diseases Covered	Images	Resolution	Device Used	Remarks	Download Link
RFMiD (Retinal Fundus Multi-Disease Image Dataset)	DR, AMD, Glaucoma, +43 other conditions	3,200	Varied (High-quality PNG)	3 different fundus cameras	Comprehensive dataset covering multiple retinal conditions	https://ieee-dataport.org
AIROGS	Glaucoma	~113,000	Varied	Multiple clinical sources	Includes 46 conditions annotated by experts	https://ieee-dataport.org
Harvard Glaucoma Dataset	Glaucoma, AMD, DR	3,300	High resolution	Clinical fundus cameras	Used for glaucoma detection and grading	https://github.com

iChallenge-AMD	AMD	400	High resolution	Fundus cameras	Includes progression and segmentation tasks	https://github.com
PAPILA	Glaucoma	Fundus + clinical data	Varied	Fundus cameras	Supports AMD vs Non-AMD classification	https://github.com
SynFundus-1M	DR, AMD, Glaucoma	1,000,000 (synthetic)	High resolution	Generated via diffusion models	Includes optic disc and cup segmentation, supports multi-label classification	https://arxiv.org
RenD (Retinal Diseases NLP Dataset)	DR, AMD, Glaucoma, DME, CSR, Cataract	1,000 (text-based)	N/A	PubMed abstracts	Annotated by multiple experts for NLP tasks	https://github.com

5. Analysis and Synthesis

The reviewed studies were compared to identify trends, strengths, and limitations of different approaches. Particular focus was given to transfer learning, lightweight architectures, and attention mechanisms, as these have demonstrated notable impact in recent research. Key challenges such as data imbalance, interpretability, and clinical integration were also highlighted.

A. Feature Extraction

The proposed IR-CNN model employs a dual-path feature extraction strategy using:

- **ResNet50**: A deep residual network that applies skip connections to address vanishing gradient issues in deep architectures. It extracts high-level features from fundus images, capturing structural patterns and abnormalities.
- **InceptionV3**: An advanced CNN architecture that uses parallel convolutional layers with varying kernel sizes to capture multi-scale features. It is computationally efficient and effective in extracting diverse retinal features.

The features obtained from both models are concatenated to form a comprehensive feature vector, which is then passed to the classification layer.

6. Conclusion

Recent developments in deep learning for fundus image-based retinal disease classification are highlighted in this survey. CNNs remain the most effective for feature extraction, while autoencoders, DBNs, and RNNs contribute to dimensionality reduction and hybrid modeling. Public datasets such as EyePACS, APTOS, MESSIDOR, and RFMiD have enabled progress, though challenges like class imbalance, limited diversity persist. Future work should emphasize lightweight architectures, diverse datasets, and transparent models to support clinical adoption. Overall, deep learning holds strong potential for scalable and cost-effective retinal disease screening.

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