Advancing Ocular Health: Deep Learning Technologies in Eye Disease Classification

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Abstract. Eye diseases, including but not limited to Cataract, Glaucoma and Diabetic Retinopathy, pose significant threats to vision and eye health. This research study underscores the importance of recognizing the profound impact of these conditions on patients' well-being and seeks to elevate detection methodologies through the application of cutting-edge technologies, particularly deep learning models. The primary objective of this study is to cultivate a model that outperforms existing classification methods, contributing to a more nuanced understanding of eye diseases and facilitating precise and timely detection. In the course of rigorous experimentation and optimization, ResNet-18, a convolutional neural network, emerged as a particularly efficient model. It demonstrated an impressive training accuracy of 96.5% and testing accuracy of 93.7% on a publicly available dataset comprising retinal images of various eye diseases. Such advancements are crucial in addressing the challenges posed by the aforementioned eye diseases, ultimately improving patient outcomes and fortifying initiatives to combat vision-related health issues.

Keywords: Eye Diseases · Cataract · Glaucoma · Diabetic Retinopathy (DR) · Eye Disease Detection · Eye Disease Classification · Retinal Images · Artificial Intelligence (AI) · Deep Learning (DL) · Convolutional Neural Network (CNN)

1 Introduction

The paradigm of healthcare monitoring, involving the systematic observation and tracking of health-related parameters, has assumed paramount importance in contemporary medical practices. The essence of healthcare monitoring lies in its pivotal role in facilitating the timely detection and intervention across various health conditions. A significant catalyst for transformation in this domain has been the integration of advanced artificial intelligence, particularly leveraging deep learning technologies. This integration marks a paradigm shift, ushering in a new era characterized by heightened accessibility and precision in health monitoring and predictive analysis. Motivated by the imperative to address the critical need for improved detection mechanisms, this study embarks on enhancing the classification systems for eye diseases, contributing to the ongoing evolution of healthcare monitoring landscape.

P. Pareek et al. (Eds.): IC4S 2024, LNICST 598, pp. 220–231, 2025.
https://doi.org/10.1007/978-3-031-77078-4_19

At its core, this study strategically hones in on harnessing deep learning technologies to amplify the classification capabilities pertaining to eye diseases, particularly Cataract, Glaucoma, and Diabetic Retinopathy. These ocular disorders, if left undetected and untreated, pose significant threats to vision and eye health. The application of deep learning models in classification and detection of eye diseases holds the promise of more accurate and efficient diagnostic tools, ensuring timely intervention and management. Recognizing the profound impact of eye diseases and their wide-ranging consequences, this study is dedicated to reshaping the existing detection landscape. By doing so, it aspires to alleviate the burden on both affected individuals and society as a whole.

Paper outline. The remainder of this research article unfolds in five sections, beginning with Sect. 2 which delves into the preliminary knowledge essential for grasping the concepts explored in this study. Section 3 reviews pertinent research studies that have paved the way for current investigation. Section 4 details the materials and methods used, providing insights into the dataset, libraries employed, and methodologies applied. The outcomes are meticulously presented in Sect. 5. Finally, Sect. 6 encapsulates the entirety of the paper and proposes potential avenues for future exploration.

2 Preliminaries

This section provides essential background information crucial for comprehending the overarching concepts addressed in the study.

A normal eye, often referred to as a non-diseased or healthy eye, functions optimally to maintain clear vision and overall ocular health. It is characterized by well-functioning components, including the cornea, lens, retina, and optic nerve, working seamlessly to provide accurate vision without any signs of disease or impairment. Figure 1 showcases non-diseased or normal right and left eye, to facilitate further comparison.

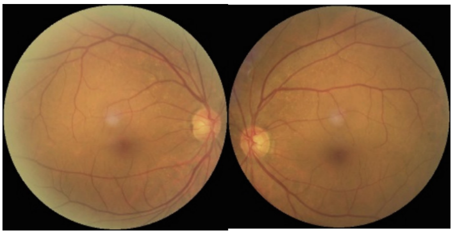

Fig. 1. An instance of dataset depicting non-diseased or normal pair of eyes.

Cataract. It is a common eye condition characterized by the clouding of the natural eye lens, which lies beyond the pupil and the iris. This clouding often leads to blurry vision, decreased color perception, and increased sensitivity to glare. Aging is the primary cause of cataracts, but other factors such as trauma, certain medications, and medical conditions can contribute. Cataracts can be dealt with by surgically replacing the cloudy lens with a synthetic intraocular lens. Figure 2 depicts an instance of the dataset, showcasing right and left eye affected by Cataract.

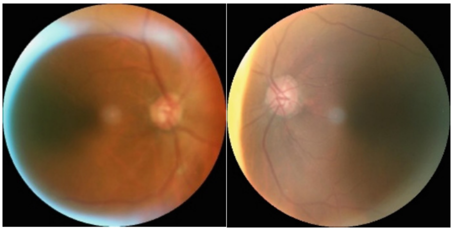

Fig. 2. An instance of dataset depicting Cataract affected pair of eyes.

Glaucoma. It refers to a collection of eye ailments that impair the optic nerve, typically because of the elevated pressure in the eye. It is often associated with progressive and irreversible vision loss. The exact cause of glaucoma is not always clear, but it is often linked to elevated intraocular pressure. Other determinants include family history, age, and certain medical ailments. Treatment aims to reduce intraocular pressure and can involve medications, laser therapy, or surgery. Figure 3 depicts an instance of the dataset, showcasing right and left eye affected by Glaucoma.

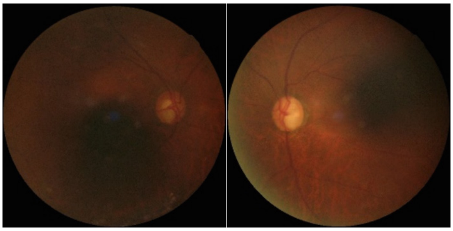

Fig. 3. An instance of dataset depicting Glaucoma affected pair of eyes.

Diabetic Retinopathy. It is an adverse effect of diabetes which impacts the blood vessels in the retina, which is the light-sensitive tissue situated at the rear of the eye. It can lead to vision impairment or blindness. Extended periods of high blood sugar levels linked to diabetes can impair the tiny blood vessels in the retina, leading to fluid leakage or bleeding. Treatment may involve laser therapy, injections into the eye, or, in more advanced cases, surgery. Strict regulation of blood sugar levels is crucial in managing and preventing diabetic retinopathy. Figure 4 depicts an instance of the dataset, showcasing right and left eye affected by Cataract.

3 Related Work

This section elucidates research studies that have contributed significantly to the field of eye disease classification and detection. Few notable examples are discussed below.

Vyas and Khanduja [1] conducted a meticulous examination, critically reviewing recent strides in leveraging AI and image processing techniques for the identification

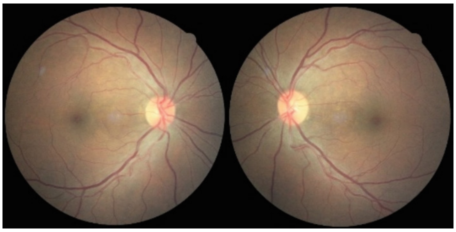

Fig. 4. An instance of dataset depicting Diabetic Retinopathy affected pair of eyes.

of DR and glaucoma. Their study underscored the significance of standardized public datasets, illuminating the supremacy of methods utilizing AI over manual classification and feature extraction techniques. Delving specifically into the detection of glaucoma-related eye diseases, Rajyaguru et al. [2] provided an extensive review of diverse AI-based learning models, highlighting their performance on datasets composed of retinal images and offering valuable insights. Their work also suggested promising directions for future research, emphasizing advancements in model development. In a systematic survey, Sarki et al. [3] explored automated eye disease detection using DL techniques. The authors proposed future research avenues that involve enhancing DL models and integrating them with cloud computing and telehealth to refine diabetic eye disease detection. They acknowledged limitations in their study, including a sole focus on deep learning approaches and the use of a limited set of keywords.

Utilizing machine learning methodologies, Ramanathan et al. [4] dedicated their focus to mitigating the global prevalence of visual impairment caused by eye diseases through early detection. The study conducted a comparison of different classifiers, with Gradient Boosting exhibiting the highest accuracy at 90%, followed closely by logistic regression at 89%, and random forest at 86%. In another insightful approach, Selvathi and Suganya [5] utilized thermography images for early detection of diabetic eye diseases. Employing Support Vector Machine classifiers, the study achieved a commendable maximum accuracy of 86.22%. In a different context, Malik et al. [6] presented a comprehensive baseline for documenting diagnostic data, enhancing ML-based disease prediction. Both random forest and decision tree models achieved prediction rates exceeding 90%, outperforming more intricate approaches like the naive Bayes algorithm.

Prasad et al. [7] proposed a simple model based on deep neural networks to overcome the pressing issue of avoidable blindness being overlooked in India. The proposed model demonstrated an accuracy of 80%, targeting detection of asymptomatic, early stages of common eyes diseases like Diabetic Retinopathy and Glaucoma.

Nazir et al. [8] leveraged a combined model constituting Fast Region-based Convolutional Neural Network (FRCNN) and fuzzy k-means (KFM) clustering for disease localization and segmentation. The approach achieved a mean Intersection over Union (IoU) of 0.95 and a mean Average Precision (mAP) value above 0.94 for all diseases.

Chakraborty and Tharini [9] criticized the shortcomings in prompt and accurate disease detection and proposed an alternative approach utilizing datasets with Optimal Coherence Tomography (OCT) images to implement CNNs. This innovative method yielded a model accuracy of approximately 90% for detecting eye diseases.

Being aware of the limited access to eye care in developing countries, Kumar et al. [10] emphasized the significance of automated detection methods. Utilizing imaging systems like ophthalmoscopy, the authors highlighted the need for early detection and treatment, especially in rural areas. The automated diagnostic process involves image procurement, preprocessing, extraction of region of interest, feature extraction, and classification, providing a timely alternative for effective eye disease diagnosis.

Puneet et al. [11] presented a deep neural network model which incorporated Attention and Transfer Learning within. Addressing historical challenges in healthcare diagnostics due to limited technology, the proposed model showcased notable accuracy rates of 95.6% on testing data and 97.79% on training.

Nazir et al. [12] proposed a novel technique utilizing a DenseNet-100 feature extractor and CenterNet model, centering on the detection of diabetic retinopathy. The performance of the model is emphasized through the resulting accuracies of 98.10% and 97.93% upon the evaluation of IDRiD and APTOS-2019 datasets, respectively.

Highlighting the current dependence on expensive instruments for image acquisition that limit accessibility, Vyas et al. [13] presented a dry eye detection technique based on tear film breakup time. The model leveraged convolution neural network that featured a high performance with an accuracy of 83%.

Munson et al. [14] introduced CRADLE: ComputeR-Assisted Detector of Leukocoria specifically modeled for detection of photographic leukocoria as a potential tool for early screening of eye disorders in children. The application demonstrated sensitivity in detecting leukocoria in 80% of children with eye disorders.

While DL methods have shown impressive success in distinguishing images in binary classification, the task of classifying multi-class retinal eye diseases remains a challenging area of research. Sarki et al. [15] aimed to fill this gap by introducing a novel neural network model designed for the automated classification of multi-class Diabetic Eye Disease and demonstrated 81.33% maximum accuracy.

In addressing the challenges of manual detection in diabetic eye diseases in retinal fundus images, Sarki et al. [16] focused on automated classification utilizing pretrained VGG16 CNN models from ImageNet resulting in a maximum accuracy of 88.3% for multi-class classification and 85.95% for mild multi-class classification.

Paradisa et al. [17] proposed a DL approach encompassing DenseNet121 and Inception-ResNetV2 architectures. Through rigorous experimentation, their model achieved notable improvement in accuracy, precision and recall showcasing its effectiveness.

The development of models for recognizing retinal health conditions has been hampered by the need for substantial annotation across various applications. Addressing this challenge, RETFound presented by Zhou et al. [18] emerged as a foundational model promising enhanced model adaptability with reduced reliance on labeled data.

Bitto and Mahmud [19] explored the use of CNN, specifically Inception-v3, ResNet-50, and VGG-16 architectures, to distinguish among cataracts, conjunctivitis and normal eyes, using Inception-v3 demonstrating the highest accuracy at 97.08% in 485 s, ResNet-50 at 95.68% in 1090 s, and VGG-16 at 95.48% in 2510 s.

Recognizing the difficulty caused by the alterations in the eye's anatomy during the initial stage, Sarki et al. [20] presented a conceptual system architecture. Thirteen CNN models were used in the analysis and were tested on a comprehensive ImageNet dataset.

In the context of medical diagnostics, infrared thermography has gained widespread acceptance. Selvathi et al. [21] explored a novel approach for detecting diabetic eye disease by use of thermal imagery. The study introduced an automatic classification method utilizing a CNN which achieved high testing accuracy of 95.38%.

Topaloglu [22] introduced a novel image classification method, called the "care model", for diagnosing diabetic retinopathy. The proposed model, incorporating a VGG19 model and a developed mathematical model, achieved promising results with a testing accuracy of 88% and a training accuracy of 87%.

Gangwar and Ravi [23] introduced a hybrid approach which utilized transfer learning on the pre-trained Inception-ResNet-v2. Evaluation on the APTOS 2019 blindness detection data and Messidor-1 diabetic retinopathy database, demonstrated superior results, with the test accuracies of 82.18% and 72.33%, respectively.

Babaqi et al. [24] focused on the early diagnosis and treatment of eye disorders. The researchers employed CNN and transfer learning techniques to distinguish between normal eyes and those with eye disorders. The use of transfer learning yielded a high accuracy of 94%, surpassing the 84% accuracy achieved by traditional convolutional neural networks.

Govindaiah et al. [25] compared their modified VGG16 neural network, incorporating batch normalization in the last fully connected layers, against other networks like AlexNet, highlighting the superior performance of the deeper VGG16 architecture in AMD detection tasks with accuracies spanning the range of 83% to 92.5%

Nguyen et al. [26] presented an automated classification system utilizing machine learning models such as VGG-16 and VGG-19, which demonstrated promising results with 82% accuracy and 0.904 AUC, providing efficient and timely DR screening to aid in controlling and managing its progression.

Sattigeri et al. [27] proposed a model that analyzed visually discernible symptoms related to multiple eye diseases – bulging eyes, cataracts, crossed eyes, uveitis and conjunctivitis. They achieved high accuracies of 96% for single-eye images and 92.31% for two-eye images, potentially serving as a cost-effective and user-friendly tool.

DeepSeeNet, introduced by Peng et al. [28], outperformed retinal specialists in patient-based classification, demonstrating high accuracy and transparency in assigning individual patients to AMD risk categories.

Ahmed et al. [29] proposed MATLAB′s Deep CNN for early detection, employing fundus images processed through techniques encompassing Complement, Grayscale, Resize, and power Transform, with texture feature extraction using Deep CNN. The model achieved a notable accuracy of 92.78% in glaucoma detection with an execution time of 5.33s.

In their study, Yadav et al. [30] addressed the issue of delayed cataract diagnosis due to poor medical access and high costs. The proposed method combined deep learning methodologies with 2D-DFT analysis of fundus images for early-stage detection. Experimental results demonstrated a remarkable 93.10% accuracy in the four-class classification benchmark.

Oh et al. [31] compared the efficacy of using early treatment DR study 7-standard field (ETDRS 7SF) images against optic disc and macula-centered images. The ETDRS 7SF outperformed, capturing around 75% of the retinal surface. However, challenges included artifacts in UWF photography and limitations in DR severity evaluation. The study developed a DL system using ETDRS 7SF from UWF photography, demonstrating superior performance compared to the ETDRS F1–F2 images.

Zhang et al. [32] introduced a novel six-level cataract grading approach utilizing multiple feature fusion based on stacking to deal with the issue of cataract diagnosis in rural China due to a shortage of ophthalmologists. The features included texture features from the gray level co-occurrence matrix and high-level features from ResNet18. They employed a fully connected neural network as a meta-learner and two support vector machines as base-learners. The proposed method demonstrated an average accuracy of 92.66% for six-level grading, with the highest reaching 93.33%.

Li et al. [33] presented a deep ensemble algorithm for the detection of diabetic macular edema and diabetic retinopathy using retinal fundus imagery. The model, based on an improvised Inception-v4 ensembling framework, was tested on 3285 patients linked to 8739 retinal fundus images. The model demonstrated an AUC of 0.992 for referable DR and 0.994 for referable DMO, with high sensitivity and specificity, on the primary test dataset. In comparison, ophthalmologists demonstrated specificities ranging from 0.912 to 0.971 and sensitivities ranging from 0.845 to 0.936 for DR, and specificities ranging from 0.926 to 0.985 and sensitivities ranging from 0.852 to 0.946 for DMO.

With the aim to estbalish automatic detection of diabetic retinopathy in retinal fundus images, Li et al. [34] introduced a deep transfer learning model with the Inception-v3 network. Out of a raw dataset of 19,233 fundus images, 8816 passed quality review and were graded by retinal experts. The proposed model demonstrated a high accuracy of 93.49%, with sensitivity of 96.93% and specificity of 93.45%. The area covered under the receiver operating characteristic curve (AUC) was up to 0.9905, on the independent testing dataset.

Using over 25,000 images sourced from population-based researches, Tham et al. [35] developed a DL model for automated detection of visually evident cataracts using retinal images, a rising cause of visual impairment among the elderlies. The implicit testing set showed an impressive area under the receiver operating characteristic curve (AUROC) of 96.6%. The external testing set over three researches demonstrated AUROCs ranging from 91.6% to 96.5%. For a different test set, the model performed comparably, if not slightly superior, demonstrating 93.3% sensitivity compared to that of 51.7–96.6% sensitivity by ophthalmologists, and 99.0% specificity compared to that of 90.7–97.9% specificity by ophthalmologists.

4 Materials and Methods

This section elucidates the materials and methods utilized for the purpose of this study.

4.1 Dataset

This study employs a comprehensive dataset obtained from a public repository on Kaggle, encompassing detailed retinal images associated with normal eye and prevalent eye diseases, like Cataract, Glaucoma and Diabetic Retinopathy. The dataset, meticulously outlined in Table 1, represents a carefully pre-processed amalgamation of diverse eye conditions. A segment of the evaluation dataset is visually depicted in Fig. 5, provides a snapshot of the range of eye disease manifestations under consideration.

Table 1. Structure of raw dataset.

Data class	Number of image samples
Normal	1074
Cataract	1038
Glaucoma	1007
Diabetic Retinopathy	1098

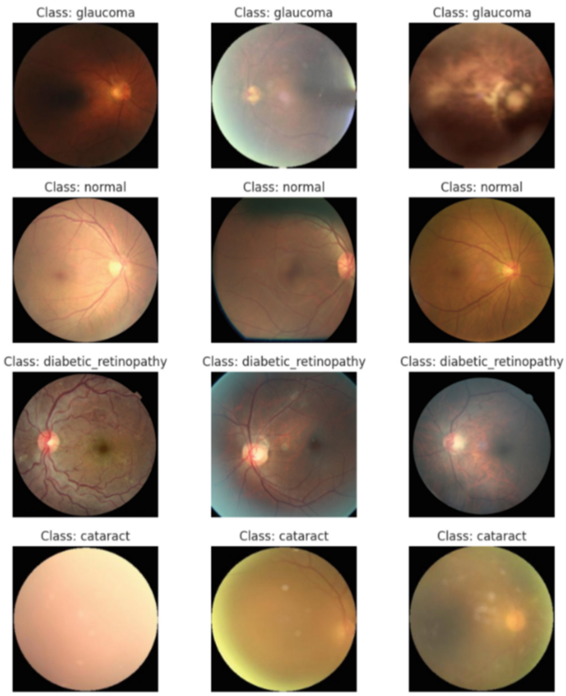

Fig. 5. An instance of evaluation dataset with class labels.

4.2 Libraries Used

This study uses an extensive array of libraries to support diverse aspects that encompass the analysis of the chosen dataset along with the implementation of the ResNet18 model. The chosen libraries play pivotal roles in offering tools for data manipulations, numerical operations and visualization. Data management was facilitated by the 'os', 'pandas' and 'numpy' libraries. Numerical operations were sup-ported by 'math'. The image processing task utilized the assistance of 'cv2'. Effective visualization of the both the data and the model results took place through the help of 'matplotlib' and 'seaborn'. The progress of the deep learning model's successive epochs was envisioned by 'tqdm.notebook'.

Considering the limited size of the dataset, the importance of employing data augmentation becomes even more significant. This is executed by 'torch.utils.data.Dataset'. The expanded dataset undergoes division into training and validation sets by use of the 'train-test-split' function sourced from the 'sklearn.model_selection' module.

The core PyTorch library is employed to construct and train the DL model. A pre-trained model is deployed by 'torchvision.models.resnet18(pretrained = True)' along with an additional sequential block using 'nn.Sequential'. The 'torchsummary' function was used in order to get a summary, encapsulating the architecture and number of parameters, of the proposed ResNet18 model. Performance metrics such as accu-racy, f1-score, recall and precision were generated through the use of the 'torch-metrics.'

4.3 Pre-processing

The dataset utilized in this study underwent pre-processing upon sourcing and was efficiently loaded using 'torch.utils.data.Dataset'. A custom class 'EyeDataset' was defined to efficiently handle its loading and augmentation. Pixel values, not confined to [0–255], were normalized using Min-Max Scaling. Data augmentation was implemented through the application of random horizontal and vertical flip transformations after resizing the images to a predetermined dimension.

Augmentation was omitted for color and brightness since it posed challenges during model's training. Then, the dataset was partitioned into training, validation and test sets. Herein, 85% of all of the data points are allocated to the training set while the remaining 15% is divided between the validation and test sets. Batches are created within the dataset for the improvement of the training performance through their shuffling.

4.4 Model Used

Neural Networks are at the heart of DL techniques. This study employs Convolutional Neural Network, a specialized neural network renowned for its superior performance in processing grid data, like speech, images and audio signals. CNNs excel at capturing spatio-temporal dependencies through strategic filter applications, emulating the nuanced information interpretation of the human brain. CNNs lead in healthcare DL applications, exceling in medical image analysis and aiding disease classification.

CNNs encapsulate three kinds of layers: convolution layers, pooling layers and fully connected layers. The first layer makes use of a filter or kernel, functioning as feature detectors. The second layer executes dimensionality reduction, thereby effectively diminishing the figure of parameters present in the input. The third layer discerns non-linear relationships within the space defined by the high-level features. The model adds vital non linearity into the model through the initiation of activation functions to the pooling and convolution layers of the model.

This study utilizes a convolutional neural network based on the ResNet-18 architecture, a pretrained model addressing vanishing gradients in deep neural networks. It is comprised of multiple residual blocks with skip connections, facilitating direct information flow to deeper layers instead of having to follow a set path through every layer of the model. This addresses the degradation problem commonly linked with deep architectures. Two additional dense layers were introduced to ResNet-18′s final layer, each comprising two linear layers, a ReLU or Rectified Linear Unit activation, along with a dropout function. This adjustment enables the model to capture intricate problem-specific features. To enhance training efficiency, 70% of ResNet-18′s parameters were frozen, leaving 30% trainable. Freezing prevents weight updates during backpropagation. The learning rates were set at 5x10^-5 for the ResNet-18 block and 8x10^-4 for the new dense layers. The training employed the AdamW optimizer with distinct learning rates for the ResNet-18 block and extra dense layers. The CrossEntropyLoss function was substituted for the loss function, suitable for the multiclass classification task. The Trainer class structured the training loop, encompassing steps for forward passes, loss computation, backpropagation, and optimization. Model evaluation utilized accuracy metric, tracked over 10 epochs, with torchmetrics supporting accuracy calculation for multiclass classification within a defined class count.

5 Results

The proposed model, ResNet-18, exhibits commendable performance, boasting a training accuracy of 96.5% and a testing accuracy of 93.7%. The detailed results for various performance parameters of the proposed convolutional neural network, ResNet-18, are elucidated in Table 2, providing a brief overview of the effectiveness of the model.

Table 2. Results for the performance parameters of the proposed model.

Model	Precision	Recall	f1-score
Normal	0.90	0.91	0.90
Cataract	0.90	0.97	0.93
Glaucoma	0.89	0.84	0.86
Diabetic Retinopathy	1.00	0.98	0.99

6 Conclusion and Future Work

In conclusion, this study delved into the critical realm of eye disease classification, emphasizing the necessity for continuous improvement in accurate and efficient detection methodologies. With a robust testing accuracy of 93.7%, the deep learning model employed, ResNet-18, showcased promising results. Rigorous evaluation on a diverse dataset comprising images relevant to Cataract, Glaucoma, and Diabetic Retinopathy underlined the models' efficacy.

Future efforts will be directed towards refining the model′s performance metrics, such as f1-score, recall, precision and specificity. A pivotal stride in this trajectory involves an expansive approach, extending beyond the current dataset limitations. Moreover, exploring a multi-modal approach by incorporating various types of eye scans and integrating additional patient data like genetic information or lifestyle factors, will be crucial for enhancing the model′s versatility and robustness in real-world applications.

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