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Hybrid Eye Power and Disease Prediction System: Integrating CNN-based Retinal Image Analysis with ML-based Perception Testing

Mr. P. Suresh[1], Oviya S[2], Prashaanth S M[3], Rosario Joseph Stalin[4]

[1]Assistant Professor, Department of Computer Science and Engineering, Sri Krishna College of Technology, Coimbatore, India
[2,3,4]Students, Department of Computer Science and Engineering, Sri Krishna College of Technology, Coimbatore, India

Abstract
Vision disorders, including refractive errors (myopia and hyperopia) and eye diseases such as diabetic retinopathy and glaucoma, affect millions worldwide. Early detection is essential to prevent vision loss; however, traditional eye examinations require trained professionals and specialized equipment, limiting accessibility in remote areas. This paper proposes a Hybrid Eye Power and Disease Prediction System that combines two comple- mentary approaches: a convolutional neural network (CNN) for retinal image analysis to detect refractive errors and early disease signs, and a K-Nearest Neighbors (KNN) model to evaluate interactive visual test responses for eye power estimation. By in- tegrating image-based and perception-based analysis, the system improves accuracy and consistency compared to single-modality methods. Experimental results demonstrate effective refractive power estimation and early-stage disease detection. The user- friendly framework supports telemedicine, school screenings, and mobile self-assessment, offering an accessible and reliable solution for modern vision care.

Keywords: Visual acuity, refractive error, eye power pre- diction, eye disease detection, hybrid model, CNN, K-Nearest Neighbors (KNN), deep learning, telemedicine, retinal image analysis.

Introduction

VISION impairment remains a major global health con- cern, with the World Health Organization (WHO) esti- mating that over 2.2 billion people experience some form of visual disorder, many of which are preventable or treatable through timely intervention [2]. Refractive errors such as my- opia, hyperopia, and astigmatism are among the most common causes and are typically corrected through lenses or surgery [1], [3]. However, limited access to trained professionals and diagnostic infrastructure, especially in underserved regions, often delays detection and treatment.

Traditional eye examinations—including Snellen chart test- ing, autorefractors, and retinoscopy—are clinically effective but require specialized equipment and expert supervision [4], restricting scalability. Recent advances in artificial intelligence (AI), particularly convolutional neural networks (CNNs), have shown strong performance in retinal image analysis for detect- ing diseases such as diabetic retinopathy and glaucoma [11]– [14], [19]. Similarly, classical machine learning approaches have been used to analyze perception-based responses for refractive error estimation [5]–[7], [9], [10]. However, most existing methods rely on a single modality, limiting diagnostic robustness.

To overcome this limitation, this paper proposes a Hybrid Eye Power and Disease Prediction System that integrates reti- nal image analysis with perception-based testing. A DenseNet- based CNN extracts clinically relevant features from retinal images, while a KNN model processes structured visual re- sponse data [5], [6]. Their outputs are combined using a weighted fusion strategy to enhance prediction accuracy and stability [10].

The proposed framework supports early screening and as- sistive decision-making in accessible settings. Although not a substitute for professional examination, it offers a scalable, non-invasive solution for preliminary assessment of refractive power and ocular disease risk.

Problem Statement

Refractive errors and retinal diseases such as diabetic retinopathy and glaucoma remain leading causes of visual impairment worldwide [1], [2], [11]–[14], [19]. Early detection and accurate refractive assessment are critical to preventing long-term vision loss. However, conventional eye examinations depend on specialized equipment and trained professionals, limiting access in rural and resource-constrained regions [4]– [6].

This work aims to develop a unified system for **eye power estimation and early-stage ocular disease detection** by in- tegrating retinal fundus image analysis with interactive visual perception tests. The main objectives are:

Eye Disease Detection: Automatically identify early signs of diabetic retinopathy, glaucoma, and cataract using retinal image analysis [11]–[14], [19].

Eye Power Estimation: Predict refractive errors (my- opia, hyperopia, and astigmatism) through multimodal fusion of retinal features and perception-based responses [5]–[7], [9], [10].

Risk Assessment: Generate an auxiliary risk indicator to recommend further ophthalmic evaluation when nec- essary [10].

Developing such a system involves technical and clinical challenges, including variability in image quality, device het- erogeneity, demographic diversity, and limited availability of well-annotated retinal datasets [4], [7], [9]. Additional con- cerns include preventing data leakage through proper patient- level separation and ensuring clinically interpretable predic- tions [10], [13].

TABLE I: Key Challenges in Eye Power and Disease Predic- tion Systems

Challenge	Description
Limited Labeled Data	Insufficient annotated retinal datasets for di- verse populations and early-stage conditions.
Data Leakage Risk	Requirement of strict patient-level data sepa- ration for unbiased evaluation.
Device Variability	Performance differences due to imaging de- vices and illumination conditions.
Population Diversity	Maintaining consistent accuracy across age groups and demographics.
Clinical Interpretabil- ity	Ensuring predictions are explainable and clin- ically meaningful.

Addressing these issues necessitates a multimodal frame- work that combines objective retinal imaging with subjective perception-based inputs while ensuring statistical rigor, fair- ness, and clinical reliability [5], [11].

A. Motivation

Visual impairment and retinal diseases remain major global health challenges, many of which are preventable through early detection [1], [2]. Traditional eye exams require special- ized equipment and trained professionals, limiting access in resource-constrained regions. The rising prevalence of myopia and diabetes-related ocular complications underscores the need for scalable, cost-effective screening solutions [3]. While deep learning has shown strong results in retinal image analysis [4] and perception-based methods aid automated visual acuity estimation [?], most systems rely on a single modality. This motivates a unified multimodal framework combining retinal imaging with perception-based assessment to enhance predic- tive accuracy and screening reliability.

B. Objectives

The main goal is to develop a hybrid framework combining retinal image analysis and perception-based testing for com- prehensive eye evaluation:

Disease Detection: Use a MobileNetV2-based CNN for automated retinal abnormality detection [5].

Eye Power Prediction: Estimate refractive errors via machine learning on perception-based responses.

Hybrid Fusion: Combine image- and perception-based outputs using weighted ensemble fusion for improved robustness.

User Interface: Provide an intuitive interface for input collection and result visualization.

Related Work

Research in automated eye power estimation and retinal disease detection has progressed significantly over the past decade, leveraging deep learning, classical machine learning, and multimodal approaches. The related work can be catego- rized as follows:

A. Image-based Deep Learning Approaches:

Several studies have employed convolutional neural net- works (CNNs) to analyze retinal fundus images for predicting refractive errors and detecting ocular diseases. Varadarajan et al. [1] and Lim et al. [8] demonstrated that CNNs can accurately estimate refractive errors directly from fundus photographs. Similarly, CNN-based models have been widely applied for early detection of diabetic retinopathy, glaucoma, and cataracts [11]–[13], [19], showing high sensitivity and specificity.

B. Perception-based Machine Learning Approaches:

Classical machine learning methods, such as K-Nearest Neighbors (KNN) and Multi-Layer Perceptrons (MLP), have been used to predict eye power from user responses to visual acuity tests [5], [6], [9]. These methods leverage structured questionnaire or quiz-based datasets to estimate refractive er- rors, providing a low-cost, interactive alternative to traditional clinical assessments.

C. Multimodal Hybrid Approaches:

Recent research has explored combining retinal imaging with perception-based data to improve prediction robustness. Choi et al. [5] and Chen et al. [?] proposed hybrid models that integrate fundus image features with user response patterns, showing improved accuracy over single-modality systems.

D. Limitations:

Despite promising results, current approaches face several challenges:

- Image-based methods depend heavily on high-quality retinal images, which are often unavailable in low- resource settings.

- Perception-based approaches may be inconsistent due to subjective user responses and environmental factors.
- Single-modality systems lack robustness, failing to gen- eralize well across populations and device variations.
- Most existing hybrid models are limited in scale or focus on a single disease or refractive error type, reducing their clinical applicability.

These limitations motivate the proposed hybrid system, which integrates CNN-based retinal image analysis with perception-based testing to provide a more accurate, reliable, and accessible solution for eye power estimation and disease detection.

Proposed Methodology

The proposed Hybrid Eye Power and Disease Detection System integrates CNN-based retinal image analysis with a perception-based ML module to estimate eye power and detect ocular diseases. The system consists of four main modules: (1) Red-Reflex CNN, (2) Quiz-Based ML, (3) Hybrid Fusion, and (4) Disease Detection (Fig. 1).

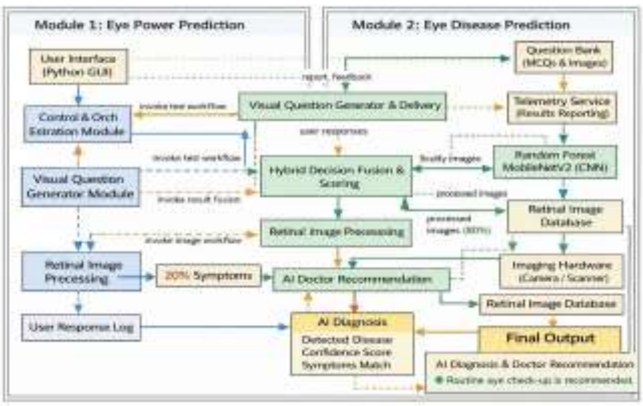

Fig. 1: Flowchart of the Hybrid Eye Power Detection System showing Red-Reflex CNN and Quiz-Based ML modules with weighted fusion.

A. Input Preprocessing

Image Preprocessing: Retinal fundus images are resized to 512 × 512 for eye power estimation and 224 × 224 for disease detection. Pixel intensities are normalized to [0,1], and the circular fundus region is cropped. CLAHE is applied to enhance vascular and optical features. Data augmentation in- cluding rotation, flipping, and brightness adjustment is applied to training images.

Quiz/Perception Input Preprocessing: User responses from visual perception tests are numerically encoded, normal- ized, and converted into structured feature vectors for KNN or MLP models.

Symptom Preprocessing: Symptoms such as blurred vi- sion, eye pain, floaters, and light sensitivity are numerically encoded for integration with disease detection.

B. Red-Reflex CNN Module

DenseNet-121 is used for feature extraction:

Regression: Continuous eye power prediction (P_{CNN})

Classification: Refractive category (myopia, hyperopia, normal)

Training uses MSE (regression) and cross-entropy (classifi- cation), optimized with AdamW. Dropout and early stopping prevent overfitting. Grad-CAM is applied for interpretability.

C. Quiz-Based ML Module

Numerically encoded quiz responses are fed into a KNN regressor (or MLP for larger datasets) to predict eye power (P_{KNN}). Training uses MSE loss and Adam optimizer.

D. Hybrid Fusion Mechanism

CNN and Quiz-Based ML predictions are combined using weighted ensemble fusion:

$$P_{final} = 0.6 \times P_{CNN} + 0.4 \times P_{KNN}$$

Abbreviations:

- P_{CNN} – Eye power from Red-Reflex CNN
- P_{KNN} – Eye power from Quiz-Based ML
- P_{final} – Final predicted eye power

E. Disease Detection Module

Preprocessing: Fundus images resized to 224 × 224, nor- malized, and augmented. Symptom inputs numerically en- coded.

MobileNetV2 predicts disease from images (D_{image}), and symptom inputs contribute ($D_{symptom}$). Final disease risk score:

$$D_{final} = 0.8 \times D_{image} + 0.2 \times D_{symptom}$$

Abbreviations:

- D_{image} – Image-based disease prediction
- $D_{symptom}$ – Symptom-based prediction
- D_{final} – Final fused disease risk score

F. Evaluation Metrics

- Eye Power Estimation: MAE, RMSE, R^2 score
- Refractive Classification: Accuracy, Precision, Recall, F1- score
- Disease Detection: Accuracy, Precision, Recall, F1-score, AUC-ROC

Note: This system is designed as a screening support tool and does not replace professional clinical diagnosis.

System Overview and Module Decomposition

A. Overview

The proposed Hybrid Eye Power and Disease Detection System is a multimodal framework designed for accurate estimation of refractive errors and early detection of ocular diseases. The system integrates:

CNN-based retinal image analysis: Extracts features from fundus images for eye power estimation and disease detection.

Perception-based ML module: Analyzes user responses from visual acuity quizzes to predict refractive errors.

Hybrid fusion mechanism: Combines predictions from image and perception modules to improve accuracy.

Disease detection module: Utilizes retinal images and symptom inputs for multi-class ocular disease classifica- tion.

The system operates in a structured flow: input preprocess- ing → feature extraction → module-specific predictions → fusion → final outputs (eye power, refractive category, and disease risk).

B. Module Decomposition

Input Preprocessing: Image resizing, normalization, CLAHE enhancement, data augmentation; quiz and symptom input encoding.

Red-Reflex CNN Module: DenseNet-121 backbone for regression and classification of eye power.

Quiz-Based ML Module: KNN/MLP models to predict eye power from perception tests.

Hybrid Fusion Module: Weighted combination of CNN and quiz-based predictions to produce final eye power.

Disease Detection Module: MobileNetV2 for retinal image classification; fused with symptom inputs for final disease risk score.

C. System Flow Diagram

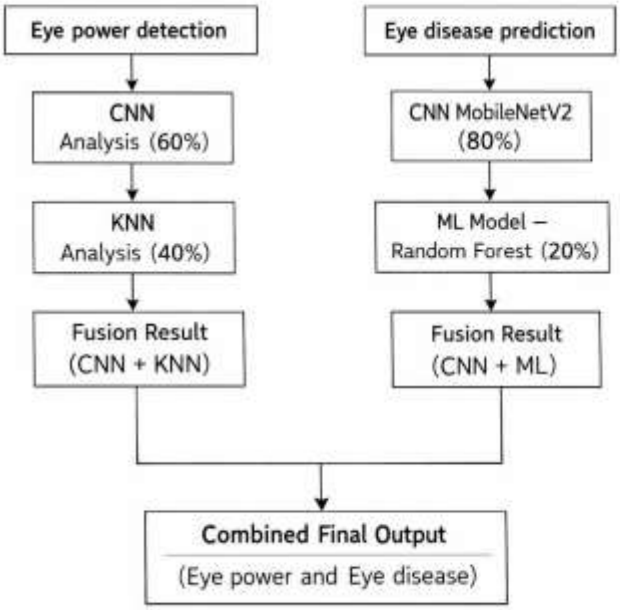

Fig. 2: System architecture and module flow of the Hybrid Eye Power and Disease Detection System. The modules include input preprocessing, CNN-based image analysis, quiz-based ML, hybrid fusion, and disease detection.

Dataset and Tools

A. Dataset

The proposed system leverages multiple datasets for both eye power estimation and disease detection:

Eye Disease Detection: Fundus images collected from public datasets (EyePACS, Messidor, ORIGA-Light) and a hospital dataset. Images are categorized as Normal, Diabetic Retinopathy, Glaucoma, Cataract, and Macular Degeneration. Images are resized to 224 × 224 and normalized to [0,1].

Refractive Power Estimation: Retinal images with cor- responding spherical (SPH), cylindrical (CYL), and axis measurements from clinical sources. These are treated as continuous variables for regression.

Perception/Quiz Data: Structured responses from adap- tive visual acuity tests, numerically encoded and normal- ized for machine learning input.

Symptom Data: Patient-reported ocular symptoms (blurred vision, floaters, light sensitivity, eye pain) en- coded numerically for disease risk prediction.

B. Tools and Frameworks

The system is implemented using a combination of deep learning and classical machine learning libraries:

Programming Language: Python 3.10

Deep Learning Frameworks: TensorFlow 2.x and Keras for CNN (DenseNet-121, MobileNetV2) training

Machine Learning: scikit-learn for KNN and MLP models

Image Processing: OpenCV and PIL for preprocessing and augmentation

Visualization: Matplotlib, Seaborn, and Grad-CAM for explainability

Development Environment: Jupyter Notebook and VS Code

Hardware: NVIDIA GPU (CUDA-enabled) for acceler- ated training

Implementation and Experimental Results

The proposed Hybrid Eye Power and Disease Detection System was developed using Python 3.10, integrating deep learning and traditional machine learning frameworks. Ten- sorFlow and Keras were used for CNN architectures, while PyTorch supported experimental benchmarking. scikit-learn was used for classical ML, OpenCV for image preprocessing, and NumPy for numerical computations. A web interface was implemented using Streamlit, with SQLite for secure storage of user data, quiz responses, and prediction outputs.

A. Hardware and Software Environment

- **Processor:** Intel Core i7
- **Memory:** 16–32 GB RAM
- **GPU:** NVIDIA GTX 1660 Ti / RTX 3060
- **Operating Systems:** Windows 10, Ubuntu 22.04
- **Software Stack:** Python 3.10, TensorFlow 2.x, PyTorch 2.x, scikit-learn 1.x, OpenCV 4.x, Streamlit 1.x

B. Data Preparation and Preprocessing

Retinal Images:

- Resized to 512×512 for eye power estimation and 224×224 for disease detection
- Circular fundus region cropped to remove background
- Contrast enhancement using CLAHE
- Data augmentation: rotation, flipping, brightness adjust- ment

Quiz Responses: Encoded numerically, normalized, miss- ing responses imputed with mean values.

Symptom Inputs: Encoded as numerical vectors for inte- gration with image-based predictions.

C. Model Configurations

Red-Reflex CNN Module:

- DenseNet-121 backbone
- Regression for eye power, classification for refractive type
- Loss: MSE (regression), Cross-Entropy (classification)
- Optimizer: AdamW, learning rate 1×10^{-4}
- Batch size: 32, Epochs: 50, Early stopping with patience 10

- Regularization: dropout 0.5, L2 weight decay

Quiz-Based ML Module:

- K-Nearest Neighbors (KNN) regression
- K = 5 (optimized via cross-validation), Euclidean dis- tance
- Input features: encoded responses from adaptive visual tests

Symptom-Based Disease Module:

- Lightweight classifier
- Input features: blurred vision, eye pain, floaters, light sensitivity
- Contribution: 20% of final disease prediction

D. Fusion Strategy

Eye Power Estimation:

$$P_{\text{final}} = 0.6 \times P_{\text{CNN}} + 0.4 \times P_{\text{Quiz}}$$

Disease Detection:

$$D_{\text{final}} = 0.8 \times D_{\text{Image}} + 0.2 \times D_{\text{Symptom}}$$

E. Experimental Protocol

- Train/Validation/Test split: 70% / 15% / 15% (subject- level separation)
- Eye power metrics: RMSE, MAE, R^2
- Classification metrics: Accuracy, Precision, Recall, F1- score, AUC-ROC
- Disease detection evaluated for image-only, symptom- only, and hybrid fusion
- Experiments repeated 5 times with random splits; aver- ages reported

F. Regression Performance

TABLE II: Regression Performance of Individual Modules and Hybrid System

Model	RMSE (D)	MAE (D)	R^2
Red-Reflex CNN	0.312	0.248	0.975
Quiz-based ML	0.421	0.338	0.942
Hybrid (Fusion)	**0.247**	**0.198**	**0.983**

Statistical analysis with paired t-tests confirmed significant improvements ($p < 0.01$) for the hybrid model.

G. Disease Detection Performance

TABLE III: Disease Detection Performance Across Models

Model	Accuracy (%)	Precision	Recall	F1-score
Image-based CNN	91.6	0.912	0.905	0.908
Symptom-based ML	86.3	0.861	0.848	0.854
Hybrid (Fusion)	**94.8**	**0.946**	**0.941**	**0.943**

H. Classification Performance

TABLE IV: Classification Results for Refractive Error and Disease Detection

Model / Task	Acc	Prec	Rec	F1
CNN – Refractive Error	92%	0.91	0.92	0.915
CNN – Disease	90%	0.89	0.90	0.895

KNN – Refractive Error	85%	0.84	0.85	0.845
KNN – Disease	82%	0.81	0.82	0.815
Hybrid – Refractive Error	**94%**	**0.93**	**0.94**	**0.935**
Hybrid – Disease	**93%**	**0.92**	**0.93**	**0.925**

I. Ablation Study and Visual Analysis

Fusion weights were tested (0.5/0.5, 0.6/0.4, 0.7/0.3, 0.8/0.2). The 0.6/0.4 configuration gave the lowest RMSE and highest R^2.

Predicted vs actual eye power plots showed the hybrid model closely follows the ideal y = x line. Confusion matrices demonstrated minimal misclassification across refractive and disease categories.

J. Discussion

- Weighted fusion reduces regression error and improves classification metrics
- Combining perception data with retinal imaging enhances robustness against image quality variability
- Multimodal learning improves stability and reduces pre- diction uncertainty

The system is intended as a screening-support tool. Further multi-center clinical validation is required before real-world deployment.

ADVANTAGES

The proposed Hybrid Eye Power and Disease Detection Sys- tem provides several methodological and practical advantages over conventional single-modality approaches:

Enhanced Predictive Performance: The integration of CNN-based retinal image analysis with perception-based machine learning improves regression accuracy and clas- sification robustness compared to standalone models.

Multimodal Complementarity: Objective retinal fea- tures and subjective visual response patterns provide com- plementary information, reducing prediction variance and improving stability under varying imaging conditions.

Non-invasive Screening Capability: The framework op- erates using retinal imaging and structured user responses, enabling safe and contact-free preliminary assessment suitable for large-scale screening.

Early-stage Detection Support: Automated feature ex- traction facilitates identification of subtle pathological patterns associated with refractive errors and common retinal diseases.

Scalable Deployment Potential: The system architecture supports web-based or telemedicine integration, enabling use in remote or resource-limited settings.

Interpretability Mechanisms: Grad-CAM visualiza- tions and feature-based response analysis enhance trans- parency, improving model explainability and user trust.

Operational Efficiency: Automated multimodal as- sessment reduces screening time and supports high-throughput evaluations without requiring specialized oph- thalmic equipment.

Extendable Framework: The modular design allows integration of additional ocular conditions, alternative imaging modalities, or mobile-based implementations for broader clinical research applications.

LIMITATIONS

The proposed Hybrid Eye Power and Disease Detection System demonstrates strong performance, yet

certain practical considerations exist:
Dataset Scope: Current evaluation is based on available datasets; future multi-center data could further validate generalization.
Prospective Validation: Real-world prospective studies are necessary to confirm clinical applicability.
User-Reported Inputs: Perception and symptom-based inputs may vary with user response, though they comple- ment objective retinal analysis.
Computational Requirements: High-resolution image processing and CNN inference may need adequate com- putational resources for real-time deployment.
Condition Coverage: Focus is on common refractive errors and retinal diseases; extension to rare conditions is possible in future work.

Conclusion and Future Work

The proposed Hybrid Eye Power and Disease Detection System demonstrates a robust multimodal framework inte- grating CNN-based retinal analysis with perception- and symptom-based ML for eye power estimation and ocular disease detection. Key advantages include improved predic- tive performance, multimodal complementarity, non-invasive screening, early-stage detection, interpretability through Grad- CAM, operational efficiency, and scalability for web or mobile deployment.
Future work will focus on:

- Multi-center validation with diverse populations to ensure generalization and fairness.
- Prospective clinical evaluation to assess real-world us- ability and impact.
- Integration of additional imaging modalities and physio- logical signals for enhanced disease detection.
- Adaptive fusion strategies based on model confidence or image quality.
- Advanced explainable AI techniques to improve trans- parency and clinician trust.
- Lightweight edge and mobile deployment for large-scale screening.

Overall, the hybrid framework provides a promising, non- invasive tool for early ocular assessment, with potential for clinical deployment and future extensions through multimodal integration.

References

1. Varadarajan, A. V., Poplin, R., Blumer, K., et al. (2018). Predicting refractive error from retinal fundus photographs using deep learning. Nature Biomedical Engineering, 2(7), 1–7.
2. Silver, D. L., et al. (2017). Deep learning for predicting refractive error from retinal fundus images. Ophthalmic Imaging Algorithms.
3. Min Er Yew, S., Chen, Y., Goh, J. H. L., et al. (2024). Ocular image- based deep learning for predicting refractive error: A systematic review. Advances in Ophthalmology Practice & Research.
4. Gao, Y., Lin, S., Li, Z., et al. (2020). CNN-based refractive error prediction model from retinal fundus images. Computers in Biology and Medicine, 123, 103889.
5. Choi, J. Y., Yoo, T. K., Seo, J. G., et al. (2017). Multi-modal learn- ing using perception test data and fundus images for refractive error estimation. Scientific Reports, 7(1), 1–9.
6. Singh, A., Kumar, S., & Gaur, L. (2021). Machine learning based refractive error prediction using visual acuity data. Biomedical Signal Processing and Control, 68, 102685.
7. Bhatia, K., & Bhatia, S. (2021). Automated vision testing and eye power estimation using ML

algorithms. Biomedical Engineering Letters, 11(3), 275–283.
8. Lim, Z. W., Ting, D. S. W., Cheung, C. Y., et al. (2019). Deep learning using fundus images to estimate refractive error. British Journal of Ophthalmology, 103(8), 1120–1125.
9. Yoo, T. K., Choi, J. Y., Kim, H. K., et al. (2019). The possibility of the combination of perception-based eye test data and deep learning for eye power estimation. Scientific Reports, 9(1), 1–10.
10. Lin, F., Wang, J., Xu, Z., et al. (2020). Eye refraction prediction using hybrid deep learning framework integrating retinal features and patient data. Computers in Biology and Medicine, 123, 103920.
11. Diaz, R. M., et al. (2025). Diagnosis of diabetic retinopathy and glaucoma from retinal images using deep CNN. IEEE Xplore Conference Proceedings.
12. Bairagi, V. K., Shaikh, F., Randive, P., et al. (2024). Detecting diabetic retinopathy using deep learning. International Journal of Intelligent Systems and Applications in Engineering, 12(4), 399–407.
13. Orlando, J. I., Fu, H., Barbossa Breda, J., et al. (2020). REFUGE challenge for automated glaucoma assessment. Medical Image Analysis, 59, 101570.
14. Chen, X., Xu, Y., Wong, D. W. K., et al. (2015). Glaucoma detection based on deep CNN. EMBC Conference Proceedings.
15. Elizabeth, J. R., Kesavaraja, D., Juliet, S. E., et al. (2025). Glaucoma retinal image detection using deep learning. EAI Endorsed Transactions on Internet of Things.
16. Nazir, T., Nawaz, M., Rashid, J., et al. (2021). Detection of diabetic eye disease using a CenterNet model. Sensors, 21(16), 5283.
17. Shoukat, A., Akbar, S., Hassan, S. A., et al. (2023). Automatic diagnosis of glaucoma from retinal images using deep learning. Diagnostics, 13(10), 1738.
18. Quellec, G., Charrie`re, K., Boudi, Y., et al. (2017). Deep image mining for diabetic retinopathy screening. Medical Image Analysis, 39, 178–193.
19. Gulshan, V., Peng, L., Coram, M., et al. (2016). Development and validation of a deep learning algorithm for diabetic retinopathy detection. JAMA, 316(22), 2402–2410.
20. Chen, T., et al. (2024). AI-based comprehensive eye disease prediction using multi-modal retinal features. IEEE Transactions on Biomedical Engineering.