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A Comprehensive Review of Multimodal and Transformer-Based AI Models for Ophthalmic Disease Detection

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ABSTRACT

Impaired vision due to retinal and optic neuropathies continues to pose a major public health challenge. Early detection is critical to prevent irreversible visual impairment, especially for conditions such as diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD), and cataracts. With the surge in artificial intelligence (AI) and deep learning (DL) capabilities, automated diagnostic frameworks are gaining traction as viable solutions to alleviate diagnostic workload, improve accessibility, and enhance screening accuracy. This review presents a comprehensive analysis of recent deep learning and hybrid machine learning models developed for the detection and classification of ophthalmic and neurodegenerative diseases. The synthesis spans fundus-based convolutional neural networks (CNNs), Vision Transformers (ViTs), multimodal architectures, and ensemble systems. Through comparative assessment, the paper highlights that ensemble CNNs and transformer-based methods consistently demonstrate superior accuracy, especially in multi-disease classification scenarios. However, challenges such as data imbalance, model interpretability, and deployment constraints persist. Despite these advancements, challenges remain, including dataset imbalance, limited model interpretability, and real-world deployment constraints. By consolidating recent trends, methodologies, and performance insights, this review aims to guide researchers and practitioners toward developing robust, interpretable, and scalable AI-driven solutions for ophthalmic disease screening and diagnosis.

Keywords— Ophthalmology, Retinal Disease Diagnosis, Deep Learning, Vision Transformers (ViT), Multimodal Medical Imagin**.**

1. INTRODUCTION

Impaired visual function diminishes productivity and overall quality of life. Retinal pathologies are a major contributor and, without timely detection and intervention, can lead to irreversible vision loss [1], [2]. Representative conditions include choroidal neovascularization (CNV), age-related macular degeneration (AMD), diabetic macular edema (DME), glaucoma, drusen, and diabetic retinopathy (DR) [3] (see Fig. 1). Early identification is essential to initiate appropriate therapy and slow disease progression [3], [4]. In particular, the global DR burden is expected to

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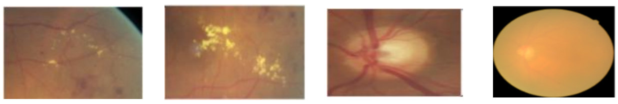
rise in parallel with diabetes prevalence, with projections reaching ~191.0 million affected individuals by 2030 [4]. Pathophysiological, chronic hyperglycemia damages the retinal microvasculature, precipitating DR. For context, cataract denotes opacification of the crystalline lens, glaucoma is characterized by elevated intraocular pressure and consequent optic-nerve injury, and AMD reflects degenerative changes of the macula [4]. In clinical practice, ophthalmic assessment typically comprises intraocular pressure (IOP) measurement, review of medical history, visual-field evaluation, and ophthalmoscopic inspection of the optic nerve head for color, size, and contour abnormalities [5]. Precise delineation (segmentation) of disease-affected regions supports detailed expert evaluation and enables robust computer-aided pipelines for detection and classification that are less sensitive to localization errors. Clinicians commonly assess DR lesions and optic-disc (OD) morphology by estimating the cup-to-disc ratio (CDR), disc diameter and area, and rim irregularity. However, constrained specialist availability often delays screening, forfeiting opportunities for early intervention [6]. To mitigate these limitations, current research focuses on computer-aided diagnosis (CAD) systems that leverage machine learning (ML) and deep learning (DL) for scalable, multi-disease retinal screening and triage.



Diabetic Retinopathy	Diabetic Macular Edema	Glaucoma	Cataract

Fig. 1. Different Types of Eye Diseases

Modern artificial intelligence (AI), encompassing machine learning (ML) and deep learning (DL), has profoundly influenced 21st-century medicine and now underpins precise, scalable decision support in ophthalmology. Early identification of ocular disease is critical to prevent downstream morbidity; however, traditional assessment, primarily based on clinician observation, can be time-consuming and susceptible to inter-observer variability. Integrating AI methods into the diagnostic pathway offers a principled means to accelerate screening, standardize interpretation, and reduce human error, thereby enabling timely clinical intervention and mitigating future complications. AI is commonly categorized into narrow, general, and superintelligent systems, with current medical deployments firmly in the narrow-AI class [7]. The human eye is highly susceptible to a spectrum of disorders, many of which progress silently and, if neglected, can culminate in irreversible vision loss [8], [9]. Below, we summarize common conditions addressed by AI-enabled screening and diagnosis:

- Diabetic Retinopathy (DR): Persistent hyperglycemia (e.g., fasting plasma glucose ≥ 7.0 mmol/L) damages microvasculature and neural tissues. Per the World Health Organization, such vascular injury extends to the retina, driving the development of DR and its complications.
- Age-Related Macular Degeneration (AMD): A leading cause of legal blindness, particularly in individuals ≥ 50 years, AMD imposes a substantial economic burden (≈ USD 30 billion

annually in the United States). AMD comprises dry (atrophic) and wet forms; the latter, characterized by choroidal neovascularization (CNV), carries the highest risk for rapid central vision loss.

- Glaucoma: A prevalent optic neuropathy often associated with elevated intraocular pressure (IOP), glaucoma progressively injures the optic nerve and can lead to blindness if untreated (see Fig. 1c).
- Cataract: Age, ultraviolet exposure, and smoking contribute to opacification of the crystalline lens, degrading visual quality. Diagnosis includes visual acuity testing, dilated fundus examination, and tonometry; definitive management involves surgical lens extraction with intraocular lens implantation.
- Refractive Error: Myopia causes blurred distance vision, astigmatism reflects corneal/optical irregularity with blur at all distances, and presbyopia, typically after age 40, reduces near focus.

Across these diseases, DL systems have achieved strong accuracy, sensitivity, and specificity supported by high-level evidence [10]–[13]. Recent efforts have extended to pediatric ophthalmology, where AI can help offset limitations in patient cooperation and streamline clinical workflows. Beyond classification, DL can mine multimodal ophthalmic imaging to discover quantitative biomarkers, potentially informing new diagnostic parameters and therapeutic strategies. Despite this promise, significant translational challenges remain: rigorous multi-site validation and monitoring, model generalizability and bias mitigation, patient acceptance, and workforce education. Progress will depend on sustained collaboration among clinicians, engineers, data scientists, and technology experts to ensure that AI-enabled systems are trustworthy, equitable, and integrated into high-quality, interdisciplinary care.

Recent advancements in deep learning and transformer-based architectures have significantly improved automated ophthalmic disease detection. Despite these achievements, challenges such as dataset limitations, model interpretability, generalizability, and integration of multimodal data persist. This review systematically analyzes recent AI-driven approaches (2019–2025) for detecting and classifying ophthalmic diseases with a comparative evaluation across benchmark datasets.

The key contributions of this paper are as follows:

- The paper presents a structured classification of deep learning based ophthalmic diagnostic systems, including CNNs, ViTs, multimodal fusion models, and ensembles.
- The paper presents an evaluation and summarization of model performance across multiple datasets, highlighting strengths and weaknesses.
- Current research analyzes the limitations, including data quality, interpretability, and clinical deployment barriers.

The remainder of this paper is organized as follows: Section 2 presents the overview of ophthalmic diseases and commonly used datasets, Section 3 presents the discussion on deep learning and transformer-based models for disease detection, Section 4 presents the current challenges and future scope, and Section 5 presents the conclusion of the paper.

2. LITERATURE REVIEW

The era of deep learning has significantly transformed diagnostic strategies in ophthalmology and the detection of neurodegenerative diseases. Early works initiated the use of fundus imaging as a diagnostic window to the brain, promoting non-invasive approaches for neurodegenerative screening. This review is based on the following taxonomy, as presented in Fig 2.

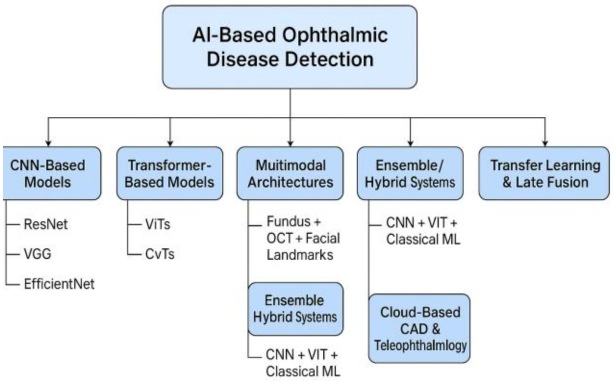


Fig. 2. Taxonomy of the Review

A prominent contribution in this direction is FundusNet proposed by Hu et al. [1]. This work used a deep learning model trained on fundus images for multi-task prediction. It demonstrated robust performance across age estimation, gender classification, and the detection of Parkinson's and multiple sclerosis, suggesting retinal imaging can reflect systemic neurological conditions. This work highlighted the use of Grad-CAM to interpret imaging biomarkers, laying the foundation for explainable medical AI systems. Zhao et al. [2] addressed limitations in multimodal learning by introducing a feature disentanglement framework to harmonize data across 2D color fundus photography and 3D optical coherence tomography. By decomposing shared and specific features and enforcing multi-level regularizations, their method enhanced classification accuracy, signifying the importance of inter-modality synergy in eye disease diagnostics. Karim et al. [3] proposed an alternative modality using facial landmarks for stroke detection. By leveraging MediaPipe for facial feature extraction and ensemble classifiers like XGB, RF, and CB within a Multimodal Voting Classifier, the study achieved 94.75% accuracy. Explainable AI (XAI) tools and t-SNE visualizations underscore critical facial regions, enabling real-time and accessible stroke diagnostics, marking a shift towards multimodal, resource-efficient diagnostics. With the rising popularity of Vision Transformers (ViTs), Singh et al. [4] explored their efficacy in glaucoma detection. Employing extensive preprocessing and optimizer experimentation across multiple datasets, their results showed that ViTs with Nadam optimizer and adaptive equalization yielded accuracies up to 97.8%. The integration of transformer-based models with traditional classifiers (SVM, Random Forest) further reinforced the effectiveness of hybrid models in vision-based disease recognition. Hossain and Shorfuzzaman [5] proposed a cloud-based cyber-physical system integrating deep CNN models with attention networks for stage-wise DR classification. Their model, embedded in a component-based CPS framework, demonstrated accelerated and accurate DR detection, emphasizing scalable architectures for remote healthcare applications. Cutur and Inan [6] proposed transfer learning by evaluating both CNNs and ViTs on ophthalmic diseases like glaucoma, DR, and cataracts. This approach advocated for transfer learning as a tool to enhance the performance of diagnostic AI with limited medical datasets. Tuwan and Iskandar [7] implemented a Convolutional vision Transformer (CvT) on the ODIR-5k dataset, achieving slightly lower performance compared to standalone ViT models. Despite promising metrics, performance inconsistencies due to convolutional layer interference with global pattern recognition highlighted the necessity for architectural optimizations tailored to ophthalmic data. Ateif and Idri [8] conducted a comparative analysis of CNN-based architectures using mono-modality and late-fusion multimodality, revealing that ResNet50V2 with late fusion achieved perfect classification on three publicly available datasets. This reinforced the utility of fusion techniques over single modality inputs, particularly when addressing complex ocular conditions. Expanding into multi-disease classification, Albelaihi and Ibrahim [9] introduced the DeepDiabetic framework, analyzing DR, DME, glaucoma, and cataracts using deep CNN variants. EfficientNetB0 emerged as the most accurate across six diverse datasets. Their findings highlighted the role of geometric augmentations and hybrid architectures in enhancing disease generalizability in multiclass models. Roopashree et al. [10] conducted a broad review of CNN applications in medical image analysis, especially DR detection. Their work underscored CNNs' feature extraction capabilities and the expanding role of deep models in augmenting diagnostic accuracy in both research and clinical settings. Chaudhari et al. [11] used a socio-technical perspective by designing a VGG-19-based eye disease classifier tailored for pediatric care in underprivileged regions. Below Table I shows recent research contribution and table II presents the comparative analysis, performance gaps, and open challenges of existing approaches.

TABLE I. RECENT RESEARCH CONTRIBUTIONS

Category	Methodology	Application	Key Insights
CNN-Based Models [10]	CNN architectures (ResNet, VGG)	DR detection, medical image analysis	Strong feature extraction; high diagnostic accuracy
Vision Transformers [4]	ViTs with Nadam optimizer	Glaucoma detection	Robust on multiple datasets
Multimodal Learning [2]	Fundus + OCT fusion	Multi-disease classification	Improved cross-modality synergy using feature disentanglement
Ensemble Models [3]	XGB + RF + CB classifiers	Stroke detection	Enabled explainable multimodal analysis
Hybrid CNN+Transformer [7]	CvT + ViT hybrid	ODIR-5k dataset	Competitive results but inconsistent due to convolutional interference
Transfer Learning [8]	Late fusion ResNet50V2	Multimodal eye disease detection	Achieved perfect classification on three datasets

Cloud-Based CAD Systems [5]	CNN + attention mechanisms	Stage-wise DR detection	Scalable, cyber-physical deployment for remote healthcare
Multi-Disease Models [9]	DeepDiabetic (EfficientNetB0)	DR, DME, glaucoma, cataracts	High generalizability; effective with geometric augmentation.

TABLE II. COMPARATIVE ANALYSIS, PERFORMANCE GAPS, AND OPEN CHALLENGES OF EXISTING APPROACHES

Approach	Core Concept	Advantages	Limitations
CNN-Based Models	Hierarchical feature extraction from fundus/OCT images	High accuracy on single-disease tasks; robust image feature extraction	Limited global context; prone to overfitting on small datasets
Vision Transformers (ViTs)	Self-attention mechanism for global feature learning	Superior performance in capturing spatial dependencies; fewer biases in lesion localization	Require large labeled datasets; computationally expensive
Multimodal Architectures	Combines fundus, OCT, clinical data, or facial features	Improved robustness; captures cross-modality biomarkers	Complex integration; inter-modality noise can degrade accuracy
Ensemble & Hybrid Models	Combines CNNs, ViTs, and classical ML classifiers	Enhanced generalizability; reduced variance	Increased computational cost; risk of redundancy
Transfer Learning & Late Fusion	Fine-tuning pre-trained models and combining features	Boosts performance on limited datasets; efficient training	May inherit biases from pre-trained models

3. DISCUSSION

The comparative analysis of machine learning architectures across diverse ophthalmic and neurodegenerative diagnostic tasks highlights a clear evolution in the selection of model types, reflecting the community's shift toward more robust, explainable, and multi-modal AI systems. As illustrated in Fig. 3, the majority of research efforts concentrated on diabetic retinopathy (DR), accounting for the highest number of models across studies. This is likely due to the availability of annotated public fundus datasets and the critical global burden of diabetes-related vision loss. Other categories, such as glaucoma, stroke, and neurodegenerative diseases, witnessed relatively fewer dedicated models, underlining a current research gap that presents potential expansion opportunities.

When evaluating model performance across architectures (see Fig. 4), transformer-based methods and ensemble models consistently reported higher classification accuracies. Ensemble CNNs with gradient boosting achieved the highest accuracy (99.5%), closely followed by ViT-integrated pipelines and hybrid configurations. These models demonstrated superior capacity in

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handling complex feature hierarchies and disease overlap, particularly in multi-disease classification settings. In contrast, CNN-ViT hybrids such as CvT slightly underperformed despite their larger parameter size, suggesting that architecture complexity does not always translate to better performance, especially when training data is limited or heterogeneous.

Interestingly, traditional convolutional deep learning models like FundusNet exhibited slightly lower performance (~75–80%) in neurodegenerative disease prediction, despite their use of interpretable frameworks like Grad-CAM. This underscores the unique challenge of extrapolating retinal biomarkers to systemic neurological conditions, a task that might benefit from incorporating additional patient metadata or genomic information into model training.

A further pattern emerged to interpretability and deployment feasibility. While ensemble models and vision transformers offered state-of-the-art accuracy, their computational requirements and lack of transparency might hinder adoption in real-time or resource-constrained clinical settings. Models like MediaPipe combined with machine learning classifiers provided a balanced alternative, achieving 94.75% accuracy in stroke detection using facial asymmetry, while being lightweight and compatible with real-time diagnostic interfaces.

The observed trends reinforce the potential of vision transformers, ensemble learning, and attention-guided models in advancing diagnostic AI. However, the successful translation of these models into clinical practice will depend not only on performance metrics but also on model explainability, generalizability, and deployment efficiency.

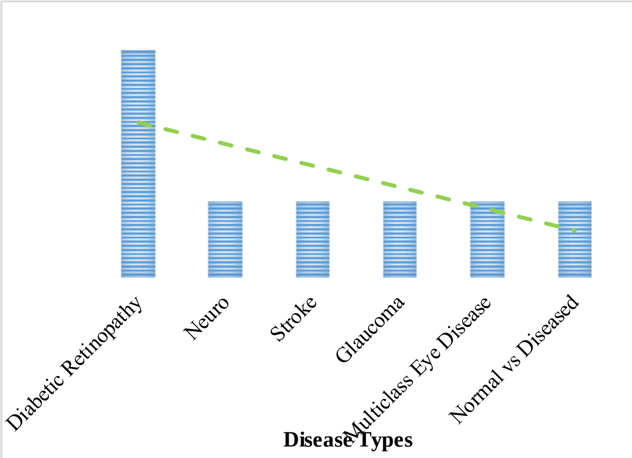

Fig. 3. Disease-Specific Existing Models

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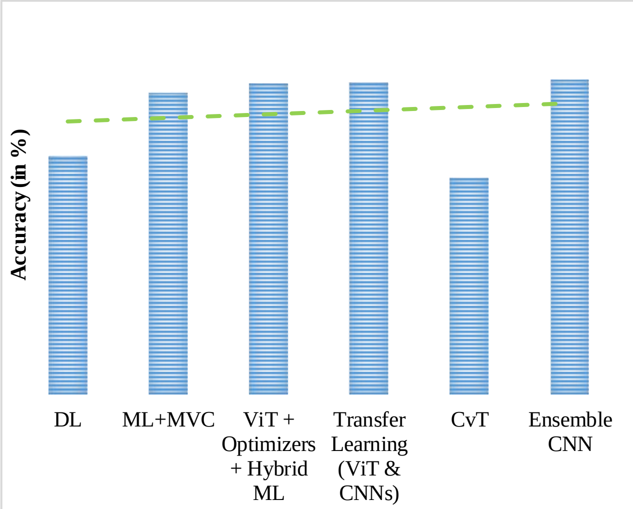

Fig. 4. Performance Evaluation of Deep Learning Techniques

4. CHALLENGES AND FUTURE SCOPE

Despite remarkable progress, several challenges persist in the development and deployment of deep learning-based diagnostic systems for ophthalmic and neurodegenerative diseases:

- Data Imbalance and Diversity: Most datasets exhibit class imbalances, particularly underrepresentation of early-stage diseases, which impacts model generalization. Furthermore, lack of diversity in ethnicity, age, and imaging conditions limits model robustness across global populations.
- Interpretability and Trustworthiness: Although methods like Grad-CAM and explainable AI (XAI) offer insights, interpretability remains limited. Medical professionals often require clearer and clinically aligned explanations to trust AI-driven decisions.
- Multimodal Integration Complexity: Integrating heterogeneous data sources such as fundus, OCT, facial landmarks, and patient metadata poses computational and semantic alignment challenges, mainly when modalities differ in resolution and temporal granularity.
- Computational and Deployment Constraints: Transformer-based models and hybrid architectures like CvT and ensemble classifiers demand substantial resources, which may hinder deployment on edge devices or in low-resource clinical settings.

5. CONCLUSION

The rapid adoption of artificial intelligence in ophthalmology and neurology has revolutionized diagnostic paradigms, paving the way for scalable and interpretable computer-aided diagnostic systems. Our review underscores that deep learning models—particularly transformer-based networks and ensemble CNNs—offer state-of-the-art performance in disease classification across a variety of visual and neurological disorders. Diabetic retinopathy remains the most studied condition, benefiting from large public datasets and an urgent clinical need. Nonetheless, the limited representation of other pathologies such as glaucoma, stroke, and neurodegenerative diseases signals a critical research opportunity. Model architectures integrating multimodal data and explainable AI, such as FundusNet with Grad-CAM and MediaPipe-based facial feature classifiers, offer promising pathways toward real-time and accessible diagnostics. While ViTs and hybrid models provide high accuracy, their computational intensity and lack of interpretability necessitate further refinement for clinical acceptance. Looking forward, the development of federated learning systems, lightweight models, unified multimodal encoders, and regulatory-compliant explainability mechanisms will be essential.

REFERENCES

[1] T. Nazir, A. Irtaza, A. Javed, H. Malik, D. Hussain, and R. A. Naqvi, "Retinal image analysis for diabetes-based eye disease detection using deep learning," Applied Sciences, vol. 10, no. 18, p. 6185, 2020, doi: 10.3390/app10186185.

[2] M. Aamir, M. Irfan, T. Ali, G. Ali, A. Shaf, S. A. Sultan, A. Al-Beshri, T. Alasbali, and M. H. Mahnashi, "An adoptive threshold-based multi-level deep convolutional neural network for glaucoma eye disease detection and classification," Diagnostics, vol. 10, no. 8, p. 602, 2020, doi: 10.3390/diagnostics10080602.

[3] P. Glaret Subin and P. Muthukannan, "Optimized convolution neural network based multiple eye disease detection," Computers in Biology and Medicine, vol. 146, art. no. 105648, 2022, doi: 10.1016/j.compbiomed.2022.105648.

[4] K. Prasad, P. S. Sajith, M. Neema, L. Madhu, and P. N. Priya, "Multiple eye disease detection using deep neural network," in TENCON 2019—2019 IEEE Region 10 Conference, Kochi, India, 2019, pp. 2148–2153, doi: 10.1109/TENCON.2019.8929666.

[5] H. Zhang et al., "Multi-omics approaches to discover biomarkers of thyroid eye disease: A systematic review," International Journal of Biological Sciences, vol. 20, no. 15, pp. 6038–6055, 2024, doi: 10.7150/ijbs.103977. Frontiersijbs.com+1

[6] A. Bali and V. Mansotra, "Analysis of deep learning techniques for prediction of eye diseases: A systematic review," Archives of Computational Methods in Engineering, vol. 31, no. 1, pp. 487–520, 2024, doi: 10.1007/s11831-023-09989-8. PMC+6ResearchGate+6MDPI+6

[7] A. A. Ahmed, A. Aldhahab, and H. M. Al Abboodi, "Review of eye diseases detection and classification using deep learning techniques," in BIO Web of Conferences, vol. 97, 2024, art. no. 00012, doi: [ADD DOI].

[8] M. A. Iqbal, J. Kim, I. Han, and S. K. Kim, "Attention-driven feature fusion integrating Swin transformer and CNN models for improved ocular disease classification," in 2024 International Conference on Engineering and Emerging Technologies (ICEET), Dubai, United Arab Emirates, 2024, pp. 1–6, doi: 10.1109/ICEET65156.2024.10913537.

[9] J. Zhao et al., "Multi-label classification of retinal diseases based on fundus images using ResNet and Transformer," Medical & Biological Engineering & Computing, vol. 62, pp. 3459–3469, 2024, doi: 10.1007/s11517-024-03144-6.

[10] M. A. Jawad et al., "Towards improved fundus disease detection using Swin transformers," Multimedia Tools and Applications, vol. 83, pp. 78125–78159, 2024, doi: 10.1007/s11042-024-18627-9.

[11] H. Yu, "An eye disease image diagnosis method based on a hybrid machine learning and deep learning model," in 2024 5th International Conference on Electronic Communication and Artificial Intelligence (ICECAI), Shenzhen, China, 2024, pp. 347–352, doi: 10.1109/ICECAI62591.2024.10675277.

[12] R. C. Joshi, A. K. Sharma, and M. K. Dutta, "VisionDeep-AI: Deep learning-based retinal blood vessels segmentation and multi-class classification framework for eye diagnosis," Biomedical Signal Processing and Control, vol. 94, art. no. 106273, 2024, doi: 10.1016/j.bspc.2024.106273.

[13] M. N. Hasan, M. E. R. Pial, S. Das, N. Siddique, and H. Wang, "DIA-VXNET: A framework for automated diabetic eye disease detection using transfer learning with feature fusion network," Biomedical Signal Processing and Control, vol. 100, pt. C, art. no. 106907, 2025, doi: 10.1016/j.bspc.2024.106907.

[14] W. Hu et al., "FundusNet: A deep-learning approach for fast diagnosis of neurodegenerative and eye diseases using fundus images," Bioengineering, vol. 12, p. 57, 2025, doi: 10.3390/bioengineering12010057.

[15] J. Zhao, S. Li, Y. Hao, and C. Zhang, "Bridging the modality gap in multimodal eye disease screening: Learning modality shared-specific features via multi-level regularization," IEEE Signal Processing Letters, vol. 32, pp. 586–590, 2025, doi: 10.1109/LSP.2025.3526094.

[16] R. U. Karim et al., "Optimizing stroke recognition with MediaPipe and machine learning: An explainable AI approach for facial landmark analysis," IEEE Access, vol. 13, pp. 32636–32660, 2025, doi: 10.1109/ACCESS.2025.3550577.

[17] P. B. Singh et al., "HViTML: Hybrid vision transformer with machine learning-based classification model for glaucomatous eye," Multimedia Tools and Applications, early access, 2025, doi: 10.1007/s11042-024-20544-w.

[18] M. S. Hossain and M. Shorfuzzaman, "Early diabetic retinopathy cyber-physical detection system using attention-guided deep CNN fusion," IEEE Transactions on Network Science and Engineering, vol. 12, no. 3, pp. 1898–1910, May–Jun. 2025, doi: 10.1109/TNSE.2025.3541138.

[19] E. S. Cutur and N. G. Inan, "Multi-class classification of retinal eye diseases from ophthalmoscopy images using transfer learning-based vision transformers," Journal of Digital Imaging, early access, 2025, doi: 10.1007/s10278-025-01416-7.

[20] A. G. Tuwan et al., "Eye diseases multiclass classification using convolutional vision transformer," TechRxiv, preprint, Feb. 2025, doi: 10.36227/techrxiv.173886337.74494015/v1.

[21] S. El-Ateif and A. Idri, "Eye diseases diagnosis using deep learning and multimodal medical eye imaging," Multimedia Tools and Applications, vol. 83, pp. 30773–30818, 2024, doi: 10.1007/s11042-023-16835-3.

[22] A. Albelaihi and D. M. Ibrahim, "DeepDiabetic: An identification system of diabetic eye diseases using deep neural networks," IEEE Access, vol. 12, pp. 10769–10789, 2024, doi: 10.1109/ACCESS.2024.3354854.

[23] R. Roopashree, R. Ghosh, and M. M. Gaur, "Exploring the potential of deep learning in diagnosing eye diseases," in 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1–6, doi: 10.1109/ICCCNT61001.2024.10724872.

[24] A. Chaudhari, P. Shelke, P. Thombare, and S. Sandbhor, "Cost-effective real-time eye disease detection and classification using deep learning techniques," in 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1–8, doi: 10.1109/ICCCNT61001.2024.10726189.