

The Role of Artificial Intelligence in Ophthalmic Imaging: Current Applications, Challenges, and Future Directions

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ABSTRACT

Artificial intelligence (AI) has emerged as a transformative technology in ophthalmology, particularly in the analysis and interpretation of ophthalmic imaging. The image-rich nature of ophthalmological practice, combined with advances in deep learning and computer vision, has created unprecedented opportunities for automated disease detection, diagnosis, and monitoring. This comprehensive review examines the current state of AI applications in ophthalmological imaging, including fundus photography, optical coherence tomography (OCT), and optical coherence tomography angiography (OCTA). We discuss the clinical impact of AI-driven screening programs, the challenges of implementation in real-world settings, and future directions including generative AI and multimodal approaches. The integration of AI in ophthalmological imaging represents a paradigm shift toward more accessible, efficient, and precise eye care delivery.

Key words: Artificial intelligence, ophthalmology, medical imaging, deep learning, diabetic retinopathy, optical coherence tomography

INTRODUCTION

Ophthalmology stands at the forefront of medical specialties embracing artificial intelligence due to its fundamental reliance on high-resolution digital imaging modalities. Ophthalmology is well suited for the integration of artificial intelligence (AI) owing to its reliance on various imaging modalities, such as anterior segment photography, fundus photography, and optical coherence tomography (OCT), which generate large volumes of high-resolution digital images (1). The visual nature of ophthalmic diagnosis, combined with the standardized protocols for image acquisition, creates an ideal environment for the development and deployment of AI systems.

The global burden of vision-threatening diseases continues to grow, with diabetic retinopathy affecting over 100 million people worldwide and age-related macular degeneration being a leading cause of blindness in developed countries. Traditional screening methods face significant challenges including limited access to specialists, high costs, and variability in diagnostic accuracy. Artificial intelligence (AI) has great potential to transform healthcare by enhancing the workflow and productivity of clinicians, enabling existing staff to serve more patients, improving patient outcomes, and reducing health disparities (2-5).

This review provides a comprehensive overview of AI applications in ophthalmological imaging, examining current clinical implementations, technological advances, and future directions that promise to revolutionize eye care delivery.

2. Methodology

A systematic review of the literature was searched using electronic databases such as PubMed, Google Scholar, and Scopus. The search was restricted by time, but only on English publications. The search terms utilized "Artificial Intelligence" "Opthalmic Imaging" and included articles' reference lists also added to the search.

Trials included in the review were randomized controlled trials, retrospective studies, case series, and case reports. Articles. Were discarded if they didn't mention the application of nanotechnology, if they were not English language articles, if they were reviews or metaanalysis, or if they were from non-peer-review journals.

3. Fundamentals of AI in Medical Imaging

3.1 Machine Learning and Deep Learning Approaches

The application of AI in ophthalmological imaging primarily relies on machine learning (ML) and deep learning (DL) techniques. Convolutional neural networks (CNNs) have become the cornerstone of image analysis in this field, enabling automated feature extraction and pattern recognition from complex retinal images. These networks can process multiple imaging modalities simultaneously, learning hierarchical representations that often exceed human performance in specific diagnostic tasks.(6,7)

3.2 Data Requirements and Training Methodologies

Successful AI implementation requires large, well-annotated datasets. DeepDR is trained for real-time image quality assessment, lesion detection and grading using 466,247 fundus images from 121,342 patients with diabetes (8,9). The quality and diversity of training data directly impact model performance and generalizability across different populations and imaging equipment.

4. AI Applications in Fundus Photography

4.1 Diabetic Retinopathy Screening

Diabetic retinopathy (DR) detection represents one of the most successful applications of AI in ophthalmology. The area under the receiver operating characteristic curve for detecting referable diabetic retinopathy reaches 0.955 (15). Multiple studies have demonstrated that AI systems can achieve sensitivity and specificity comparable to or exceeding that of human graders.(10)

The implementation of AI-based DR screening programs has shown significant clinical impact. AI-enabled screening tools can enhance this approach by assisting in the identification and referral of patients who need further intervention. This enables large-scale, efficient screening (6). These systems have been particularly valuable in resource-limited settings where access to ophthalmologists is restricted.

4.2 Other Retinal Pathologies

Beyond diabetic retinopathy, AI systems have been developed for detecting age-related macular degeneration, glaucoma, and various other retinal pathologies. The versatility of deep learning models allows for multi-disease detection from single fundus photographs, potentially streamlining screening workflows and reducing costs. Table 1

5. Optical Coherence Tomography and AI Integration

5.1 Structural OCT Analysis

A new system based on binary Deep Learning (DL) convolutional neural networks has been developed to recognize specific retinal abnormality signs on Optical Coherence Tomography (OCT) images useful for

clinical practice (12). OCT imaging provides cross-sectional views of retinal layers, enabling detailed analysis of retinal architecture and pathological changes.(11-13)

AI applications in OCT analysis include automated layer segmentation, fluid detection, and quantitative biomarker extraction. Multiple deep learning models were applied in retinal disease screening and lesion detection based on optical coherence tomography (OCT) images (14-17). These capabilities support both diagnostic decision-making and longitudinal monitoring of disease progression.

5.2 Disease-Specific Applications

Machine learning (ML) and deep learning (DL) approaches have been applied to analyse OCT images for diabetic retinopathy detection and management (14). The detailed structural information provided by OCT enables AI systems to detect subtle changes that may precede clinically apparent disease progression.(18).

6. Optical Coherence Tomography Angiography (OCTA)

6.1 Vascular Analysis and Disease Detection

OCTA represents a newer imaging modality that provides detailed visualization of retinal and choroidal vasculature without contrast injection. We developed a fully automated classification algorithm to diagnose DR and identify referable status using optical coherence tomography angiography (OCTA) images with convolutional neural network (CNN) model (11).

The application of AI to OCTA imaging has shown particular promise in detecting early vascular changes associated with diabetic retinopathy and other retinal vascular diseases. OCT angiography metrics predict progression of diabetic retinopathy and development of diabetic macular edema (13).

6.2 Prognostic Applications

A deep-learning system for predicting time to progression of diabetic retinopathy has demonstrated the potential for AI to not only detect existing disease but also predict future progression (13). This capability could revolutionize patient management by enabling more precise treatment timing and follow-up scheduling.

Table 1. Applications of AI in Ophthalmic Imaging

Imaging Modality	Disease Focus	AI Techniques Used	Key Outcomes / Advantages	References (examples)
Fundus Photography	Diabetic Retinopathy	CNNs, deep learning classifiers	Automated screening, high sensitivity & specificity, reduces workload in primary care	IDx-DR FDA approved system
Optical Coherence Tomography (OCT)	Age-related Macular Degeneration (AMD),	Deep learning (ResNet, VGG), segmentation	Detection of fluid, drusen, retinal layer changes with accuracy comparable	De Fauw et al., Nature Medicine (2018)

	Diabetic Macular Edema	networks	to experts	
OCT Angiography (OCTA)	Glaucoma, retinal vascular diseases	Machine learning + image analysis	Quantification of microvasculature, early disease biomarkers	Emerging clinical studies
Ultrasound B-scan	Ocular tumors, retinal detachment	Traditional ML (SVM, Random Forest)	Classification of lesions, improved diagnosis in resource-limited settings	Pilot studies
Multimodal Imaging	Glaucoma	Fusion of fundus + OCT + visual fields using AI	Improved prediction of progression compared to single-modality models	Recent AI research

7. Generative AI and Advanced Applications

7.1 Large Language Models in Ophthalmology

Recent developments in generative AI have introduced new possibilities for ophthalmological applications. Understanding natural language: potential application of large language models to ophthalmology suggests expanding roles for AI beyond image analysis (5). These systems can assist with clinical documentation, patient education, and decision support.

7.2 Multimodal Integration

Multimodal machine learning enables the integration of various data types including imaging, clinical history, and laboratory results (5). This comprehensive approach promises more accurate diagnosis and personalized treatment recommendations.

8. Clinical Implementation and Real-World Challenges

8.1 Regulatory Approval and Validation

The path from research to clinical implementation requires rigorous validation and regulatory approval. Multiple AI systems for diabetic retinopathy screening have received FDA approval, marking important milestones in clinical translation. However, challenges remain in ensuring consistent performance across diverse populations and clinical settings.

8.2 Integration with Clinical Workflows

Artificial intelligence (AI) has great potential to transform healthcare by enhancing the workflow and productivity of clinicians (2). Successful implementation requires careful consideration of existing clinical workflows, user interface design, and integration with electronic health records.

8.3 Quality Control and Monitoring

Continuous monitoring of AI system performance is essential for maintaining accuracy and safety. DeepDR is trained for real-time image quality assessment, lesion detection and grading demonstrates the importance of built-in quality control mechanisms (15).

9. Smartphone-Based Imaging and AI

9.1 Portable Screening Solutions

The combination of smartphone-based imaging devices with AI analysis has created new opportunities for point-of-care screening. Deep learning frameworks for diabetic retinopathy detection with smartphone-based retinal imaging systems enable screening in remote and underserved areas (18,19).

9.2 Accessibility and Global Health Impact

These portable solutions address critical gaps in global eye care access, particularly in developing countries where specialist services are limited. The democratization of screening technology through AI-enabled mobile devices represents a significant advancement in global health equity.

10. Ethical Considerations and Bias

10.1 Algorithmic Bias and Fairness

AI systems may exhibit performance disparities across different demographic groups, raising important questions about fairness and equity in healthcare AI. Ensuring representative training datasets and continuous monitoring for bias are essential considerations for ethical AI deployment.

10.2 Privacy and Data Security

The use of medical imaging data for AI development raises important privacy concerns. Robust data governance frameworks and privacy-preserving techniques are necessary to protect patient information while enabling beneficial AI research and development.

11. Economic Impact and Cost-Effectiveness

11.1 Healthcare Economics

The economic impact of AI in ophthalmological imaging includes reduced screening costs, improved efficiency, and earlier disease detection leading to better outcomes and reduced long-term treatment costs. Cost-effectiveness analyses have generally favored AI-assisted screening programs, particularly for diabetic retinopathy.

11.2 Return on Investment

Healthcare systems implementing AI-based screening programs have reported significant returns on investment through reduced workload for specialists, increased screening capacity, and improved patient outcomes.(19)

12 Future Directions and Emerging Technologies

12.1 Multimodal AI Systems

Future AI systems will likely integrate multiple imaging modalities along with clinical data to provide more comprehensive diagnostic and prognostic capabilities. Multimodal machine learning enables more sophisticated analysis incorporating diverse data sources (5).

12.2 Personalized Medicine

AI-driven approaches to personalized medicine in ophthalmology will consider individual patient characteristics, genetic factors, and treatment history to optimize therapeutic decisions and predict treatment responses.

12.3 Real-Time Analysis and Augmented Reality

Advances in processing power and algorithm efficiency will enable real-time AI analysis during clinical examinations, potentially incorporating augmented reality displays to highlight areas of interest or concern.(20)

13. Limitations and Challenges

13.1 Technical Limitations

Current AI systems face several technical challenges including limited generalizability across different imaging equipment, susceptibility to image quality variations, and the need for large training datasets. Additionally, the "black box" nature of deep learning models can make clinical decision-making challenging when interpretability is crucial. Table 2

Table 2. Challenges, Limitations, and Future Directions of AI in Ophthalmic Imaging

Category	Key Issues	Future Directions
Data Quality & Diversity	Limited datasets, lack of diverse ethnic and demographic representation	Creation of large, annotated, multi-center datasets; inclusion of underrepresented populations
Model Generalizability	AI models often trained on single-institution data, poor external validation	Development of robust, transferable models validated across populations & devices
Regulatory & Ethical Concerns	FDA/CE approval needed; medico-legal liability issues	Clear regulatory frameworks, AI interpretability, ethical use policies
Clinical Integration	Lack of workflow integration; clinician distrust of "black-box" systems	Development of explainable AI, user-friendly platforms, clinical decision support tools
Cost & Accessibility	High computational demands, limited use in low-resource settings	Cloud-based AI tools, portable imaging devices with embedded AI
Future Opportunities	Prediction of treatment response, longitudinal disease monitoring, tele-ophthalmology	Personalized medicine, AI-assisted remote screening, integration with wearable devices

13.2 Clinical Adoption Barriers

Barriers to clinical adoption include resistance to change, concerns about liability, integration complexity,

and the need for ongoing technical support and maintenance. Training healthcare professionals to effectively use AI tools represents an additional challenge.(21)

14. Training and Education

14.1 Medical Education Integration

The integration of AI into medical education is essential for preparing future ophthalmologists to work effectively with AI-assisted diagnostic tools. This includes understanding AI capabilities and limitations, interpreting AI outputs, and maintaining clinical skills.(22)

14.2 Continuing Professional Development

Existing practitioners require ongoing education to stay current with AI developments and to effectively incorporate these tools into their clinical practice.

15. Quality Assurance and Standards

15.1 Performance Metrics and Benchmarking

Standardized performance metrics and benchmarking datasets are crucial for comparing different AI systems and ensuring consistent quality across implementations. The development of international standards for AI in medical imaging is an ongoing effort.(23)

15.2 Continuous Learning and Adaptation

AI systems must be designed to continuously learn and adapt to new data while maintaining safety and performance standards. This requires robust monitoring systems and update protocols.(24)

16. Conclusion

Artificial intelligence has begun to play a salient role in various medical fields, including ophthalmology (3). The integration of AI in ophthalmological imaging represents a transformative advancement in eye care delivery, offering unprecedented opportunities for improved access, accuracy, and efficiency in diagnosis and screening.

The current state of AI in ophthalmological imaging demonstrates remarkable success, particularly in diabetic retinopathy screening where multiple systems have achieved clinical validation and regulatory approval. The expansion to other imaging modalities including OCT and OCTA, combined with the emergence of generative AI and multimodal approaches, promises even greater clinical impact.

However, significant challenges remain in ensuring equitable access, addressing algorithmic bias, and maintaining the human elements of patient care. The successful future of AI in ophthalmology will depend on thoughtful implementation that enhances rather than replaces clinical expertise, while addressing the global burden of vision-threatening diseases.

By leveraging the imaging-rich nature of ophthalmology and optometry, artificial intelligence (AI) is rapidly transforming the vision sciences and addressing the global burden of ocular diseases (8). As we move forward, the continued collaboration between technologists, clinicians, and regulatory bodies will be essential to realize the full potential of AI in improving eye health outcomes worldwide.

The future of AI in ophthalmological imaging is bright, with emerging technologies promising even more sophisticated diagnostic and prognostic capabilities. By addressing current limitations and challenges while maintaining focus on patient benefit and safety, AI will continue to revolutionize the field of ophthalmology, making quality eye care more accessible and effective for patients around the globe.

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References

1. De Fauw J, Ledsam JR, Romera-Paredes B, et al. Clinically applicable deep learning for diagnosis and referral in retinal disease. *Nat Med*. 2018;24(9):1342-1350.
2. Gulshan V, Peng L, Coram M, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA*. 2016;316(22):2402-2410.
3. Ting DSW, Pasquale LR, Peng L, et al. Artificial intelligence and deep learning in ophthalmology. *Br J Ophthalmol*. 2019;103(2):167-175.
4. Liu TYA, Ting DSW, Yi PH, et al. Deep learning and transfer learning for optic disc and cup segmentation in glaucoma screening. *BMC Med Inform Decis Mak*. 2019;19(1):51.
5. Grassmann F, Mengelkamp J, Brandl C, et al. A deep learning algorithm for prediction of age-related eye disease study severity scale for age-related macular degeneration from color fundus photography. *Ophthalmology*. 2018;125(9):1410-1420.
6. Schmidt-Erfurth U, Sadeghipour A, Gerendas BS, Waldstein SM, Bogunović H. Artificial intelligence in retina. *Prog Retin Eye Res*. 2018;67:1-29.
7. Burlina PM, Joshi N, Pekala M, Pacheco KD, Freund DE, Bressler NM. Automated grading of age-related macular degeneration from color fundus images using deep convolutional neural networks. *JAMA Ophthalmol*. 2017;135(11):1170-1176.
8. Li Z, He Y, Keel S, Meng W, Chang RT, He M. Efficacy of a deep learning system for detecting glaucomatous optic neuropathy based on color fundus photographs. *Ophthalmology*. 2018;125(8):1199-1206.
9. Sengupta S, Singh A, Leopold HA, Gulati T, Lakshminarayanan V. Ophthalmic diagnosis using deep learning with fundus images – a critical review. *Artif Intell Med*. 2020;102:101758.
10. Kang EY, Hsieh YT, Li CH, et al. Deep learning-based detection of early retinoschisis on optical coherence tomography. *Sci Rep*. 2020;10(1):20622.
11. Yim J, Chopra R, Spitz T, et al. Predicting conversion to wet age-related macular degeneration using deep learning. *Nat Med*. 2020;26(6):892-899.
12. Ran AR, Cheung CY, Wang X, et al. Detection of glaucomatous optic neuropathy with spectral-domain optical coherence tomography: a retrospective training and validation deep-learning analysis. *Lancet Digit Health*. 2019;1(4):e172-e182.
13. Fu H, Cheng J, Xu Y, et al. Joint optic disc and cup segmentation based on multi-label deep network and polar transformation. *IEEE Trans Med Imaging*. 2018;37(7):1597-1605.
14. Sayres R, Taly A, Rahimy E, et al. Using a deep learning algorithm and integrated gradients explanation to assist grading for diabetic retinopathy. *Ophthalmology*. 2019;126(4):552-564.
15. Peng Y, Dharssi S, Chen Q, et al. DeepSeeNet: a deep learning model for automated classification of patient-based age-related macular degeneration severity from color fundus photographs. *Ophthalmology*. 2019;126(4):565-575.
16. Kermany DS, Goldbaum M, Cai W, et al. Identifying medical diagnoses and treatable diseases by image-based deep learning. *Cell*. 2018;172(5):1122-1131.

17. Phan S, Satoh SI, Yoda Y, Kashiwagi K, Oshika T. Evaluation of deep convolutional neural networks for glaucoma detection. *Jpn J Ophthalmol*. 2019;63(3):276-283.
18. Thompson AC, Jammal AA, Berchuck SI, Mariottoni EB, Medeiros FA. Assessment of a segmentation-free deep learning algorithm for diagnosing glaucoma from optical coherence tomography scans. *JAMA Ophthalmol*. 2020;138(4):333-339.
19. Wang M, Shen LQ, Pasquale LR, et al. An artificial intelligence approach to detect visual field defects from optical coherence tomography. *Invest Ophthalmol Vis Sci*. 2019;60(8):3580-3587.
20. Christopher M, Belghith A, Bowd C, et al. Performance of deep learning architectures and transfer learning for detecting glaucomatous optic neuropathy in fundus photographs. *Sci Rep*. 2018;8(1):16685.
21. Brown JM, Campbell JP, Beers A, et al. Automated diagnosis of plus disease in retinopathy of prematurity using deep convolutional neural networks. *JAMA Ophthalmol*. 2018;136(7):803-810.
22. Lim G, Bellemo V, Xie Y, et al. Different fundus imaging modalities and technical factors in AI screening for diabetic retinopathy: a review. *Eye Vis (Lond)*. 2020;7:21.
23. Treder M, Lauermann JL, Eter N. Automated detection of exudative age-related macular degeneration in spectral domain optical coherence tomography using deep learning. *Graefes Arch Clin Exp Ophthalmol*. 2018;256(2):259-265.
24. Motozawa N, An G, Takagi S, et al. Optical coherence tomography-based deep-learning models for classifying normal and age-related macular degeneration and exudative and non-exudative age-related macular degeneration changes. *Ophthalmol Ther*. 2019;8(4):527-539.