

The AI Revolution and How to Prepare for It

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Introduction

Artificial intelligence (AI) applications in fundus photography, optical coherence tomography, and visual fields hold great promise to improve the detection, screening, and diagnosis of ocular disorders, such as diabetic retinopathy,^{1,2} retinopathy of prematurity,^{3,4} macular degeneration,^{5,6} and glaucoma.^{7,8} The performance of today's AI programs often exceeds manual classification tasks,⁹ thus heralding the potential for AI to transform the future of ophthalmology. Additionally, with advances in computation and the increasing availability of cloud computing services, we are able to parallelize computation and reduce start-up costs and run times, accelerating the development and translation of AI-based technologies.

This editorial focuses on how to prepare for the AI revolution in ophthalmology. To prepare for the steady growth of AI applications in ophthalmology, there is a need to standardize the methods for tackling ophthalmic real-world big data and complex computing problems by forging collaborations within ophthalmology among ophthalmic researchers, clinicians, and educators. Collaborations outside ophthalmology may also be needed—with information technology research laboratories, health care systems, and technology companies—for more widespread translation of machine learning and AI into ophthalmic practice.

Research

AI researchers in informatics and data science who are working on algorithms to diagnose ophthalmic diseases and predict their progression need access to properly labeled, initial real-world datasets, as well as continuous data inputs, for algorithm validation and refinement. Collaboration with ophthalmologists will enable them to develop targeted algorithms for

diagnosis, treatment justification, and evaluation of patient outcomes. The quality of data inputted affects the performance of AI algorithms. Generalizability is improved when neural net systems learn characteristics from diverse populations, with varying ethnicities and geographical locations, and adjust to different imaging methodologies used for image production and processing.

Research efforts toward building the needed infrastructure for developing databases for AI applications in ophthalmology, as well as the ability to share data across health systems, will also improve the generalizability and accuracy of AI technologies. Examples of such ongoing efforts include developing large, diverse cohorts that are deeply phenotyped, such as the National Institutes of Health All of US Program¹⁰ and the Million Veteran Program.¹¹ Additionally, the Food and Drug Administration (FDA) has announced new initiatives, such as the Collaborative Communities network, one of which is the Ophthalmic Imaging Collaborative Community.¹² This community will develop solutions to medical device innovation challenges and will include national and international stakeholders to build datasets and develop scientific solutions for ophthalmic imaging and advanced technologies to refine diagnosis and treatment management.

Algorithms should be more interpretable and explainable to ensure targeted representation and to identify potential bias in training data, all while protecting data safety and privacy.⁹ Some researchers worry about the AI “black box effect,” as they cannot easily know how algorithm outputs are exactly determined.⁹ Ongoing research efforts to increase the explainability of AI include back-propagation methods and creating frameworks to find part of an image most responsible for a classifier decision. Other efforts involve modifying convolutional neural nets to increase AI transparency. Another example is the use of LIME and SHAP as post hoc explanations of

individual predictions of a given black box classifier. These have been praised as breakthroughs in machine learning applications¹³; however, there may be risks associated with AI transparency related to hacking of protected data and intentional manipulation of explanations.^{13,14} Therefore, as AI applications in medicine continue to grow, academic centers and health care organizations will need to update their privacy and security systems to include AI methods and impose strict guidelines to protect patient data privacy and security.

Clinical

AI will help with screening patients, improving diagnoses, and suggesting personalized treatments, as well as clinical documentation, triaging patient inquiries, and processing claims. AI-based technologies and big-data analytics are currently employed in primary care settings for patient monitoring and referable diagnostics; in specialized areas for disease classification, prediction, and treatment; and in telemedicine for connectivity and remote care. To date, two ophthalmic devices have received FDA approval, the IDx-DR for detection of diabetic retinopathy¹⁵ and the RightEye Vision System for identifying visual tracking impairment.¹⁶ IDx-DR, a diagnostic system that uses AI to detect diabetic retinopathy, is employed in primary care clinics to provide immediate diagnosis at point of care by detecting greater than a mild level of diabetic retinopathy in adults who have diabetes. If a positive result is detected, the patient is referred to a retinal specialist for further diagnosis and treatment. This will help to identify patients early, allowing treatment and, potentially, preventing vision loss.¹⁵

Health care systems are increasingly integrated, connected, and heavily reliant on AI, data analytics, and virtual/augmented reality for routine operations. Developing joint clinical workflows and technologies for effective communication—across clinics and systems—will help to prepare for the increased reliance on AI and provide high-quality care to patients. For the practicing ophthalmologist, it is important to realize that the potential benefits of AI in improving screening, diagnoses, clinical documentation, and personalized treatments are not without potential pitfalls, such as biased algorithms or patient safety concerns, nor are they without ethical and liability concerns. Hence, ophthalmologists should prepare for the AI future by (1) adopting new methods for information management and continuously integrating what they know with what an AI application may output and summarize, (2) questioning why an AI application is needed

and what it may be doing, and (3) adopting best practices guidelines for electronic health record (EHR) documentation and patient data management. AI-enabled technologies that use natural language processing systems will increasingly rely on data from EHRs for disease classification and predictions. It is therefore important to minimize errors of inputted data and maximize details related to diagnosis and prognosis. Additionally, with EHR systems comes the risk of using digital tools such as pre-populating or copying and pasting existing medical data. This may cause incorrect information, potentially developing faulty algorithms and putting patients at risk. Health care systems may have to develop new guidelines to avoid these potential pitfalls.

Education

Central to the implementation of AI-based technologies is the education of physicians, health care workers, patients, and the general public about data, computer science applications, and information management. Over 100 years ago, the Flexner report established the biomedical model of education and training as an enduring basis of US medical education.¹⁷ Throughout the 20th century, medical schools across the United States and the globe have successfully adopted this research-based educational model. Today, another revolution in medical education is brewing, fueled by AI. In order to prepare future ophthalmologists, training programs may have to include informatics, statistics, and computer science courses as part of their new curricula. Additionally, there needs to be a renewed focus on the humanistic elements of medicine to counteract the potential impersonal aspects of AI. Training programs preparing future ophthalmologists for the new world of AI should place special emphasis on professionalism, communication, empathy, compassion, and respect. As always, diagnostic and treatment plans will continue to involve understanding patients' expectations and fears. Maintaining effective communication and compassionately educating patients about their disease remain the fundamental pillars of ophthalmologic care.

Conclusions

With the concomitant growth of microelectronics and miniature sensors in medicine, AI is likely to transform our future, both inside and outside ophthalmology. AI researchers will need to mine

multiple real-world clinical data sources to ensure rigorous validation studies with diverse population representation. To realize the full translational potential of AI applications and minimize the risk of unreliable algorithms, health care systems will have to establish secure infrastructures and improve proper access to ophthalmologic and other protected health data. Industries such as technology companies will need to collaborate and interact more with academic institutions and health care systems to understand the patient care and clinical trial landscapes for AI implementation. Clinicians are advised to adopt a responsible approach to integrating AI systems in their decision-making processes, ideally seeking an AI-assisted clinical approach that integrates pertinent information from automated and non-automated sources. Importantly, educators should work closely with researchers and clinicians to integrate comprehensive overviews of data analytics and computational methods into the ophthalmological education curriculum, with a central emphasis on the humanistic elements of patient care.

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