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# The Role of Artificial Intelligence in Ophthalmic Anterior Segment Disorders

Brian M DeBroff MD[1], Yahya Akbour[2]

[1]Department of Ophthalmology and Visual Science, Yale University School of Medicine
[2]Université Libre de Bruxelles

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## ABSTRACT

Artificial intelligence involves machines that can synthesize data on a scale that exceeds human ability, the capacity to analyze, learn, predict, and reason using algorithms that have the potential to improve over time. Artificial intelligence is beneficial in accuracy, speed, ability to analyze vast amounts of data, automating workflow, and reducing the need for repetitive tasks, and reducing human error. These tasks are particularly important for speech and image recognition, analyzing data, and creating predictive models. In health care, artificial intelligence can help guide diagnosis, treatment options, compliance, teaching, and administration activities. These activities have been demonstrated in many areas of medicine including Ophthalmology and in particular the retina and posterior segment subspecialty. This paper is a comprehensive review of the current applications of artificial intelligence in anterior segment specialties of Ophthalmology. This paper will demonstrate the applications of artificial intelligence in 1) Glaucoma to predict progression of disease, need for surgery, and who may develop acute angle closure glaucoma, 2) Keratoconus to identify early or subclinical keratoconus and predict who may experience progressive disease, 3) Keratitis to predict causation and which cases are more prone to rapidly progress, 4) Cataract to detect and give diagnostic objectivity, to calculate IOL power with more precision, to create smart surgery operating theaters, to aid in surgical training and to assess post-operative healing.

## Introduction

Artificial intelligence (AI) has demonstrated enhancements to medicine by predicting how diseases may progress over time, predicting which treatments may be most effective, enhancing productivity, and improving patient outcomes. When it comes to detecting early disease and improving treatment algorithms, AI has been shown to beneficial in medicine in general[1] and within the field of Ophthalmology.[2,3] The field of retina has been dominant in some of the early uses of AI given its dependence on specialized image techniques including fundus photography and OCT technology. By utilizing machine learning (use of data to optimize computer performance criteria) and Deep Learning (building neural networks that simulate how the human brain works to not only analyze but to learn to interpret), AI is able to optimize data analysis and guide disease diagnosis. Many practitioners are realizing that AI offers opportunity in the anterior segment of the eye including glaucoma detection and progression, cataract imaging and predictive models of IOL implantation, corneal diseases such as keratoconus and endothelial disease. This paper is a retrospective review of the current literature to demonstrate the current applications of artificial intelligence in the fields of glaucoma, keratoconus, keratitis, and cataract and how this technology is helping to improve efficiency, accuracy, safety, and effectiveness in diagnosis, treatment, and teaching.

## Glaucoma

Glaucoma is a group of eye conditions characterized by an optic neuropathy that is often associated with optic nerve cupping and visual field defects and may be associated with elevated intraocular pressure. For people over the age of 60, it is one of the leading causes of blindness. All glaucomatous eyes demonstrate loss of retinal ganglion cells and retinal nerve fiber layer thinning.[4] Early diagnosis and treatment are necessary to prevent progressive visual impairment. Of the two major types of glaucoma (primary open angle glaucoma (POAG) and angle closure glaucoma (ACG), POAG is most common. Due to POAG's gradual and painless development, it may go unnoticed until advanced and irreversible changes have occurred.[5]

Thus, early detection and timely intervention are key to managing glaucoma and preventing visual loss. Simple methods of intraocular pressure measurement, tracking optic nerve cupping, and visual field testing may miss initial diagnosis, determining who is most at risk of progression, and subtle changes that indicate disease progression is occurring. Artificial intelligence has been demonstrated to detect longitudinal progression with visual field (VF) testing significantly earlier using a machine learning technique.[6]

Measurement of retinal nerve fiber layer (RNFL) thickness has improved the detection of early changes of glaucoma. There are many parts of the world where this technology is not available or feasible for use. In such cases, AI has been demonstrated by using deep learning and a system algorithms to detect glaucomatous optic neuropathy using fundus photographs alone.[7,8,9,10]

More recently, spectal-domain optical coherence tomography (SD-OCT) has allowed a more three-dimensional analysis of the optic nerve structure and has been useful to evaluate the optic nerve for structural damage.[11] Detecting glaucoma by analyzing optical coherence tomography (OCT) is important as ganglion cell loss and thinning of the RNFL most often occurs before functional loss is detected by VF testing.[12] By measuring the nerve fiber layer and the ganglion cell-inner plexiform layer, SD-OCT, very subtle changes can be detected with an accuracy comparable or better to glaucoma specialists with years of training.[13] A Meta-analysis looking at 20 studies and 51 models found a high accuracy in the performance of AI in detecting glaucoma with SD-OCT images.[14]

One of the most promising applications of AI in glaucoma is the prediction of glaucoma progression and future visual field loss. With more advanced stages of glaucoma, VF defects which measure functional visual loss are more predictive of further progression.[15] Neural networks have been successfully developed than can automatically differentiate glaucomatous from non-glaucomatous VF's.[16] Deep learning models have been utilized to generate visual field predictions based on large datasets of VF testing. Yousefi used AI to identify longitudinal progression of glaucoma earlier than global mean deviation, region wise deviation and point-wise deviation in over 1200 subjects.[17] In addition, by merging visual field data with clinical longitudinal datasets, a machine learning model has demonstrated enhanced diagnostic capabilities.[18] Combined approaches without VF input, but only using history, intraocular pressure, refractive error, cup-disc ration, RNFL defects and employing an artificial neural network have been shown to predict open angle glaucoma with an accuracy of 84%.[19]

Artificial intelligence has also been utilized to help identify individuals with narrow angles who are at risk of developing angle closure glaucoma. A deep learning program analyzed anterior segment OCT images from over 2100 patients and achieved sensitivity and specificity better than qualitative features measured by clinicians. [20] Algorithms are being developed to screen for angle closure by processing images for angle structure measurements and segmentation.[21] Niwas demonstrated an accuracy of 89.2% using an fully automated model classifying angle closure from anterior segment OCT scans.[22]

Additional uses of AI for glaucoma include modeling data from electronic health records to predict the probability of a patient needing advanced treatment or surgery and integrating parameters to predict the best individual progression of treatment for a given patient. AI is making advances in robotic surgical procedures and AI guided surgical platforms to improve outcomes of glaucoma surgery.[23] In addition, surgical training can be enhanced by artificial intelligence by providing real-time feedback and guidance. Artificial intelligence is being tested to support patient education and improve adherence and compliance with treatment.[24]

The advancements in AI are creating many benefits for detecting and diagnosing glaucoma, monitoring disease progression, optimizing treatment options, and improving surgical outcomes. The algorithms and interaction between AI and the treating physician need to continue to develop the best options for this new technology. Challenges remain especially regarding clinical integration, data diversity, and ethical considerations.

## Keratoconus

Keratoconus is a progressive and asymmetric corneal ectasia characterized by abnormal thinning and bulging of the central or paracentral stroma with corneal protrusion and the potential for severe visual impairment due irregular corneal astigmatism or loss of corneal transparency.[25] Early identification of keratoconus, especially in its subclinical form, and subsequent treatment such as corneal crosslinking and intrastromal corneal ring segments are crucial to stabilizing the disease and improving visual prognosis.[26,27] In addition, missing the diagnosis of keratoconus in patients considering refractive corneal surgery can lead to corneal weakness and ectasia.[28]

Advanced keratoconus can be detected through classic clinical signs (e.g., Vogt's striae, Munson's sign, Fleischer ring) during slit-lamp examination, or via corneal topographical characteristics such as increased corneal refractive power, steeper radial axis tilt, and inferior-superior (I-S) corneal refractive asymmetry from corneal topographical maps. However, detecting subclinical keratoconus remains a significant challenge.[29]

Recent advancements in artificial intelligence have shown promise in improving the diagnosis of subclinical keratoconus.[30,31,32] Most AI diagnostic studies use Scheimpflug-based corneal topography scans or indices for their input.[33] A study by Yousefi utilized deep feature fusion of AI models (Xception and InceptionResNetV2) to diagnose subclinical keratoconus with an area under the curve (AUC) of 0.99 and an accuracy of 97-100%.[27] Similarly, Haque developed a DenseNet201-based deep learning model which achieved 89.14% accuracy in detecting keratoconus, normal eyes, and suspected keratoconus.[29] A meta analysis and systematic review of artificial intelligence articles by Afifah found that neural networks were not only the most used AI model in diagnosing keratoconus, but also had the highest accuracy with a sensitivity of 1.00.[34] These advancements demonstrate the power of AI in early diagnosis, especially for the more elusive subclinical forms.

In another significant development, Al-Timemy introduced a hybrid deep-learning construct based on anterior and posterior eccentricity, anterior and posterior elevation, anterior and posterior sagittal curvature, and corneal thickness maps and utilizing an EfficientNet-B0 (a convolutional neural network from the ImageNet database) for keratoconus detection. This model, trained on a large dataset of corneal topographic images, achieved accuracy rates as high as 99%.[35] The robustness of AI models like this makes them valuable tools for clinicians dealing with keratoconus patients.

Early and accurate prediction of keratoconus progression is critical for treatment considerations, especially with regards to performing prophylactic corneal cross-linking to strengthen corneal integrity. Artificial intelligence has been used to help predict keratoconus progression. Kindu used AI model involving the random forest algorithm using ocular surface and clinical factors to predict progressive keratoconus.[36] Garcia proposed a time-delay neural network to predict keratoconus progression by analyzing sequential tomography data and identifying significant baseline variations, with predictive values between 71.4% and 80.2%.[37] Additional AI studies are investigating multimodal data: corneal images, demographics, and environmental risk factors to predict disease progression.[33]

Future applications of AI in keratoconus include identifying genetic susceptibility, timing of therapeutic options, and surgical planning. Artificial intelligence has the potential to revolutionize keratoconus diagnosis and management by providing clinicians with precise, data-driven insights into disease detection and progression.

## Keritit is

Keratitis, especially microbial keratitis, is a major cause of corneal blindness that is often misdiagnosed in areas of the world with limited availability of ophthalmic care. Many types of keratitis can progress rapidly leading to permanent visual impairment and corneal perforation. Early detection using AI and corneal images can lead to more timely management of keratitis and have been helpful to distinguish viral, fungal, and bacterial keratitis.

Artificial intelligence utilizing a deep learning system has been established to detect keratitis and microbial keratitis biomarkers from slit lamp images[38,39] and confocal microscopy.[40] A deep learning system using ResNet50 combined with a cost-sensitive deep attention mechanism by Jiang et al, achieving an area under the curve (AUC) of 0.91 and an accuracy of 92.5% in detecting bacterial and fungal keratitis from slit-lamp images.[41] Sarayar et al conducted a systematic review that consolidated findings from multiple studies, revealing that AI models, particularly CNNs like DenseNet121 and Inception-v3, consistently outperform traditional diagnostic methods.[42] Their review reported AUCs ranging from 0.988 to 0.997 in differentiating between various types of infectious keratitis.

A deep learning approach by Kuo et al. has also been shown to diagnose fungal keratitis versus corneal photographs with an AUC of 0.65 based on 288 corneal photgraphs[43] and another by Hung et al. using deep learning model achieved an AUC of 0.85[44] and finally Ghosh et al. using convolutional neural network achieved an AUC of 0.90.[45] Redd et al. was able to use a convolutional neural network to differentiate bacterial keratitis from fungal keratitis with an AUC of 086.[46] Artificial intelligence has been used to aid in the diagnosis of Acanthamoeba keratitis using *in vivo* confocal microscopy images. Lincke et al.'s deep learning model demonstrated an accuracy of 88.3% in detecting Acanthamoeba cysts, which is a significant improvement over traditional methods and highlights the potential of AI in managing complex keratitis cases.[47]

In summary, AI has been demonstrated to be particularly effective in identifying keratitis early via imaging modalities, which is crucial for preventing severe complications especially in regions where immediate access to an ophthalmologist may be limited. In addition, AI is helping to distinguishing between bacterial, fungal, and viral keratitis based on ocular imaging.

## Cataract

Cataracts remain a leading cause of reduced visual acuity and blindness, affecting over 90 million people worldwide.[48] With a disease of this magnitude and frequency, AI offers innovative methods to diagnose, improve surgical outcomes, train Ophthalmic residents, and improve post-operative care.

Cataract can be detected and objectively quantified by AI-based image analysis using slit lamp photos.[49] In addition the support vector machine regression used in this study can grade the cataract and thus improve grading objectivity when assessing cataracts and help surgical planning.[49,50] In addition, AI can recognize any pre-exiting dislocation of the lens.[50]

Calculating of intraocular lens power is being improved by AI by combining the best aspects of modern intraocular formulas and 3-dimentional surface computation to create super formulas to maximize accuracy.[51] Other AI generated IOL calculation formula use both biometric parameters and complex nonlinear ocular parameters to increase accuracy.[52,53] Artificial intelligence has been used in cataract surgery video analysis, tracking, and instrument detection as a method to increase efficiency, improve workflow, enable feedback, and enhance training.[54,55,56] Smart operating theaters using artificial intelligence will enhance connectivity, integrate different equipment and diagnostic tools, and offer higher level functionality.[57] Artificial intelligence will likely increase the role of automation in cataract surgery. Currently, semi automation with OCT guidance is employed in femtolaser cataract surgery to aid in corneal incisions, capsulorhexis, astigmatism correction, and nuclear softening techniques.[57]

Artificial intelligence has been utilized to help with post-operative care to identify and prioritize patients after cataract surgery who need additional Ophthalmic care. This was accomplished by an autonomous telemedicine care (Dora, version R1) in detecting patients who need further in-person management, potentially reducing the burden on healthcare systems and improving patient outcomes.[58]

These AI-driven advancements in the field of cataract have the potential to improve diagnosis, surgical treatment, and enhance cataract surgery outcomes. These measures should increase the global accessibility of cataract screening and treatment, especially in underserved regions and help decrease the incidence of this treatable cause of blindness.

## Conclusion

Artificial intelligence is creating a technology revolution for many industries including health care. By improving image recognition, data analysis, creating predictive models, stratifying risk, enhanced data exchange, this technology can improve accuracy, safety, effectiveness, accessibility, and efficiency. The technology has shown benefit in many medical arenas which include Ophthalmology. Historically, posterior segment disease and retina subspecialty areas which are heavily image dependent have been initial areas to benefit from AI. This paper has also described how the anterior segment areas of glaucoma, keratoconus, keratitis, and cataract are benefitting from the technological advances of AI. Future studies and research to provide safeguards are needed prior to fully deploying artificial intelligent systems. For AI to be successful, we need not only quality, uniformly accepted data, but ethical uses of these systems that protect human autonomy, ensure transparency, and foster responsibility.[59] Even with all these technological tools, we cannot forget the importance of continuing to involve both the patient and the treating physician in the decision-making process. Robots may be very helpful in future healthcare decisions, but we cannot overlook the importance of personal touch and empathy, that only human medical care providers are currently capable of providing.

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