• Intelligent Ophthalmology •

Guidelines for the application of artificial intelligence in the diagnosis of anterior segment diseases (2023)

Yi Shao[1], Ying Jie[2], Zu-Guo Liu[3], Expert Workgroup of Guidelines for the application of artificial intelligence in the diagnosis of anterior segment diseases(2023); Ophthalmic Imaging and Intelligent Medicine Branch of Chinese Medicine Education Association; Ophthalmology Committee of International Association of Translational Medicine; Chinese Ophthalmic Imaging Study Groups

[1]Department of Ophthalmology, the First Affiliated Hospital of Nanchang University, Nanchang University, Nanchang 330006, Jiangxi Province, China
[2]Beijing Institute of Ophthalmology, Beijing Tongren Eye Center, Beijing Tongren Hospital, Capital Medical University; Beijing Ophthalmology & Visual Sciences Key Laboratory, Beijing 100730, China
[3]Eye Institute of Xiamen University, Xiamen 361102, Fujian Province, China

Correspondence to: Yi Shao. Department of Ophthalmology, the First Affiliated Hospital of Nanchang University, Nanchang University, Nanchang 330006, Jiangxi Province, China. freebee99@163.com; Ying Jie. Beijing Institute of Ophthalmology, Beijing Tongren Eye Center, Beijing Tongren Hospital, Capital Medical University; Beijing Ophthalmology & Visual Sciences Key Laboratory, Beijing 100730, China. jie_yingcn@aliyun.com; Zu-Guo Liu. Eye Institute of Xiamen University, Xiamen 361102, Fujian Province, China. zuguoliu@xmu.edu.com

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Abstract

● The landscape of ophthalmology has observed monumental shifts with the advent of artificial intelligence (AI) technologies. This article is devoted to elaborating on the nuanced application of AI in the diagnostic realm of anterior segment eye diseases, an area ripe with potential yet complex in its imaging characteristics. Historically, AI's entrenchment in ophthalmology was predominantly rooted in the posterior segment. However, the evolution of machine learning paradigms, particularly with the advent of deep learning methodologies, has reframed the focus. When combined with the exponential surge in available electronic image data pertaining to the anterior segment, AI's role in diagnosing corneal, conjunctival, lens, and eyelid pathologies has been solidified and has emerged from the realm of theoretical to practical. In light of this transformative potential, collaborations between the Ophthalmic Imaging and Intelligent Medicine Subcommittee of the China Medical Education Association and the Ophthalmology Committee of the International Translational Medicine Association have been instrumental. These eminent bodies mobilized a consortium of experts to dissect and assimilate advancements from both national and international quarters. Their mandate was not limited to AI's application in anterior segment pathologies like the cornea, conjunctiva, lens, and eyelids, but also ventured into deciphering the existing impediments and envisioning future trajectories. After iterative deliberations, the consensus synthesized herein serves as a touchstone, assisting ophthalmologists in optimally integrating AI into their diagnostic decisions and bolstering clinical research. Through this guideline, we aspire to offer a comprehensive framework, ensuring that clinical decisions are not merely informed but transformed by AI. By building upon existing literature yet maintaining the highest standards of originality, this document stands as a testament to both innovation and academic integrity, in line with the ethos of renowned journals such as Ophthalmology.

● **KEYWORDS:** artificial intelligence; corneal disease; lens disease; conjunctive disease; eyelid disease; guideline

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Background and Development Methods of the "Guidelines for the Application of Artificial Intelligence in the Diagnosis of Anterior Segment Diseases (2023)" The anterior segment of the eye, which consists of the frontal third of the ocular anatomy–including the conjunctiva, cornea, anterior chamber, iris, pupil, ciliary body, and lens–plays a pivotal role as the light's gateway and the eye's refractive system. The most crucial refractive components are the cornea and the lens, whose impairment can potentially instigate visual defects or blindness. The World Health Organization states that cataracts and uncorrected refractive errors are responsible for roughly 55% of global reversible blindness[1]. Originally conceived to address retinal diseases and glaucoma[2], artificial intelligence (AI) has been increasingly adapted for the diagnosis of anterior segment diseases. This adaptation is chiefly due to the necessity for comprehensive image analysis in diagnosing such diseases, involving methods like slit-lamp photography (SLP), anterior segment optical coherence tomography (AS-OCT), corneal topography, corneal endothelial microscopy, and *in vivo* confocal microscopy (IVCM)[3]. While diagnosing retinal diseases primarily relies on fundus images from ophthalmoscopy or fundus photography, the intricate structure and physiological functions of the anterior segment necessitate multifaceted examinations. Consequently, the significance of AI applications based on anterior segment images in ophthalmology is on the rise. Leveraging big data and image-based analysis, AI enhances the precision of disease diagnosis and classification while enabling the prediction of disease progression. This increased involvement of AI in ophthalmology highlights the absence of a unified guideline for its applications in anterior segment diseases. To bridge this gap, an expert group was convened by the Ophthalmic Imaging and Intelligent Medical Branch of the China Medical Education Association and the Ophthalmic Committee of the International Association of Translational Medicine in July 2022. This group was tasked with creating the "Guidelines for the Application of Artificial Intelligence in the Diagnosis of Anterior Segment Diseases (2023)". The team, comprised of AI researchers, refractive experts, and ophthalmologists, diligently examined national and international literature regarding AI applications in anterior segment diseases on July 3, 2023. They integrated their findings with practical insights from clinical ophthalmic AI research, engaging in comprehensive discussions during both offline and online meetings. They identified current challenges and proposed future development directions, which guided the creation of the guideline's first draft. The draft was then distributed among the experts for independent review and amendment suggestions, which were submitted *via* email and WeChat to the core members of the writing group. The suggestions were compiled, discussed, and summarized through WeChat, email, and online meetings, with the guideline undergoing numerous iterations to incorporate expert guidance. The final draft, taking over a year to develop, is aimed at equipping ophthalmologists with a better understanding of AI technology's research and clinical applications. International Practice Guidelines Registration: http://www.guidelines-redistry.cn/, IPGRP-2023CN487.

Primary Diagnostic Imaging Modalities and Artificial Intelligence Model Construction for Anterior Segment Diseases

Key diagnostic imaging patterns for anterior segment diseases The AI-assisted diagnosis of anterior segment diseases employs a spectrum of ophthalmic imaging techniques such as SLP, AS-OCT, corneal topography, corneal endothelial microscopy, and IVCM. These methodologies are complemented by the use of structured data. The diagnostic techniques are depicted in Figure 1.

Artificial intelligence model construction for anterior segment diseases Building an AI model involves several steps, including system data preparation (image preprocessing), dataset partitioning, model construction, optimization, and evaluation, as depicted in Figure 2. The recent advancements in AI suggest further refinement and sophistication in these processes, potentially leading to improved diagnostic accuracy and patient outcomes.

Fundamental Principle of Artificial Intelligence The essence of AI lies in its ability to mimic human cognitive processes, decision-making, and behaviors[1]. A subset of AI, machine learning (ML), uses training data samples to construct predictive models, such as logistic regression, artificial neural networks, and decision trees, without the need for explicit programming[4]. However, due to computational constraints, handling high-dimensional input data like millions of pixels, can present substantial challenges for ML. Deep learning (DL) algorithms, a more advanced aspect of artificial neural networks (ANN), can perform complex multi-level data extraction without manual feature labeling[5-6], making them more adept at addressing these challenges. Convolutional neural networks (CNN) and recurrent neural networks (RNN) are quintessential models of DL methods. The primary focus of DL lies in image recognition, speech recognition, and natural language processing[7]. Considering these principles, the utilization of AI in ophthalmology exhibits immense potential in enhancing diagnostic processes and patient care.

Clinical Application of Artificial Intelligence in the Diagnosis of Anterior Segment Diseases

Corneal diseases

Infectious keratitis Infectious keratitis (IK) presents a diagnostic challenge with its low pathogen culture yield and absence of pathogen specificity, frequently accompanied by

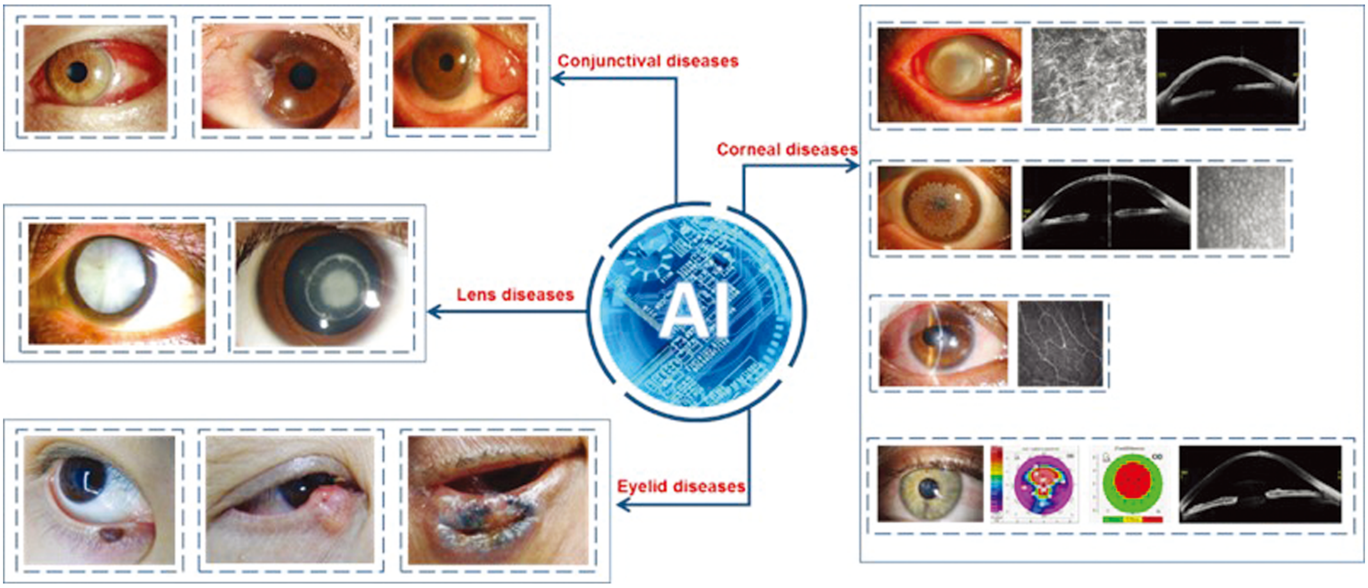

Figure 1 Application of artificial intelligence in anterior segment diseases.

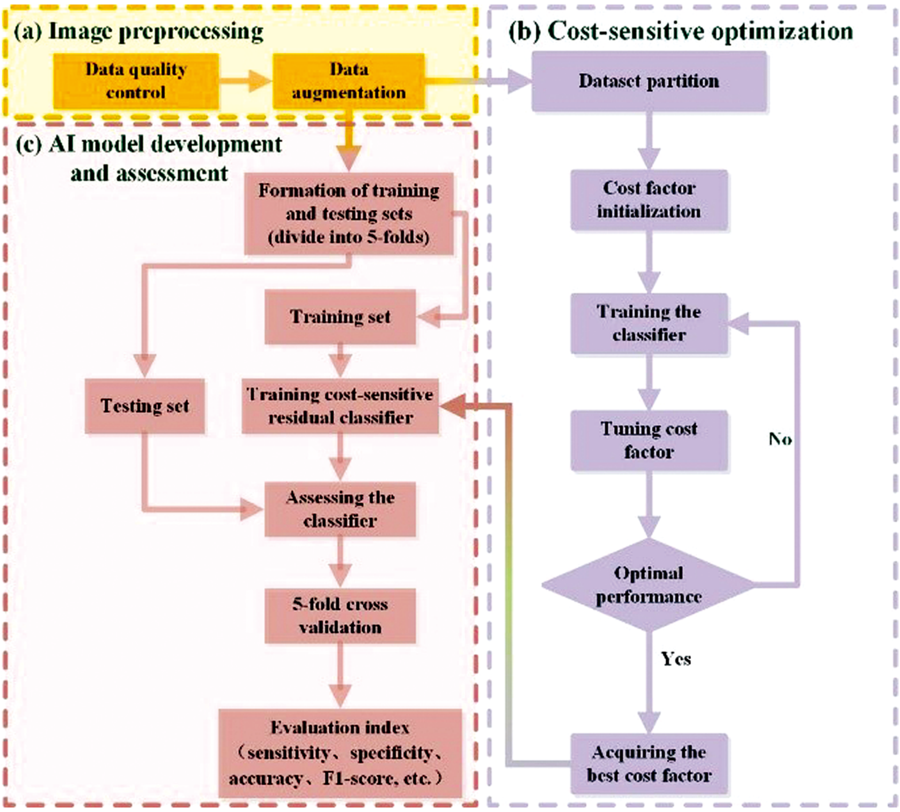

Figure 2 The construction procedure of the artificial intelligence (AI) model of general image classification.

multiple microbial infections (2%-15%). This complexity has been a formidable obstacle to attaining accurate diagnoses[8]. Swift identification and appropriate treatment of IK are paramount for halting disease progression and securing a more favorable visual prognosis[9-10]. Unfortunately, the current clinical diagnostic accuracy, hovering between 33% and 80%, leaves much to be desired[11], typically necessitating an experienced ophthalmologist's evaluation. This is the juncture where AI steps in, offering potential enhancement in diagnostic precision through AI models. For instance, Saini *et al*[12] developed an ANN classifier utilizing data from 106 corneal ulcer patients who were confirmed *via* lab testing and successfully treated with specific antibiotics or antifungal agents. This ANN classifier showed promising specificity rates: 76.5% for bacterial categories and a striking 100% for fungal categories. AI models have exhibited improved performance for various types of keratitis, with a notable upward trajectory in their foundational accuracy. Models trained using image-level classification tags integrated with anatomical and pathological tags have demonstrated superior performance compared to those relying solely on image-level classification tags[13]. In the realm of corneal physiology and pathology, AI has proved its capability not just in identifying pathological features, but also in quantifying them. As an illustration, Loo *et al*[14] designed a fully automated DL algorithm for segmenting eye structures and microbial keratitis biomarkers in SLP images. This system proficiently segmented four pathological markers, including stroma infiltration, hyphema, leukocyte boundary, and corneal edema boundary, demonstrating the potential of AI for biomarker segmentation on SLP images.

Keratoconus Early detection of keratoconus (KC) is still a significant clinical challenge, especially prior to refractive surgery. Diagnoses typically depend on various imaging techniques, primarily corneal topography, corneal tomography, and AS-OCT. In recent times, AI techniques, including feed-forward neural networks, CNN, support vector machine (SVM) learning, and automatic decision tree classification, have shown efficiency in distinguishing KC from normal eyes[15-19]. The advent of AI has facilitated the generation of thousands of features from big data, thereby boosting the accuracy of early KC detection, a task notoriously difficult with a single anterior corneal topography[20]. Recent studies have employed ML for early KC detection through corneal topography. For example, Accardo and Pensiero[21] used a neural network (NN) approach to distinguish early KC from normal eyes, achieving a sensitivity of 94.1% and specificity of 97.6%. The incorporation of Scheimpflug cameras in ophthalmology has enabled the collection of anterior and posterior corneal surface data, proving beneficial for early KC detection. Kovacs *et al*[22] applied an ML algorithm along with a Scheimpflug camera for early KC detection and reported a sensitivity of 92%. Additionally, Xu *et al*[23] developed an ML model called KerNet using the raw data from the entire cornea. KerNet proved to be valuable in distinguishing between asymmetric KC eyes and normal eyes, achieving an impressive area under the curve (AUC) of 0.985. A recent study by Chen *et al*[24] introduced a CNN model that amalgamates color coding maps of axial, front, and rear elevation and thickness maps, achieving 90% accuracy in differentiating healthy eyes from early KC. Though the accuracy varies among different studies, AI displays immense potential in early KC detection using Scheimpflug cameras. The limited information derived from the low-resolution images captured by the Scheimpflug camera might be a potential drawback. Recent research has endeavored to integrate corneal information from multiple instruments to enhance early KC detection accuracy. Shi *et al*[25] combined a Scheimpflug camera and AS-OCT to extract corneal morphological features from 121 eyes, attaining an AUC of 0.93. Thus, multi-dimensional corneal information can significantly boost the detection accuracy of early KC. AI is poised to become an influential tool in early KC detection through a comprehensive analysis of corneal features.

Diabetes keratoneuropathy Diabetic peripheral neuropathy (DPN), the most common complication associated with both type 1 and type 2 diabetes[26], calls for swift detection and diagnosis to ameliorate risk factors and slow down disease progression[27]. IVCM, offers a valuable tool for quantifying the subbasal corneal plexus, thereby detecting early signs of DPN[28]. Scarpa *et al*[29] utilized the CNN algorithm to differentiate IVCM images of 50 healthy subjects and 50 diabetic patients with neuropathy, securing a formidable accuracy rate of 96% in discerning clinically significant features of corneal nerves. Preston *et al*[30] applied the CNN algorithm to detect abnormalities of the corneal sub-basal plexus and classify DPN based on IVCM images from 369 subjects, resulting in an F1 score of 0.91. Additionally, Williams *et al*[31] leveraged a DL algorithm to scrutinize parameters such as the length, branching, fractal dimensions, and curvature of nerve fibers from IVCM images of 222 subjects in order to diagnose DPN and estimate its severity. This algorithm emerged as a superior choice compared to the ACCMetrics automatic nerve analysis software across all measured nerve parameters, yielding 87% specificity and 68% sensitivity for DPN identification. Meng *et al*[32] introduced a DL algorithm, targeting corneal confocal microscopy (CCM) images from the sub-basal nerve plexus. Their dataset consisted of 279 participants either with diabetes or at pre-diabetic stages. The focus was to determine the presence or absence of peripheral neuropathy (PN). Their findings were stellar; with a diagnostic sensitivity of 0.91 (95%CI, 0.79 to 1.0), specificity of 0.93 (95%CI, 0.83 to 1.0), and an AUC of 0.95 (95%CI, 0.83 to 0.99). Thus, deploying AI-driven diagnostic modalities using rapid ophthalmic imaging technology like CCM offers a promising avenue for screening both DPN and diabetic retinopathy.

Corneal dystrophy Corneal dystrophies, often linked to genetic aberrations in corneal endothelial cells or basement membranes, traditionally rely on slit lamp microscopy and genetic testing for identification. Nevertheless, AI has sprung onto the scene as a promising ally in this diagnostic quest. Gu *et al*[33] engineered a pioneering hierarchical DL network composed of an array of multi-task and multi-label learning classifiers. The efficacy of this algorithm was critically evaluated by ten ophthalmologists on a dataset encompassing 510 new outpatients presenting with a range of conditions, including IK, non-infectious keratitis, corneal dystrophy or degeneration, and corneal neoplasms. For the corneal dystrophy or degeneration category, the algorithm marked an AUC of 0.939, with sensitivity and specificity rates that equaled or surpassed the average of all participating ophthalmologists.

Fuchs' endothelial corneal dystrophy (FECD) is characterized by a progressive loss of corneal endothelial cells, potentially resulting in corneal decompensation and visual impairment. A groundbreaking study by Eleiwa *et al*[34] leveraged DL techniques to autonomously distinguish between healthy corneas and those affected by early and advanced stages of FECD. Drawing from a pool of 18 720 AS-OCT images—9180 denoting healthy corneas, 5400 early-stage FECD, and 4140 advanced-stage FECD—they developed and validated a DL classification network. Impressively, their model attained an AUC of 0.997±0.005, with a sensitivity of 91% and specificity of 97% in early FECD detection. For late-stage FECD, the model exhibited a specificity of 98%, an exceptional sensitivity of 100%, and an AUC of 0.998±0.001. Such findings accentuate the precision of DL algorithms as novel autonomous diagnostic tools for FECD, ideal for high-accuracy grading of the disease's severity.

Corneal surgery 1) Refractive surgery: With escalating demands for optimal vision and management of postoperative complications, the number of AI-driven studies in the domain of refractive surgery has surged, especially concerning pre-operative screening for the risk of post-laser refractive surgery ectasia. The biomechanics of a seemingly normal cornea could be compromised either by inherent biomechanical weakness, such as subclinical KC, or as a consequence of surgical intervention. Pre-operative screening, crucial for pinpointing patients at heightened risk of iatrogenic ectasia[35], remains a challenge given the subtle changes in corneal surface or thickness. Lopes *et al*[36] introduced the Pentacam random forest index, achieving a sensitivity of 85.2% and specificity of 96.6% when considering ectasia on a backdrop of normal corneal topography. Xie *et al*[35] employed a dataset of 6465 corneal tomography images to devise the Pentacam InceptionResNetV2 Refractive Surgery Screening System (PIRSS)—a tomography-based screening apparatus grounded in DL, tailored for detecting post-operative ectasia risk. This system discerned ectatic suspects with a sensitivity of 80%, identified early KC with a sensitivity of 90%, and commanded an overall diagnostic accuracy of 95% with an AUC of 0.99. Notably, when distinguishing between normal corneas, suspected irregular corneas, and KC, PIRSS outperformed the Belin-Ambrósio enhanced ectasia display classifier (93.7% *vs* 86.2%). Furthermore, while the false-positive rate with Belin-Ambrósio enhanced ectasia display's suspect category stood at 10%, PIRSS significantly reduced it to 1.7%. Despite these high accuracies, longitudinal follow-ups are paramount to discern which patients indeed manifest ectasia, and external validations are crucial before such technology can be judiciously implemented[37].

2) Keratoplasty. As reported by eye banks, there's a rising demand for corneal transplant tissues, invoking substantial financial and public health implications[38]. Advanced AI techniques can assist corneal surgeons in determining the necessity for corneal transplantation. Yousefi *et al*[39] proposed an AI-powered system, incorporating linear and nonlinear data transformations, applied to baseline corneal parameters from patient visits. This innovative approach, leveraging AS-OCT data, aptly identifies patients at a higher risk for KC or endothelial transplantation among a cohort of 3495 subjects. Furthermore, this mechanism provides clinicians with enhanced decision-making insights on when to adopt minimally invasive interventions based on corneal data. Hayashi *et al*[40] pioneered a deep neural network model, the Visual Geometry Group-16, to anticipate the efficacy of generating a successful big-bubble during the deep anterior lamellar keratoplasty procedure. The model exhibited an AUC of 0.75, with a successful big-bubble formation success rate of 78.3% (18/23 eyes; 95%CI 56.3%-92.5%), highlighting the system's potential in deep anterior lamellar keratoplasty. Treder *et al*[41] employed a DL-centric methodology, harnessing 1172 AS-OCT images (609 of attached grafts; 563 of detached grafts) to develop and assess a deep CNN for the autonomous detection of graft detachment post-descemet membrane endothelial keratoplasty. Their findings revealed the classifier's sensitivity, specificity, and accuracy rates at 98%, 94%, and 96%, respectively. Vigueras-Guillén *et al*[42] crafted a DL technique to analyze post-operative images from 41 eyes at intervals of 1, 3, 6, and 12mo post-ultra-thin posterior lamellar keratoplasty, procured *via* the Topcon SP-1P corneal endothelial microscopy. The evaluated parameters were endothelial cell density, coefficient of variation, and hexagonality. With manual segmentation on all images, the DL approach boasted a success rate of 98.4% for corneal metric determinations, surpassing the 71.5% achieved by the native Topcon software. Consequently, this validates the DL technique's reliable and accurate estimations even amidst challenging pathological corneal microscopy images.

Conjunctival disease

Pterygium Pterygium, characterized by aberrant corneal subepithelial conjunctival proliferation, is a common clinical issue that warrants attention[43]. Current pterygium evaluation protocols largely hinge on physicians' subjective judgments, which underscore the necessity and opportunity for AI-powered solutions that promise objectivity and efficiency[44]. Recognizing this imperative, Wan *et al*[45] developed a pioneering image analysis method utilizing anterior segment photography. This innovative approach incorporates four integral components: preprocessing, corneal segmentation, feature extraction, and classification. By meticulously distinguishing pterygium from normal ocular conditions, the team employed SVM and ANN to appraise the algorithm's performance. The results were commendable, boasting a sensitivity of 88.7%, a specificity of 88.3%, and an AUC of 95.6%. Simultaneously, Xu *et al*[46] ventured to construct a more sophisticated diagnostic framework, anchored on DL principles, specifically designed for pterygium assessment. Their AI-assisted diagnostic model, in conjunction with expert opinions, classified the images into three discernible categories: normal, pterygium under observation, and pterygium requiring surgical intervention. Upon evaluating 470 images, the AI diagnostic system achieved an impressive accuracy rate of 94.68%, demonstrating remarkable diagnostic alignment. These advancements underscore the extraordinary potential of AI models to improve diagnostic accuracy and prognostic prediction in managing pterygium. Zheng *et al*[47] integrated transfer learning to conceptualize a lightweight intelligent model to aid in the diagnostic procedure of pterygium, discerning normal images from observational pterygium and those necessitating surgical intervention. This embedded model facilitates user self-screening through mobile devices. Addressing the inherent opacity of ensemble learning predictions (often termed as "black box" systems), Gan *et al*[48] introduced the gradient-weighted class activation mapping. This method visualized the penultimate layer filters in the DL process, illuminating critical regions predicted by the DL model for pterygium classification. These highlighted regions corresponded with the actual pterygium sites. Notably, the integration of AI in this context opens a promising avenue to offset subjectivity, augment diagnostic precision, and enhance patient management, thereby revolutionizing clinical practices in ophthalmology.

Allergic conjunctivitis Allergic conjunctivitis, a persistent ocular inflammation induced by eosinophils and mast cells, commonly manifests as conjunctival congestion, an important marker for inflammation intensity[49]. Many cases of AC present without distinctive symptoms or signs. Diagnosis often hinges on a detailed medical history, intricately tied with clinical manifestations and, when essential, supplemented by laboratory testing. Conjunctival hyperemia stands as an indicative marker of the severity of ocular inflammation, therefore, precise assessment of conjunctival congestion is of pivotal significance for managing ocular inflammation. Yoneda *et al*[50] introduced an innovative software solution, designed to quantify congestion severity *via* digitization of bulbar conjunctiva slit lamp photographs. The proprietary algorithm, utilizing the RGB color model, meticulously analyzed and isolated conjunctival vessels. The conjunctival congestion was then appraised based on the proportion of the region of interest occupied by blood vessels. An optimal region of interest, comprising 400 vertical pixels and 300 horizontal pixels, was identified for reliable and replicable vascular image extraction. In parallel, Tabuchi and Masumoto[51] crafted a severity grading system for congestion, grounded in the VGG-16 DL model. Their study encompassed a vast collection of 10 186 images, employing an AI-based slit lamp model to extract images distributed on a scale from 0 to 3. The resultant system demonstrated a compelling weighted κ coefficient of 0.74, reflecting high congruence with clinical expert grading and substantially reducing subjectivity in score disparities.

Lens diseases

Age-related cataract Simultaneously, the rise in cataract prevalence, in tandem with societal aging, has invoked a paradigm shift toward AI-aided solutions. Harnessing data from slit lamp images, visible wavelength images, and fundus images, a suite of ML and DL algorithms, including SVM, deep CNN, and convolutional recurrent neural network, have been explored for automated diagnosis and grading of cataracts, screening and distinguishing cataract severities, quantifying the degree of posterior capsule opacification (PCO), and fine-tuning intraocular lens (IOL) parameters[52]. Adding to this, Xu *et al*[53] leveraged fundus imaging technology in concert with stack-based multi-feature technology. They utilized a synergistic combination of ResNet18 and GLCM, coupled with SVM and a fully connected neural network, to discriminate six levels of cataract severity, boasting an accuracy of 92.7%. Extending the scope of AI beyond mere detection and grading, Jiang *et al*[54] demonstrated that TempSeq-Net, a DL algorithm integrating depth CNN and long short-term memory, could proficiently predict the progression of after-cataracts necessitating YAG laser capsulotomy. This prediction was based on slit lamp images acquired two years post-follow-up and reported an impressive accuracy of 92.2%. Numerous investigations have underscored AI's pivotal role in diagnosing PCO subsequent to cataract surgery. Mohammadi *et al*[55] conceived an algorithm based on ANN that could predict the risk of severe PCO with an 87% accuracy rate. Moreover, AI-guided IOL degree calculations displayed superior accuracy utilizing methods such as the Hill-Radial Basis Function calculator, Kane formula, PEARL-DGS formula, and Ladas formula[56]. In a noteworthy advancement, Li *et al*[57] mitigated prediction errors in existing IOL calculation formulas by deploying an integrated ML algorithm to accurately predict anterior chamber depth. By partitioning data from 4806 patients into a training set (5761 eyes) and a test set (961 eyes), the algorithm significantly improved the prediction accuracy of all four crystal calculation formulas (Haigis, HofferQ, Holladay, and SRK/T). This case underscores the potential of integrating AI in streamlining diagnosis and enhancing prediction accuracy in ophthalmological conditions, setting the stage for a new era of patient-centric, technology-empowered clinical practice.

Congenital cataract Pediatric cataracts, unlike those in adults, are characterized by a lack of uniformity due to insufficient visual stimulation. The decision for surgical intervention is often predicated upon the risk of amblyopia and the challenge of obtaining consistently high-quality slit lamp images during pediatric examinations[58]. As such, early and accurate differentiation between congenital cataract (CC) patients and healthy children becomes paramount. Recently, an innovative model has been devised by Lin *et al*[59] to pinpoint individuals with a heightened risk of CC. This study integrated birth history, family history, and other environmental factors from 2005 individuals, among which 1274 were diagnosed with CC, while 731 were healthy controls (non-imaging). The model leveraged random forest and adaptive boosting methods to display an AUC between 0.94 to 0.96 across multiple subgroups, indicating robust performance. In addition, AI can be used for accurate and effective follow-up management of CC patients and screening of complications. Concurrently, Long *et al*[60] formulated CC-guardian using Bayesian and DL algorithms. This fusion model amalgamated personalized prediction, scheduling, and smart telemedicine follow-ups, primarily targeting two high-risk complications in CC patients: increased intraocular pressure and visual axis opacification. The results revealed an AUC of 0.944 for predicting visual axis opacification and 0.961 for predicting ocular hypertension. This investigation underscores the tangible medical benefits AI can bring, heralding a novel approach to effective CC management.

Eyelid diseases

Eyelid malignant tumor Eyelid tumors represent some of the most recurrent malignancies encountered in ophthalmic clinical practice[61-62]. Predominantly superficial, these tumors are often easily detectable. Diagnostic modalities encompass imaging studies like CT or MRI, ocular ultrasonography, color Doppler examination, and histopathological evaluation. Owing to the eyelid's diverse tissue composition, a myriad of both benign and malignant tumors can emerge. The proximity of malignant eyelid tumors to vital structures like the eyeball, brain, and sinuses can culminate in disfigurement, or in gravest scenarios, mortality owing to intracranial or systemic metastases[63-64]. Hence, early detection and intervention ensure the best cosmetic and functional outcomes. Moreover, malignancies like eyelid melanoma and sebaceous gland carcinoma, though rare, carry a significant mortality rate[65-66]. However, early-stage detection (skin infiltration depth ≤0.76 mm) can yield a 5-year survival rate exceeding 99%[65]. Consequently, the early identification of these malignancies is pivotal. Benign and malignant eyelid tumors sometimes present with overlapping features, challenging primary care physicians, dermatologists, and less experienced ophthalmologists in their differentiation. Deploying DL algorithms in tandem with eyelid tumor imaging could potentiate early automated detection of malignant eyelid tumors. The inherent advantages would augment the accessibility and affordability of suspicious cases. Moreover, to empower physicians and suspected patients in proactive eyelid tumor tracking and expedite malignant tumor identification, the algorithm should autonomously localize the eyelid tumor within the image.

Challenges and Strategies in Artificial Intelligence-assisted Diagnosis of Anterior Segment Diseases Notwithstanding the promise of AI, its nascent application in anterior segment diseases raises numerous challenges prior to clinical implementation. The principal obstacles include: 1) The standardization of anterior segment imaging techniques and methods is more difficult than that of fundus imaging, mainly due to the changes in beam magnification, contrast, angle and width, and corneal transparency. Efforts toward standardization must address these factors to guarantee image quality and utility[1]. Overcoming limitations in large-scale labeled data acquisition is a persistent challenge in the integration of AI in ophthalmic imaging. Semi-supervised and unsupervised learning paradigms are emerging as pivotal solutions to this conundrum. Specifically, for data-sensitive algorithms like CNNs, these methods are gaining traction. They harness the potential of unlabeled data to enhance model performance, thereby attenuating the reliance on extensive annotated datasets. By leveraging such techniques, ophthalmologists can capitalize on the wealth of raw, unlabeled image data, facilitating more robust and adaptive diagnostic AI models in anterior segment disease evaluation. Therefore, large data sets obtained from heterogeneous cohorts that reflect real-world environments are necessary, but the process must comply with medical laws and data security and set rules. 2) The external validation of algorithms faces numerous impediments[67]. Despite several DL algorithms having been validated and tested on open datasets, their performance might degrade in real-world clinical scenarios due to variances in image quality, imaging equipment, and patient cooperation, necessitating improvements in these areas. 3) In certain studies, the sample size is insufficient[68], leading to unstable AI model performance with significant result disparities. Enlarging the sample size can boost AI's clinical diagnostic accuracy. 4) Bias exists in AI model datasets[69]. AI models trained and validated with high-quality datasets typically succeed. However, many studies utilize smaller or common datasets, which may be biased, resulting in skewed results and limiting the external applicability of the AI model. To avoid the "garbage in, garbage out" issue, AI models should focus on relevant factors and avoid confounding ones. An ideal diagnostic framework necessitates inputs of high image

Table 1 Evaluation criteria for image recommendations in datasets

Evaluation project	Description	Score	Definition
Image resolution and color depth	Whether the resolution and color depth of the image reach the average value of the image captured in this inspection, and whether the typical features can be detected	10	Resolution and color depth are above average and have detectable features
		5	The resolution and color depth are below average and have detectable characteristics
		0	Resolution and color depth are below average and cannot be used
Image feature	Whether the specific characteristics of the disease can be identified and not blocked	10	>80% of the features are recognizable
		5	40-80% of the features can be recognized
		0	<40% of the features are recognizable
Image source	Check whether the image is original or non-original	10	Original image
		5	A non-original image with recognizable features
		0	With unrecognized non-original images
Anatomical structure	Whether the important anatomical structures in the image are intact and have disease-specific characteristics	10	Intact structure
		5	Preserve the incomplete structure of a feature
		0	The structure is incomplete and cannot be used
Image distortion	The difference between image and real environment shooting	10	Low distortion, <20%
		5	Medium distortion, 20%-50%
		0	High distortion, >50%
Image fidelity	The degree of deviation between image and standard image	10	Conform to the standard
		0	Not up to the standard
Notes	Whether the annotation is made by a professionally certified and trained ophthalmologist	10	Completed by more than 2 qualified commentators
		5	Completed by a qualified commentator
		0	Completed by unqualified commentators
Image format	Is the image format consistent with the dataset format?	10	Consistent
		0	Inconsistent
Description	Whether the image description is complete and accurate, including standard diagnostic name, anatomical structure, *etc*.	10	Complete and accurate
		5	Complete and inaccurate
		0	Incomplete
Source of information	Whether the image source information is complete, including the corresponding patients	10	Complete
		5	The patient information is incomplete
		0	The device information is incomplete

resolution and precision, coupled with minimal inter-observer variability. The integration of modern tools, such as slit-lamp adapters, smartphones, and cloud computing platforms, holds the promise of streamlining the workflow, enriching the diagnostic efficacy. To ensure a high level of reliability, we advocate for a comprehensive image quality assessment prior to its incorporation into datasets. Several parameters play into this evaluation: image resolution and color depth, distinctive features, image provenance, anatomical integrity, distortion levels, realism, annotations, format, description, and source of information. Each of these parameters is gauged on a scale ranging from 0 (poor) to 10 (optimal). A detailed assessment matrix is provided in Table 1. 5) "Black box" effect[1]. The opacity surrounding decision-making processes, particularly the disproportionate weightage assigned to certain parameters or features, remains a concern. The clandestine nature of some of these models necessitates further exploration. The clinical domain demands more than just accuracy. It also requires transparency. Clinicians seek clarity on the foundational logic behind AI-driven decisions to deliver judicious patient care. Hence, algorithms with decipherable decision-making steps and high explainability are not just desirable but crucial. Such transparent algorithms could assuage clinicians' reservations, fostering a more widespread and confident adoption in patient care.

Future Directions in the Development of Artificial Intelligence-assisted Diagnoses for Anterior Segment Diseases Several facets of anterior segment diseases in both adults and children remain relatively untouched by AI, thus presenting a myriad of opportunities for future exploration. The fusion of automated detection systems with telemedicine promises to amplify the scope of healthcare services, particularly if such systems can match or even surpass the performance of trained professionals. At present, a notable discrepancy exists between the theoretical utility of algorithms and their practical implementation within a clinical environment, underscoring the importance of focusing on translational research. Electronic health records, as a form of big data, constitute a largely untapped wellspring capable of enhancing the training and development of robust AI systems[70]. The recognition of corneal diseases and cataracts as global health burdens highlights the pressing necessity for comprehensive disease screening, especially within resource-constrained settings. As innovations within the field of anterior segment diseases continue to progress, both image-based and non-image-based AI algorithms may hold the potential to promptly diagnose and treat corneal diseases and cataracts, consequently making significant advancements in refractive surgery. While AI research has indeed made remarkable strides over the past decade, it has predominantly depended on static datasets and environments. AI systems are usually defined and refined during the development stage. Nonetheless, in an ever-evolving world, AI systems, much like clinical ophthalmologists, should be able to continuously learn in dynamic environments to maintain adaptability. Incorporation of continual learning techniques such as gradient-based learning, modular neural networks, and Meta-learning could enable AI systems to persistently learn throughout their lifecycle, mirroring the learning curve of a clinical ophthalmologist. Such methodologies could propel AI towards unprecedented heights by augmenting learning efficiency and facilitating the transfer of knowledge across related tasks.

CONCLUSION

Notwithstanding the multiple challenges that beset the application of AI in the clinical diagnosis of anterior segment diseases, existing research suggests that AI possesses the capacity to extract disease characteristics from training datasets and apply these to validation or test sets for disease diagnosis. AI has the capability to categorize images into diverse categories based on disease characteristics, including disease classification and staging. Additionally, AI can detect and segment anatomical structures within images, such as lesion shapes, thus enabling automatic quantification of image biomarkers and aiding in diagnoses. Considering these merits, the integration of AI technology in clinical diagnosis and treatment holds enormous potential and foretells a future replete with exciting prospects[71].

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Expert Group Members

Leading authors

Yi Shao	The First Affiliated Hospital of Nanchang University
Ying Jie	Bejing Tongren Hospital, Capital Medical University
Gang Tan	The First Affiliated Hospital of University of South China
Zu-Guo Liu	Ophthalmic Institute of Xiamen University
Wei Chen	Eye Hospital, Wenzhou Medical University; Zhejiang Eye Hospital
Jin-Hai Huang	Eye & ENT Hospital of Fudan University
Jing Zhong	Zhongshan Ophthalmic Center, Sun Yat-Sen University
Wei Li	Ophthalmic Institute of Xiamen University
Zhong-Wen Li	Wenzhou Medical University Ning Bo Eye Hospital
Hui Zhang	First Affiliated Hospital of Kunming Medical University
Liang Hu	Eye Hospital, Wenzhou Medical University; Zhejiang Eye Hospital
Cheng Li	Ophthalmic Institute of Xiamen University
Feng Wang	Meizhou People's Hospital (Huangtang Hospital)
Ting-Ting Shao	Eye & ENT Hospital of Fudan University
Jian-Zhang Hu	Fujian Medical University Union Hospital
Gui-Gang Li	Tongji Medical College of Huazhong University of Science Technology
Wen-Jin Zou	The First Affiliated Hospital of Guangxi Medical University
Yong Tao	Bejing Chao-Yang Hospital, Capital Medical University
Yuan Gao	Shanxi Medical University
Xiao-Dan Huang	The Second Affiliated Hospital Zhejiang University School of Medicine
Die Liu	Nanjing Hospital of Chinese Medicine Affiliated to Nanjing University of Chinese Medicine
Zhi-Hong Deng	The Third Xiangya Hospital of Central South University
Hua-Tao Xie	Union Hospital Tongji Medical College Huazhong University of Science and Technology
Shi-Ying Li	Xiang'an Hospital of Xiamen University
Nuo Dong	Xiamen Eye Center of Xiamen University
Qi-Kua Le	Eye & ENT Hospital of Fudan University
Qin-Xiang Zheng	Eye Hospital, Wenzhou Medical University; Zhejiang Eye Hospital
Lei Tian	Bejing Tongren Hospital, Capital Medical University
Wei-Hua Yang	Shenzhen Eye Hospital
Hui Zhao	Shanghai General Hospital (The First People's Hospital Affiliated to Shanghai Jiao Tong University School of Medicine)
Zhen-Yuan Fu	Zhongshan Ophthalmic Center, Sun Yat-Sen University
Dan Wen	Xiangya Hospital of Central South University
Jian-Qi Cai	China National Institute of Standardization
Xin-Jian Chen	Suzhou University
Yan-Wu Xu	South China University of Technology
Juan Peng	The Second Affiliated Hospital of Guangzhou Medical University
Wen-Qing Shi	Jinshan Hospital of Fudan University
Qian-Min Ge	The First Affiliated Hospital of Nanchang University
Xin Wen	Sun Yat-Sen Memorial Hospital, Sun Yat-Sen University

Writing experts

Cheng Chen	The First Affiliated Hospital of Nanchang University
Jing-Yao Chen	Yan'an Hospital of Kunming Medical University
Jun Chen	Jiangxi University of Chinese Medicine
Ping Chen	Renji Hospital of Shanghai Jiao Tong University
Xu Chen	Maastricht University
Yu Chen	Shanghai University
Zhe Cheng	Aier Eye Hospital (Changsha)
Yu-Qing Deng	Zhongshan Ophthalmic Center, Sun Yat-Sen University
Jing Dong	The First Affiliated Hospital of Shanxi University
Zhi-Xin Geng	Tianjin MasterVision Technology Co., Ltd.
Zheng-Yu Gu	The First Affiliated Hospital of Anhui Medical University
Yi Han	Ophthalmic Institute of Xiamen University
Yun Han	Ophthalmic Institute of Xiamen University
Xin He	The First Affiliated Hospital of Xiamen University
Jia He	Jining Medical University
Li-Dan Hu	Children's Hospital Affiliated to Zhejiang University School of Medicine
Jin-Yu Hu	The First Affiliated Hospital of Nanchang University
Xiao-Qin Hu	Eye Hospital of Nanchang University

Cai-Hong Huang	Ophthalmic Institute of Xiamen University
Xiao-Ming Huang	Aier Eye Hospital (Sichuan Province)
Yong-Zhi Huang	West China Hospital of Sichuan University
Hong-Hua Kang	Ophthalmic Institute of Xiamen University
Min Kang	The First Affiliated Hospital of Nanchang University
Li Li	The First Affiliated Hospital of Xi'an Jiaotong University
Hai-Bo Li	Xiamen Eye Center of Xiamen University
Heng-Hui Li	The First Affiliated Hospital of Nanchang University
Jie Li	Eye Hospital, Wenzhou Medical University; Zhejiang Eye Hospital
Kai-Jun Li	The First Affiliated Hospital of Guangxi Medical University
Nai-Yang Li	Zhongshan City People's Hospital
Qing-Jian Li	Huashan Hospital of Fudan University
Zhi-Yuan Li	Chenzhou No.1 People's Hospital
Li-Dan Luo	Meizhou People's Hospital (Huangtang Hospital)
Rong-Bin Liang	Jinshan Hospital of Fudan University
Jing-Wei Lin	Ophthalmic Institute of Xiamen University
Zhi-Rong Lin	Xiamen Eye Center of Xiamen University
Qian Ling	The First Affiliated Hospital of Nanchang University
Guang-Hui Liu	Affiliated People's Hospital (Fujian Provincial People's Hospital), Fujian University of Traditional Chinese Medicine
Yuan Liu	Bascom Palmer Eye Institute, USA
Qiu-Ping Liu	The First Affiliated Hospital of the University of South China
Zhao-Lin Liu	The First Affiliated Hospital of the University of South China
Ze-Yu Liu	Ophthalmic Institute of Xiamen University
Jian Ma	The Second Affiliated Hospital of Zhejiang University School of Medicine
Wei Ma	Zhongshan Ophthalmic Center, Sun Yat-Sen University
Shang-Kun Ou	The Affiliated Hospital of Guizhou Medical University
Wei-Jie Ouyang	The Affiliated Hospital of Guizhou Medical University
Wei Qiang	Wenzhou Medical University Ning Bo Eye Hospital
Kun-Liang Qiu	Joint Shantou International Eye Center of Shantou University and the Chinese University of Hong Kong
Wei-Qiang Qiu	Peking University Third Hospital
Sheng-Wei Ren	Henan Provincial People's Hospital
Yi-Lei Shao	Eye Hospital, Wenzhou Medical University; Zhejiang Eye Hospital
Ce Shi	The Second Affiliated Hospital Zhejiang University School of Medicine
Ting Su	Renmin Hospital of Wuhan University
Zhao-An Su	The Second Affiliated Hospital Zhejiang University School of Medicine
Li-Ying Tang	Zhongshan Hospital Xiamen University
Li-Yang Tong	Wenzhou Medical University Ning Bo Eye Hospital
He Wang	The Affiliated Hospital of Xuzhou Medical University
Shen Wang	Beijing Ming Optometry Ophthalmology
Shao-Pan Wang	Institute of Artificial Intelligence Xiamen University
Xue-Lin Wang	The First Affiliated Hospital of the Jiangxi Medical College
Yi-Xin Wang	Cardiff University
Hong Wei	The First Affiliated Hospital of Nanchang University
Jie-Li Wu	Aier Eye Hospital (Changsha)
Kai Wu	The First Affiliated Hospital of University of South China
Yang Wu	Zhongshan Hospital, Fudan University (Xiamen Branch)
Wei Xia	The First Affiliated Hospital of Soochow University
San-Hua Xu	The First Affiliated Hospital of Nanchang University
Yang Yang	Yueyang Central Hospital
Yong Yao	C-MER (Guangzhou) Dennis Lam Eye Hospital
Hai-Jun Yang	Nanchang Puri Eye Hospital
Qi-Chen Yang	West China Hospital of Sichuan University
Shu Yang	The First Hospital of Kunming
Wen-Li Yang	Bejing Tongren Hospital, Capital Medical University
Yi-Ran Yang	Henan Provincial People's Hospital
Yu-Li Yang	The Southwest Hospital of Army Medical University
Yi-Feng Yu	The Second Affiliated Hospital of Nanchang University
Yao Yu	The First Affiliated Hospital of Nanchang University
Qing Yuan	Jiu Jiang No.1 People's Hospital
Bing Zhang	Hangzhou Children's Hospital
Qing Zhang	The Second Hospital of Anhui Medical University
Yan-Yan Zhang	Wenzhou Medical University Ning Bo Eye Hospital
Yu-Qing Zhang	The Second Affiliated Hospital of Chongqing Medical University
Yu-Jie Zhang	Xiamen Eye Center of Xiamen University
Zhen Zhang	The First Affiliated Hospital of Xiamen University
Zhen-Hao Zhang	Suzhou Science Technology Town Hospital
Pei-Wen Zhu	Eye & ENT Hospital of Fudan University
Xin-Yue Zhu	Shanghai General Hospital
Zhuo-Ting Zhu	The Centre For Eye Research Australia (CERA)
Jie Zou	The First Affiliated Hospital of Nanchang University
Jing Zou	Xiangya Hospital of Central South University

Consensus Statement: All the experts involved in the formulation of this consensus attest to the fact that their recommendations are guided by a commitment to objectivity, rooted in professional knowledge, research data, and clinical experience. This consensus was primarily crafted by certain members of the Ophthalmic Imaging and Intelligent Medicine Branch of the Chinese Medical Education Association and the Ophthalmology Special Committee of the World Society of Translational Medicine.

Disclaimer: The content of this consensus is representative of the expert guidance provided to clinicians and is not meant to be prescriptive. Despite the extensive consultations and discussions undertaken by the experts, there may still be limitations in the recommendations provided. Deviations from this guide do not necessarily imply errors or irregularities in practice. Clinical practice is a constantly evolving field with ongoing research often presenting new evidence that may necessitate alterations in diagnostic and treatment approaches. Consequently, with the growing body of clinical experience and the advent of new treatment modalities, it is expected that this consensus will undergo regular revisions and updates to continue delivering optimal clinical benefits to patients.

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