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Applications of Artificial Intelligence in the Diagnosis and Management of Keratitis and Conjunctivitis: A Review

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Abstract

Ocular surface diseases, such as conjunctivitis and keratitis, are an important global health concern because of their socioeconomic burden and potential for visual impairment. Early diagnosis and appropriate management are key to preventing complications, yet traditional diagnosis based on clinical examination and investigations is resource-intensive and varies among clinicians. Artificial intelligence (AI), particularly machine learning and deep learning, has shown promise in image-focused specialties such as ophthalmology. This narrative review summarizes published studies evaluating AI in the diagnosis and management of keratitis and conjunctivitis, including image-based diagnostic models, chatbots, natural language processing tools, and smartphone applications, along with future directions and ethical considerations. Convolutional neural networks applied to slit-lamp, anterior segment optical coherence tomography, in vivo confocal microscopy, and smartphone images showed high performance in detecting infectious keratitis, with areas under the curve above 0.96 in large multicenter datasets. Performance was lower for differentiating causative organisms, with accuracies of approximately 76% to 92% for bacterial, fungal, and *Acanthamoeba* keratitis and fungal subtypes. In allergic conjunctival disease, an AI pipeline achieved a diagnostic accuracy of 86.2%, compared with 60.0% for board-certified ophthalmologists. Chatbots correctly answered 51% to 68% of questions on corneal and conjunctival diseases, and incorrect AI suggestions significantly reduced the diagnostic accuracy of non-specialist ophthalmologists. Ensemble learning, mobile imaging applications, and chatbot-supported triage may extend tele-ophthalmology to under-resourced areas. However, most models rely on retrospective, single-center datasets, and concerns remain regarding generalizability, accountability, transparency, and clinician trust. Prospective multicenter validation and explainable, multimodal systems are needed before AI can be routinely adopted as a supportive tool in clinical practice.

Categories: Quality Improvement, Ophthalmology, Healthcare Technology
Keywords: artificial intelligence, conjunctivitis, keratitis, machine learning, visual impairment

Introduction And Background

Ocular surface diseases are common worldwide and impose a substantial social and economic burden. Keratitis, or inflammation of the cornea, may be infectious or non-infectious. Infectious keratitis is caused by bacteria (such as *Staphylococcus* and *Pseudomonas* species), fungi (such as *Fusarium* and *Aspergillus* species), viruses (most commonly herpes simplex virus), or parasites such as *Acanthamoeba*, with contact lens wear, ocular trauma, and agricultural injury being major risk factors [1]. The reported incidence of microbial keratitis varies widely, from fewer than 10 per 100,000 person-years in some high-income settings to as many as 799 per 100,000 person-years in Nepal [1]. In the United States, the annual incidence is 11 to 27.6 per 100,000 people, with a rising trend in contact lens-related ulcerative keratitis [2]. Corneal opacity, to which keratitis is a major contributor, ranks fifth among the global causes of blindness [3]. Corneal ulceration and ocular trauma together cause an estimated 1.5 to 2 million new cases of monocular blindness each year, more than 90% of which occur in developing countries, and this burden has been described as a "silent epidemic" [4,5].

Conjunctivitis, or inflammation of the conjunctiva, is one of the most common causes of red eye. It may be infectious, caused by viruses or bacteria, or non-infectious, caused by allergens, irritants, or medications [6]. Viral conjunctivitis is the most common infectious form, and adenovirus accounts for up to 90% of viral cases [7]. Although usually self-limiting, conjunctivitis can progress to serious ocular and extraocular complications, and its different causes are difficult to distinguish clinically, which often leads to unnecessary antibiotic prescribing [6,7].

Both conditions are diagnosed mainly by clinical examination. Conjunctivitis is usually diagnosed from the

history and examination, with laboratory testing reserved for severe, recurrent, or chronic cases [6]. In suspected infectious keratitis, slit-lamp examination (examination with a specialized microscope that combines magnification with a bright, adjustable beam of light to view the front of the eye) is followed by corneal scraping for microscopy and culture, which remain the reference standard. However, culture results can take several days, require laboratory facilities that are often unavailable in resource-limited settings, and are negative in a substantial proportion of cases [1]. Clinicians therefore frequently begin empirical treatment based on clinical appearance alone, yet distinguishing bacterial from fungal or *Acanthamoeba* keratitis on examination is difficult and varies between observers [1,8]. In practice, this means that a patient with fungal or *Acanthamoeba* keratitis may first be given standard antibacterial eye drops, which are ineffective against these organisms and allow the infection to progress, sometimes rapidly, to irreversible corneal scarring or perforation [1]. Delays and errors in diagnosis increase the risk of complications and the need for urgent corneal transplantation [8].

Because both diseases are recognized largely through visible signs on the anterior segment, such as conjunctival redness, discharge, corneal infiltrates, and ulcer morphology, they are well suited to image-based artificial intelligence (AI). Deep learning (DL) models learn these visual patterns directly from large sets of labeled slit-lamp, smartphone, or other ocular images and can then classify new images within seconds [8,9]. In much the same way that face recognition software learns to identify a person after being shown many photographs of that person, these programs learn to recognize the characteristic appearance of eye redness, corneal infiltrates, and ulcers after being shown thousands of labeled examples. Keratitis and conjunctivitis are reviewed together because both commonly present as a red eye, both are assessed using the same anterior segment imaging, and a key task in frontline and tele-ophthalmology settings is distinguishing usually benign conjunctivitis from sight-threatening keratitis. Key AI and diagnostic accuracy terms used in this review are defined in Table *1*.

Term	Definition
Artificial intelligence (AI)	Computer systems that perform tasks normally requiring human intelligence
Machine learning (ML)	AI methods that learn patterns from data rather than following explicitly programmed rules
Deep learning (DL)	A type of ML that uses multilayered artificial neural networks to learn features directly from raw data such as images
Convolutional neural network (CNN)	A DL architecture designed for images, in which successive layers detect simple features such as edges and then more complex patterns such as corneal infiltrates
Transfer learning	Adapting a model pretrained on a large general image dataset to a specific medical task, reducing the amount of medical data needed
Ensemble learning	Combining predictions from several models to improve accuracy and reliability
Overfitting	When a model learns features specific to its training images, including noise, and therefore performs less well on new data
Natural language processing (NLP)	Methods that analyze human language, such as text in clinical records
Large language model (LLM)	A DL model trained on large amounts of text that generates human-like responses; the basis of chatbots such as ChatGPT
Accuracy	Proportion of all cases correctly classified
Sensitivity	Proportion of patients with the disease who are correctly identified
Specificity	Proportion of patients without the disease who are correctly identified
Positive predictive value (PPV)	Proportion of positive results that are truly positive
Negative predictive value (NPV)	Proportion of negative results that are truly negative
Area under the receiver operating characteristic curve (AUC)	Overall ability of a model to distinguish disease from non-disease, ranging from 0.5 (chance) to 1.0 (perfect)
Area under the precision-recall curve (AUPRC)	Summary of the balance between PPV and sensitivity; unlike the AUC, its value depends on how common the disease is in the dataset
External validation	Testing a model on data from centers or populations different from those used to develop it
Calibration	Agreement between a model's predicted probabilities and the outcomes actually observed

TABLE 1: Key artificial intelligence and diagnostic accuracy terms

Previous reviews have described AI in corneal disease broadly [8,10], and systematic reviews and meta-analyses have evaluated the diagnostic accuracy of DL for infectious keratitis [11,12] and AI-based pathogen detection in infectious keratitis [13]. However, these have focused mainly on image-based diagnosis of keratitis, and few have considered conjunctivitis or non-imaging applications such as chatbots, large language models, and natural language processing. The present review adds to this literature by examining both conditions together, including these non-imaging applications, and by discussing the ethical and clinical considerations relevant to their use. The evidence for conjunctivitis remains considerably smaller than that for keratitis, and this imbalance is reflected in the present review.

This narrative review aims to summarize current evidence on AI applications in keratitis, including infectious and non-infectious forms, and in conjunctivitis, including infectious and allergic forms. It covers image-based diagnostic models, chatbots and large language models, natural language processing, and smartphone applications. No date restriction was applied to the literature search, however, all included studies were published from 2020 onward, reflecting the recent development of this field with a focus on studies published from 2020 onward. It also discusses future directions and the ethical and clinical considerations relevant to the use of these tools in practice.

Review

Methods

This narrative review was conducted using a structured literature search, and the study selection process was reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses

(PRISMA) 2020 guidelines where applicable.

Search Strategy

PubMed/MEDLINE, Scopus, and Google Scholar were searched from inception to September 2026, with the last search conducted in September 2026, and no restriction on publication date was applied. The following search string was used in PubMed: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "convolutional neural network" OR "large language model") AND (keratitis OR conjunctivitis OR "ocular surface disease").

In Scopus, the same terms were applied to titles, abstracts, and keywords: TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "convolutional neural network" OR "large language model") AND (keratitis OR conjunctivitis OR "ocular surface disease")).

In Google Scholar, the same terms were entered using the advanced search; results were sorted by relevance, and the first 340 records were screened by title and abstract. The reference lists of relevant articles were also screened to identify additional studies. Keratoconjunctivitis, trachoma, and allergic conjunctivitis were not included as separate search terms, and some studies on these conditions may therefore not have been captured by the search; this is acknowledged as a limitation of this review.

Eligibility Criteria

Studies were eligible if they evaluated AI, including machine learning (ML), DL, natural language processing, or chatbots based on large language models, for the diagnosis, classification, triage, monitoring, or education related to keratitis or conjunctivitis, and reported diagnostic performance or outcome data. Original studies of any design were eligible, including full-text conference papers and conference abstracts that reported sufficient performance data. Review articles, editorials, letters, non-English publications, and studies not related to ocular surface disease were excluded. Studies that applied AI to keratitis or conjunctivitis data but reported clinical outcome data rather than diagnostic performance metrics were also eligible; on this basis, one study that used natural language processing and ML to characterize patients with acute conjunctivitis from electronic health records was included as the only identified application of AI to clinical records in conjunctivitis [14]. Two authors (AS and JS) independently screened titles and abstracts, followed by full-text review of potentially eligible articles, and disagreements were resolved by discussion. The literature search was subsequently updated to include six additional relevant studies that met the eligibility criteria. The selection process is summarized in Table *2*.

Stage	Number of records
Records identified through database searching	800 (PubMed 186, Scopus 274, Google Scholar 340)
Additional records identified through reference lists	0
Duplicate records removed	176
Records screened by title and abstract	624
Records excluded after title and abstract screening	542
Full-text articles assessed for eligibility	82
Full-text articles excluded	62
No AI component	28
No diagnostic performance or outcome data	22
Review article or editorial	12
Studies included from the database search	20
Additional studies included after the literature search was updated	6
Studies included in the review	26 (conjunctivitis: 10; keratitis: 16)

TABLE 2: Summary of literature search and study selection

Data Extraction and Quality Assessment

Data were extracted using a standardized form recording the author, country, condition, study design, dataset, AI model, and main performance outcomes. Because the included studies addressed different tasks, such as disease detection, pathogen classification, and evaluation of chatbot responses, used different imaging modalities and data types, and reported different performance metrics, pooling was not appropriate, and no meta-analysis or meta-regression was performed. The synthesis was structured following the Synthesis Without Meta-analysis (SWiM) guideline, with studies grouped by condition and type of AI application. Studies were grouped by type of AI application and, for keratitis, by imaging modality, and were listed by year of publication within each group. Where available, the area under the receiver operating characteristic curve (AUC) was used as the main metric for comparing diagnostic models, with sensitivity, specificity, and accuracy reported where the AUC was not available; chatbot studies were summarized using the proportion of correct responses or expert rating scores. No statistical comparisons between studies were performed. A formal risk-of-bias assessment, such as Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2), was not undertaken. Instead, key methodological features, including retrospective or prospective design, single- or multicenter data, sample size, reference standard, and internal or external validation, were considered qualitatively when interpreting the results. Findings were synthesized narratively and placed in context using pooled estimates from published meta-analyses [11,12].

Overview of AI in ophthalmology

AI refers to computer systems that perform tasks that would otherwise require human intelligence [14]. Most AI applications are based on ML, in which a system learns patterns from large datasets, and DL, a subset of ML that uses artificial neural networks, has surpassed conventional ML methods in image analysis [14,15]. Ophthalmology and radiology lead AI research because both specialties are rich in images [9]. Established examples include the FDA-approved IDx-DR system for detecting diabetic retinopathy on fundus images [16], algorithms for grading lens opacity and calculating intraocular lens power in cataract management [17], and systems that analyze optical coherence tomography (OCT), optic disc, and visual field data to detect and monitor glaucoma [18].

AI in keratitis and conjunctivitis

With the advancement of AI/ML, ocular surface pathologies such as keratitis and conjunctivitis have also been influenced by this technology [8,9].

AI systems have also been applied to anterior segment optical coherence tomography (AS-OCT) and in vivo confocal microscopy (IVCM), for example, to measure and monitor keratitis infiltrates on AS-OCT [19] and to identify fungal genera and *Acanthamoeba* on IVCM images [20,21]. These systems rely mainly on convolutional neural networks (CNNs) [8]. A variety of CNN architectures have been used in keratitis, including VGG, ResNet, DenseNet, and EfficientNet [22,23]. These models can extract complex visual details from medical images, helping physicians identify subtle disease patterns that could easily be missed or misdiagnosed [11,24,25].

Likewise, AI/ML has improved the automated assessment of ocular surface images to aid in diagnosing conjunctivitis. CNNs are particularly useful in image-driven medical diagnosis because they can autonomously learn visual patterns from digital images [15]. AI technologies can also evaluate slit-lamp images or smartphone photographs of the eye to identify features of conjunctival disease, such as conjunctival hyperemia, giant papillae, and follicles [26-28].

Another method of improving the power of AI is ensemble learning, which combines multiple trained models [22]. Ensemble systems can reduce the errors of single models and increase diagnostic reliability by combining predictions from different algorithms [22,29]. Similarly, transfer learning, which involves fine-tuning AI models pretrained on large image datasets, is often employed in medical imaging applications [30].

AI-powered chatbots are increasingly being studied in eye care. They can help educate patients, check symptoms, and triage common ocular surface problems such as conjunctivitis and keratitis [31]. These chatbots use natural language processing and large language models to converse with patients and understand their symptoms through text [32]. In conjunctivitis, which typically presents with redness, discharge, irritation, and tearing, chatbots can help identify likely causes and advise on hygiene or whether a doctor's visit is needed [33,34]. Chatbots can also help with keratitis, a condition that can lead to permanent blindness if left untreated [35,36]. Acting as screening agents, chatbots can flag warning signs that need urgent eye care, which makes them useful in tele-ophthalmology services [31]. They can also provide information on disease causes, treatment options, and prevention, helping patients become more aware of and involved in their eye health [33,34,36]. However, research on large language models in medical settings has shown mixed results, with chatbots sometimes giving wrong or misleading answers [33-36]. More recent evaluations have shown improved performance. In a 2026 study of 34 questions on epidemic keratoconjunctivitis, ChatGPT and Meta AI both achieved a mean accuracy score of 4.87 out of 5, as rated by two cornea specialists [37]. Large language models have also been used to classify social media posts about conjunctivitis to help detect possible outbreaks, with moderate correlation with the ratings of human assessors [38]. Because chatbots are updated frequently, the versions evaluated in earlier studies may no

longer reflect current performance. These systems should therefore be used as tools, not as replacements for a doctor's diagnosis.

AI-based diagnostic systems and chatbots are very promising for screening and tele-ophthalmology, especially in underserved areas where access to eye care specialists is limited [24]. Smartphone-based imaging with automated AI analysis can help screen patients with red-eye conditions, improving access to care and reducing delays in treatment [10]. Automated image analysis can also help identify corneal infections early, prompting timely referral and possibly lowering the risk of vision loss [11,24].

Table *3* summarizes studies evaluating AI in conjunctivitis, including allergic conjunctival disease and trachoma, covering slit-lamp image-based diagnostic pipelines, chatbot and large language model evaluations, objective tools for conjunctival provocation testing, natural language processing of health records and social media posts, and smartphone applications [26-28,33,34,36-40]. Table *4* summarizes studies evaluating AI in keratitis, including DL systems based on slit-lamp, handheld camera, AS-OCT, IVCM, and smartphone images, synthetic image generation, and AI-assisted clinician decision-making [19-21,23,24,29,30,41-49].

Author	Country	Condition	Study type	Description
Image-based diagnosis and smartphone applications				
Mukherjee et al. [27]	UK	Conjunctivitis	Mobile healthcare application (iConDet) using deep learning	Reported accuracy of 84%.
Socia et al. [28]	USA	Trachoma (trachomatous inflammation-follicular)	ResNet101 and VGG16 trained on about 2,300 everted eyelid images from Tanzania (about 5% positive)	Best models achieved a sensitivity of 95% and PPV of 50-70%, reducing the number of images requiring expert grading by 66-75%.
Yarin et al. [39]	Germany	Conjunctival provocation test (CPT)	Open-label prospective study of AllergoEye for quantitative evaluation of conjunctival allergic reactions in 41 patients	Sensitivity 98% and specificity 90% compared with human assessment of the allergic reaction; an efficient tool for objective measurement in CPT.
Yonehara et al. [26]	Japan	Allergic conjunctival diseases (ACD)	Dataset of 4,942 slit-lamp images from 10 ophthalmological institutions	AI pipeline diagnostic accuracy of 86.2% versus 60.0% for board-certified ophthalmologists (not statistically compared). The pipeline extracted key indicators such as hyperemia, giant papillae, and shield ulcer.
Chatbots and large language models				
Sensoy et al. [36]	Turkey	Cornea, conjunctiva, and eyelid diseases	41 questions on cornea, conjunctiva, and eyelid diseases asked to ChatGPT, Bing, and Bard	Correct answers: ChatGPT 51.2%, Bing 53.7%, and Bard 68.3% (not statistically compared). Answers may not be up to date, so caution is needed in interpretation.
Deiner et al. [38]	USA	Conjunctivitis outbreaks	12,194 conjunctivitis-related tweets from 9 locations assessed by GPT-3.5 and GPT-4	GPT-3.5 correlated with two human raters (0.60 and 0.53), with higher correlations for GPT-4; modest correlation with known epidemics.
Saad et al. [33]	Pakistan	Vernal keratoconjunctivitis (VKC)	125 responses generated by Google Gemini to 25 VKC-related questions, assessed by two independent cornea specialists	Gemini provided reliable information for diagnostic, treatment, and prognosis-related queries, with minor gaps in complex grading and treatment.
Hasnain et al. [34]	Pakistan	Conjunctivitis	ChatGPT, Claude, and DeepSeek were evaluated on conjunctivitis questions and image classification	DeepSeek provided precise and comprehensive information; ChatGPT provided generalized information for less technical discussion. Claude achieved 100% accuracy in binary image classification versus 62.5% for ChatGPT. DeepSeek showed limited ability to interpret conjunctivitis images.
Es'haghi et al. [37]	Iran	Epidemic keratoconjunctivitis (EKC)	Cross-sectional expert evaluation; 34 EKC questions answered by ChatGPT and Meta AI, scored by two cornea specialists on a 5-point scale	Mean accuracy 4.87 for both models; completeness 4.90 (ChatGPT) and 4.93 (Meta AI); inter-rater agreement κ 0.78-0.88.
Natural language processing of clinical records				
Valdés Sanz et al. [40]	Spain	Acute bacterial conjunctivitis (ABC)	EHRead® technology, based on NLP and machine learning, used to extract and analyze clinical information from 11,110 cases of acute conjunctivitis	Provided clinically relevant outcomes that could be used in clinical practice. No diagnostic performance metrics were reported.

TABLE 3: Studies evaluating artificial intelligence in conjunctivitis

Author	Country	Condition	Study type	Description
Slit-lamp, handheld camera, and smartphone photographs				
Kuo et al. [48]	Taiwan	Fungal keratitis	DenseNet-based deep learning framework compared with ophthalmologists using corneal photographs	Sensitivity, specificity, PPV, and NPV of approximately 71%, 68%, 60%, and 78%; a promising tool for identifying fungal keratitis in rural settings.
Li et al. [44]	China	Keratitis (prevention of corneal blindness)	Deep learning system for automated classification of keratitis based on 6,567 slit-lamp images	Excellent performance on images from digital slit-lamp cameras and smartphones (all AUC > 0.96); sensitivity and specificity reported as comparable to those of cornea specialists.
Sajeev et al. [45]	Australia	Infective keratitis	Conference paper; CNN applied to 446 keratitis images (271 bacterial and 175 viral)	Sensitivity 0.715, specificity 0.880, precision 0.807, accuracy 0.812, AUC 0.856.
Redd et al. [29]	India/USA	Bacterial versus fungal keratitis	Five CNNs trained on handheld-camera images of culture-proven ulcers from four centers in South India; compared with 12 cornea specialists	CNN ensemble AUC 0.84 versus 0.76 for specialists ($P < 0.01$). CNNs were more accurate for fungal (81%) than bacterial (75%) ulcers; specialists were more accurate for bacterial (88%) than fungal (56%) ulcers.
Tiwari et al. [49]	USA/India	Active corneal ulcers versus healed scars	CNN trained on 1,313 ulcer and 1,132 scar photographs; tested in India (n = 200) and the USA (n = 101)	India: sensitivity 93.5%, specificity 84.4%, AUC 0.97. USA: sensitivity 78.2%, specificity 91.3%, AUC 0.95. Grad-CAM highlighted clinically relevant features.
Li et al. [30]	China	Fungal keratitis	DenseNet121, MobileNet_v2, and SqueezeNet1_0 features with LASSO and an MLP classifier, using automatic or manual segmentation of 423 anterior segment images	Model 1 (automatic segmentation) on the testing set: accuracy 77.65%, sensitivity 86.05%, specificity 76.19%, F1-score 81.42%, AUC 0.839. Model 2 (manual segmentation) improved accuracy by 6.87% and AUC by 0.086. Images were randomly split 8:2 into training and testing sets.
Li et al. [41]	China	Multi-type infectious keratitis (bacteria, fungi, viruses, and *Acanthamoeba*)	23,055 slit-lamp images from 12 clinical centers; deep learning system DeepIK	Excellent performance in internal, external, and prospective datasets (all AUC > 0.96); outperformed DenseNet121, InceptionResNetV2, and Swin-Transformer.
Soleimani et al. [24]	USA	Microbial keratitis	Conference abstract (ARVO 2024); retrospective study of 10,739 slit-lamp images using CNNs to detect MK, differentiate bacterial, fungal, and *Acanthamoeba* keratitis, and differentiate fungal subtypes	Healthy corneas versus MK: accuracy 99.01% and 99.23%, AUC 0.99. Bacterial, fungal, and *Acanthamoeba*: accuracy 91.91%, 79.77%, and 81.27% (AUC 0.88, 0.87, 0.90). Fungal subtypes: accuracy 76.19% and 77.84% (AUC 0.78).
Taki et al. [47]	Japan	Normal cornea, infectious keratitis, and non-infectious keratitis	CorneAI for iOS applied to published journal photographs	PPV 0.91 for infectious and 0.42 for non-infectious keratitis; AUC 0.76 for infectious and 0.81 for non-infectious keratitis.
Prajna et al. [23]	India	Bacterial versus fungal keratitis	Prospective, consecutively collected dataset over one year; clinical, computer vision (EfficientNet), and multimodal models compared	Computer vision model AUC 0.81 (95% CI 0.76-0.85), AUPRC 0.94 (95% CI 0.92-0.96), accuracy 77%; the multimodal model did not substantially improve performance.
Anterior segment optical coherence tomography				
Hart et al. [19]	Australia	Microbial keratitis	Prospective observational study; DeepLabV3-based model to detect and track infiltrate size over time on AS-OCT	Lesions captured by AI in 93% of cases, with no artefacts falsely detected. Sensitivity 93% (95% CI 88-97%), specificity 100% (95% CI 88-100%), PPV 100% (95% CI 98-100%), NPV 73% (95% CI 61-83%). Identified change in most cases compared with corneal specialists.
In vivo confocal microscopy				

Tang et al. [20]	China	Fungal keratitis	Deep learning to identify fungal genera using 3,364 IVCM images from 100 patients	*Fusarium*: AUC 0.887, accuracy 0.817, sensitivity 0.791, specificity 0.831. *Aspergillus*: AUC 0.827, accuracy 0.757, sensitivity 0.756, specificity 0.759.
Shareef et al. [21]	USA	*Acanthamoeba* keratitis	Retrospective study of 3,312 IVCM images (Heidelberg Retinal Tomograph 3) from 17 patients using deep learning	Inter-rater agreement for presence or absence of AK 84%; accuracy, sensitivity, and specificity of 76% each; precision 78%.
Synthetic images and education				
Wang et al. [42]	USA	Microbial keratitis	Cross-sectional study; slit-lamp photographs of 67 healthy and 36 MK eyes; StyleGAN2-ADA used to generate synthetic images	Synthetic images depicted anatomy and pathology accurately (96.3% ± 2.19%). A screening model trained on real plus synthetic data (AUC 0.93) outperformed one trained on real data only (AUC 0.76).
Xie et al. [43]	China	Infectious keratitis (IK)	AI-generated images used to train 97 fourth-year medical students	AI-generated images significantly improved students' diagnostic accuracy for IK; may be useful where educational resources are limited.
AI-assisted clinician decision-making				
Maehara et al. [46]	Japan	Infectious and immunological keratitis	Cross-sectional study of 30 cases of each type; seven corneal specialists and 16 non-corneal specialists diagnosed images alone and then with AI classification results	Overall accuracy did not change with AI assistance (75.2 ± 8.1% vs. 75.9 ± 7.2%; P = 0.59). When AI was incorrect, accuracy of non-corneal specialists fell from 54.5 ± 27.8% to 31.6 ± 29.3% (P < 0.001). The change among the seven corneal specialists was not statistically significant.

TABLE 4: Studies evaluating artificial intelligence in keratitis

Because the included studies used different datasets, outcome measures, and validation approaches, their results cannot be compared directly, and pooled estimates from published meta-analyses provide a more reliable summary. In a meta-analysis of 35 studies including 136,401 corneal images, DL models achieved a pooled sensitivity of 91.6% (95% CI 86.8-94.8) and specificity of 90.7% (95% CI 84.8-94.5) for infectious keratitis in internal validation studies, and a sensitivity of 86.2% (95% CI 71.6-93.9) and specificity of 96.3% (95% CI 91.5-98.5) in seven external validation studies including 10,675 images. In the seven studies that compared DL models with ophthalmologists on the same images, the differences in sensitivity (89.2% (95% CI 82.2-93.6) versus 82.2% (95% CI 71.5-89.5); P = 0.20) and specificity (93.2% (95% CI 85.5-97.0) versus 89.6% (95% CI 78.8-95.2); P = 0.45) were not statistically significant; however, the absence of a significant difference does not demonstrate that the two perform equivalently. These estimates also used individual images rather than patients as the unit of analysis, which may make them unduly precise [11]. An earlier meta-analysis of 11 studies reported a pooled AUC of 0.851 and a pooled accuracy of 96.6% for distinguishing infectious from non-infectious keratitis, and a pooled AUC of 0.895 but an accuracy of only 64.38% for differentiating bacterial from fungal keratitis, highlighting that identifying the causative organism remains more difficult than detecting infection [12]. These AUC and accuracy values were pooled separately from the values reported by each study rather than derived from reconstructed 2 × 2 tables, an approach that has been criticized [11], which may explain why a very high pooled accuracy accompanies a more modest pooled AUC; these estimates should therefore be interpreted with caution. Among the included studies, an AI pipeline for allergic conjunctival disease achieved a higher diagnostic accuracy than board-certified ophthalmologists (86.2% vs. 60.0%), although no statistical comparison was reported [26], and a keratitis classification system was reported by its authors to perform comparably to cornea specialists [44]. In a direct comparison with 12 cornea specialists, an ensemble of CNNs achieved a significantly higher AUC than the specialists for differentiating bacterial from fungal keratitis (0.84 vs. 0.76; P < 0.01); the CNNs were more accurate for fungal ulcers, whereas the specialists were more accurate for bacterial ulcers [29]. When AI was tested as an aid to clinicians, it did not improve overall accuracy, and incorrect AI suggestions significantly reduced the accuracy of 16 non-corneal specialists (from 54.5% to 31.6%; P < 0.001). The change among the seven corneal specialists was not statistically significant, but this small number limits any conclusion that specialists are protected from being misled [46]. In a head-to-head comparison of model architectures on the same dataset, DeepIK outperformed DenseNet121, InceptionResNetV2, and Swin-Transformer [41], and among chatbots answering the same 41 questions, Bard answered 68.3% correctly, compared with 53.7% for Bing and 51.2% for ChatGPT, although these differences were not statistically tested [36]. These comparisons should be interpreted with caution, as most studies did not report 95% confidence intervals or test for differences. In addition, accuracy can be misleading when the numbers of diseased and healthy cases are unequal, and positive predictive value (PPV), negative predictive value (NPV), and the area under the precision-recall curve (AUPRC) depend on disease prevalence, which was rarely

reported.

The quality of the underlying evidence varied considerably. Many keratitis studies relied on retrospective image datasets, and few reported external or prospective validation [11], with notable exceptions including the 12-center DeepIK study [41], a prospective AS-OCT study [19], a prospective, consecutively collected dataset from South India [23], and a model tested in patients from India and the United States [49]. Several studies used small datasets (Table *4*) [21,30,42,45], which increases the risk of overfitting, in which a model learns features specific to its training images and performs less well on new data. Most analyses used individual images rather than patients as the unit of analysis, which may overestimate performance when several images from the same eye are included, and reference standards ranged from microbiological confirmation to clinical diagnosis [11]. Similarly, when images rather than patients are randomly divided into training and testing sets, as in one fungal keratitis study [30], images from the same eye may appear in both sets, which can also overestimate performance. Chatbot studies assessed responses to small sets of 25 to 41 questions graded by experts, which limits their generalizability [33,36]. Some sources were conference papers or abstracts with limited methodological detail [24,27,45], and their findings should be interpreted with caution.

Future directions

The possibilities for AI in ophthalmology are vast. Expected developments include multimodal AI systems that combine imaging with clinical data, real-time AI diagnostic tools, integration with tele-ophthalmology networks, and AI-assisted personalized treatment plans [14].

Currently, DL models show high accuracy in diagnosing infectious keratitis from images, with pooled sensitivity and specificity that did not differ significantly from those of ophthalmologists [11], and in one study, an ensemble of CNNs outperformed cornea specialists in differentiating bacterial from fungal keratitis [29]. However, limitations include dataset quality and a lack of generalizability [13]. Most models have been developed using relatively homogeneous datasets with limited external validation [11]. This highlights the need for prospective, multicenter validation to translate these emerging findings into real-world settings.

Several further limitations affect the reliability of current models. Image quality varies with focus, illumination, and corneal reflections, and models trained on images from one type of slit-lamp camera or acquisition protocol may perform less well on images from other devices or smartphones [11,13]. For example, when CorneAI was applied to published journal photographs, its AUCs were 0.76 for infectious keratitis and 0.81 for non-infectious keratitis [47].

Geographic and demographic representation is also limited, as many keratitis datasets originate from a small number of countries, particularly China (Table *4*), although causative organisms and patient characteristics vary widely between regions [13]. However, a model trained on images from India maintained high performance when tested in patients from the United States, with AUCs of 0.97 in India and 0.95 in the United States [49]. Few studies have performed external validation, and calibration, which reflects how closely predicted probabilities match observed outcomes, is rarely reported, limiting the use of model outputs for clinical risk estimation.

Finally, false-negative results carry particular risk in sight-threatening keratitis, where a missed or delayed diagnosis of bacterial, fungal, or *Acanthamoeba* keratitis can lead to corneal perforation and permanent vision loss. Even models with high specificity may have modest NPV; for instance, an AS-OCT-based system reported an NPV of 73% [19]. AI tools used for screening should therefore prioritize high sensitivity, and a negative AI result should not delay specialist review in patients with suggestive clinical features. AI-derived lesion measurements, such as infiltrate size tracked over time on AS-OCT [19], may also serve as objective markers of treatment response, although their relationship with final visual outcomes has not yet been established.

Federated multicenter validation trials can test generalizability globally, across different continents, pathogens, and imaging devices [13]. These trials can determine whether AI maintains its performance across different populations, assess geographic bias, and provide external validation [13].

Another limitation of current studies is the use of single-modality imaging, such as slit-lamp photographs or OCT, with limited clinical context. Multimodal AI systems aim to integrate imaging with clinical findings, such as pain, photophobia, and discharge, and risk factors, such as contact lens use, trauma, and immunosuppression, to improve pathogen differentiation. However, the evidence so far is mixed. In a prospective study from South India, a computer vision model achieved an AUC of 0.81 for differentiating bacterial from fungal keratitis, and adding clinical data in a multimodal model did not substantially improve performance [23]. The same study showed that a model trained on prospective, consecutively collected data outperformed an identical model trained on images from earlier clinical trials, highlighting the importance of representative training data [23].

Multimodal AI has been used in other specialties, such as dermatology, with promising diagnostic accuracy, showing great potential for multimodal DL in assisting primary care doctors in diagnosing skin conditions [50]. This may be equally applicable to ophthalmic AI in low- and middle-income countries (LMICs) that have limited access to specialized tertiary centers. There, it could enable faster diagnosis, which is essential in a disease such as keratitis, where quick and accurate diagnosis is key to preventing blindness [1].

The integration of AI with tele-ophthalmology can be extremely valuable because noninvasive imaging is routinely used in the diagnosis and monitoring of various ophthalmological conditions [51]. Wu et al. proposed a future model that integrates AI with at-home patient monitoring, telemedicine, remote robot-assisted surgery, and tertiary centers [51]. The proposed system aims to enable diagnostic screening and follow-up monitoring while reducing unnecessary physical visits and healthcare resource consumption [51]. Although this model was designed for retinal diseases, the same principles may be applied to keratitis and conjunctivitis.

Ethical and clinical considerations

The rapid incorporation of AI technology into the diagnosis and assessment of keratitis and conjunctivitis calls for a critical analysis of the ethical and clinical frameworks that govern its application. Although AI holds great promise for diagnostic accuracy in ophthalmology [12], a host of issues complicate accountability and raise critical questions about the fundamental nature of the clinician-patient relationship.

The ethical issues in applying AI in ophthalmology center on ensuring patient safety and accountability in the event of a misdiagnosis. Given the rapid progression of keratitis to permanent blindness [1], there is a critical need to ensure "algorithmic accountability." However, current research shows that although AI performs well compared with human clinicians, physicians remain considerably skeptical [12,52]. In a 2025 study, only 12.1% of ophthalmologists reported trusting AI recommendations as much as those of their peers, and 74.8% cited legal liability as a major barrier to incorporating AI into clinical practice [52]. Moreover, there is a critical risk of "automation bias," whereby a clinician could be misled by a false AI recommendation, posing a risk to patient safety [46]. Because there are no standardized guidelines for "AI malpractice," the burden of a missed diagnosis currently rests entirely on the clinician [53].

The biggest impediment to the clinical application of DL models has been the so-called "black box" problem, in which the logic behind the system's decision remains unknown [54]. In ocular surface disorders, however, explainable AI (XAI) has been recognized as a crucial innovation for promoting transparency [26]. For instance, heatmap visualization methods such as Grad-CAM [55] show the regions of an image on which a model relied; in one keratitis model, these heatmaps highlighted clinically relevant features such as corneal infiltrates, hypopyon, and conjunctival injection [49]. A more recent XAI innovation is the Eye-XAI framework, which combines XAI techniques with analysis of patient symptoms and clinical data to provide a comprehensive explanation for the diagnosis [56]. This enables the clinician to understand the logic behind the diagnostic recommendation rather than simply receiving a "yes/no" answer [56].

Ultimately, AI has been recognized as a supplement to the expertise of clinical staff [46]. One study showed that incorrect AI suggestions significantly reduced the diagnostic accuracy of non-corneal specialists, whereas no significant change was observed among corneal specialists, although only seven specialists were included [46]. AI is therefore best positioned as a screening tool in resource-scarce settings or as a "second reader" that can analyze extensive information presented in a variety of formats [24,54]. This allows the ophthalmologist to concentrate on the human side of the patient interaction and to be more deeply human [57], taking into account determinants of health such as the patient's personal preferences in the final management plan for keratitis or conjunctivitis.

Limitations of this review

This review has several limitations. Although a structured search was performed, the review was not prospectively registered, and study selection may be subject to bias. Only English-language publications were included, and no formal risk-of-bias assessment or meta-analysis was performed. Six studies were added when the literature search was updated, and keratoconjunctivitis, trachoma, and allergic conjunctivitis were not included as separate search terms, indicating that the original search may not have captured all relevant studies. The included studies used heterogeneous designs, datasets, and outcome measures, which precluded direct quantitative comparison. Some evidence was drawn from conference papers and abstracts with limited methodological detail. In addition, most included studies did not report confidence intervals or the unit of analysis, which limits the assessment of the precision of their results. Finally, AI, and large language models in particular, is evolving rapidly, and the performance of the chatbots evaluated in the included studies may not reflect that of their current versions.

Conclusions

The use of AI-driven diagnostic models has the potential to accelerate clinical workflows, reduce the burden of inappropriate antibiotic use, and extend expertise-based screening to resource-poor and rural areas within a teleophthalmic context. However, the transition from controlled, retrospective projects to the clinic

poses a series of complex issues. The field must address problems of dataset generalizability, geographic bias, and the opaque nature of the processes of making expert decisions using DL algorithms. Also, the ethical and legal implications of algorithmic accountability are crucial. This involves using XAI, which facilitates transparency and clarifies the reasoning behind AI-driven recommendations, to ensure patient safety. Also, AI must function as a robust multimodal add-on, an efficient "second reader" that can interpret complex clinical and imaging data. In this way, AI can relieve diagnostic bottlenecks and support ophthalmologists and primary care physicians.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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References

1. Ung L, Bispo PJ, Shanbhag SS, Gilmore MS, Chodosh J: The persistent dilemma of microbial keratitis: global burden, diagnosis, and antimicrobial resistance. Surv Ophthalmol. 2019, 64:255-71. 10.1016/j.survophthal.2018.12.003
2. Merali FI, Schein OD: Epidemiology of corneal diseases. Foundations of Corneal Disease, Past, Present and Future. Colby K, Dana R (ed): Springer, Cham; 2019. 10.1007/978-3-030-25335-6_26
3. Flaxman SR, Bourne RRA, Resnikoff S, et al.: Global causes of blindness and distance vision impairment 1990-2020: a systematic review and meta-analysis. Lancet Glob Health. 2017, 5:1221-34. 10.1016/S2214-109X(17)30393-5
4. Whitcher JP, Srinivasan M, Upadhyay MP: Corneal blindness: a global perspective. Bull World Health Organ. 2001, 79:214-21.
5. Whitcher JP, Srinivasan M: Corneal ulceration in the developing world - a silent epidemic . Br J Ophthalmol. 1997, 81:622-3. 10.1136/bjo.81.8.622
6. Varu DM, Rhee MK, Akpek EK, et al.: Conjunctivitis Preferred Practice Pattern®. Ophthalmology. 2019, 126:P94-P169. 10.1016/j.ophtha.2018.10.020
7. O'Brien TP, Jeng BH, McDonald M, Raizman MB: Acute conjunctivitis: truth and misconceptions . Curr Med Res Opin. 2009, 25:1953-61. 10.1185/03007990903038269
8. Tahvildari M, Singh RB, Saeed HN: Application of artificial intelligence in the diagnosis and management of corneal diseases. Semin Ophthalmol. 2021, 36:641-8. 10.1080/08820538.2021.1893763
9. Li JO, Liu H, Ting DS, et al.: Digital technology, tele-medicine and artificial intelligence in ophthalmology: a global perspective. Prog Retin Eye Res. 2021, 82:100900. 10.1016/j.preteyeres.2020.100900
10. Nusair O, Asadigandomani H, Farrokhpour H, et al.: Clinical applications of artificial intelligence in corneal diseases. Vision (Basel). 2025, 9:71. 10.3390/vision9030071
11. Ong ZZ, Sadek Y, Qureshi R, et al.: Diagnostic performance of deep learning for infectious keratitis: a systematic review and meta-analysis. EClinicalMedicine. 2024, 77:102887. 10.1016/j.eclinm.2024.102887
12. Sarayar R, Lestari YD, Setio AA, Sitompul R: Accuracy of artificial intelligence model for infectious keratitis classification: a systematic review and meta-analysis. Front Public Health. 2023, 11:1239231. 10.3389/fpubh.2023.1239231
13. Assaf JF, Ahuja AS, Kannan V, Yazbeck H, Krivit J, Redd TK: Applications of computer vision for infectious keratitis: a systematic review. Ophthalmol Sci. 2025, 5:100861. 10.1016/j.xops.2025.100861
14. Ting DS, Pasquale LR, Peng L, et al.: Artificial intelligence and deep learning in ophthalmology . Br J Ophthalmol. 2019, 103:167-75. 10.1136/bjophthalmol-2018-313173

15. Shobayo O, Saatchi R: Developments in deep learning artificial neural network techniques for medical image analysis and interpretation. Diagnostics (Basel). 2025, 15:1072. 10.3390/diagnostics15091072
16. Ahuja AS, Wagner IV, Dorairaj S, Checo L, Hulzen RT: Artificial intelligence in ophthalmology: a multidisciplinary approach. Integr Med Res. 2022, 11:100888. 10.1016/j.imr.2022.100888
17. Ahuja AS, Paredes Iii AA, Eisel ML, Kodwani S, Wagner IV, Miller DD, Dorairaj S: Applications of artificial intelligence in cataract surgery: a review. Clin Ophthalmol. 2024, 18:2969-75. 10.2147/OPTH.S489054
18. Lan CH, Chiu TH, Yen WT, Lu DW: Artificial intelligence in glaucoma: advances in diagnosis, progression forecasting, and surgical outcome prediction. Int J Mol Sci. 2025, 26:4473. 10.3390/ijms26104473
19. Hart C, Chen X, Ahmed M, et al.: AI-MK: artificial intelligence for assessing and monitoring microbial keratitis. BMJ Open Ophthalmol. 2026, 11:2556. 10.1136/bmjophth-2025-002556
20. Tang N, Huang G, Lei D, et al.: An artificial intelligence approach to classify pathogenic fungal genera of fungal keratitis using corneal confocal microscopy images. Int Ophthalmol. 2023, 43:2203-14. 10.1007/s10792-022-02616-8
21. Shareef O, Soleimani M, Tu E, et al.: A novel artificial intelligence model for diagnosing Acanthamoeba keratitis through confocal microscopy. Ocul Surf. 2024, 34:159-64. 10.1016/j.jtos.2024.07.010
22. Ghosh AK, Thammasudjarit R, Jongkhajornpong P, Attia J, Thakkinstian A: Deep learning for discrimination between fungal keratitis and bacterial keratitis: DeepKeratitis. Cornea. 2022, 41:616-22. 10.1097/ICO.0000000000002830
23. Prajna NV, Assaf J, Acharya NR, et al.: Multimodal deep learning for differentiating bacterial and fungal keratitis using prospective representative data. Ophthalmol Sci. 2025, 5:100665. 10.1016/j.xops.2024.100665
24. Soleimani M, Rahdar A, Esmaili K, et al.: AI-assisted diagnosis and subtype differentiation of microbial keratitis: one step forward to mitigate health disparities. Invest Ophthalmol Vis Sci. 2024, 65:1503.
25. Hu S, Sun Y, Li J, et al.: Automatic diagnosis of infectious keratitis based on slit lamp images analysis . J Pers Med. 2023, 13:519. 10.3390/jpm13030519
26. Yonehara M, Nakagawa Y, Ayatsuka Y, et al.: Use of explainable AI on slit-lamp images of anterior surface of eyes to diagnose allergic conjunctival diseases. Allergol Int. 2025, 74:86-96. 10.1016/j.alit.2024.07.004
27. Mukherjee P, Bhattacharyya I, Mullick M, Kumar R, Dutta Roy N, Mahmud M: iConDet: an intelligent portable healthcare app for the detection of conjunctivitis. Applied Intelligence and Informatics. Mahmud M, Kaiser MS, Kasabov N, Iftekharuddin K, Zhong N (ed): Springer, Cham; 2021. 1435:10.1007/978-3-030-82269-9_3
28. Socia D, Brady CJ, West SK, Cockrell RC: Detection of trachoma using machine learning approaches . PLoS Negl Trop Dis. 2022, 16:e0010943. 10.1371/journal.pntd.0010943
29. Redd TK, Prajna NV, Srinivasan M, et al.: Image-based differentiation of bacterial and fungal keratitis using deep convolutional neural networks. Ophthalmol Sci. 2022, 2:100119. 10.1016/j.xops.2022.100119
30. Li DJ, Huang BL, Peng Y: Comparisons of artificial intelligence algorithms in automatic segmentation for fungal keratitis diagnosis by anterior segment images. Front Neurosci. 2023, 17:1195188. 10.3389/fnins.2023.1195188
31. Ma R, Cheng Q, Yao J, et al.: Multimodal machine learning enables AI chatbot to diagnose ophthalmic diseases and provide high-quality medical responses. NPJ Digit Med. 2025, 8:64. 10.1038/s41746-025-01461-0
32. Huo B, Boyle A, Marfo N, et al.: Large language models for chatbot health advice studies: a systematic review. JAMA Netw Open. 2025, 8:e2457879. 10.1001/jamanetworkopen.2024.57879
33. Saad M, Moqeet MA, Mansoor H, et al.: Evaluating the efficacy of artificial intelligence-driven chatbots in addressing queries on vernal conjunctivitis. Cureus. 2025, 17:e79688. 10.7759/cureus.79688
34. Hasnain M, Aurangzeb K, Alhussein M, Ghani I, Mahmood MH: AI in conjunctivitis research: assessing ChatGPT and DeepSeek for etiology, intervention, and citation integrity via hallucination rate analysis. Front Artif Intell. 2025, 8:1579375. 10.3389/frai.2025.1579375
35. Antaki F, Touma S, Milad D, El-Khoury J, Duval R: Evaluating the performance of ChatGPT in ophthalmology: an analysis of its successes and shortcomings. Ophthalmol Sci. 2023, 3:100324. 10.1016/j.xops.2023.100324
36. Sensoy E, Citirik M: Assessing the proficiency of artificial intelligence programs in the diagnosis and treatment of cornea, conjunctiva, and eyelid diseases and exploring the advantages of each other benefits. Cont Lens Anterior Eye. 2024, 47:102125. 10.1016/j.clae.2024.102125
37. Es'haghi A, Aliyariparand M, Jamalipour Soufi K, Aghaei H: Accuracy and completeness of large language models in epidemic keratoconjunctivitis queries: a comparative study. Int J Med Inform. 2026, 213:106363. 10.1016/j.ijmedinf.2026.106363
38. Deiner MS, Deiner NA, Hristidis V, McLeod SD, Doan T, Lietman TM, Porco TC: Use of large language models to assess the likelihood of epidemics from the content of tweets: infodemiology study. J Med Internet Res. 2024, 26:e49139. 10.2196/49139
39. Yarin Y, Kalaitzidou A, Bodrova K, Mösges R, Kalaidzidis Y: Validation of AI-based software for objectification of conjunctival provocation test. J Allergy Clin Immunol Glob. 2023, 2:100121. 10.1016/j.jacig.2023.100121
40. Valdés Sanz N, García-Layana A, Colas T, Moriche M, Montero Moreno M, Ciprandi G: Clinical characterization of inpatients with acute conjunctivitis: a retrospective analysis by natural language processing and machine learning. Appl Sci. 2022, 12:12352. 10.3390/app122312352
41. Li Z, Xie H, Wang Z, et al.: Deep learning for multi-type infectious keratitis diagnosis: a nationwide, cross-sectional, multicenter study. NPJ Digit Med. 2024, 7:181. 10.1038/s41746-024-01174-w
42. Wang D, Sklar B, Tian J, Gabriel R, Engelhard M, McNabb RP, Kuo AN: Improving artificial intelligence-based microbial keratitis screening tools constrained by limited data using synthetic generation of slit-lamp photos. Ophthalmol Sci. 2025, 5:100676. 10.1016/j.xops.2024.100676
43. Xie W, Yuan Z, Si Y, Huang Z, Li Y, Wu F, Yao YF: Enhancing medical students' diagnostic accuracy of infectious keratitis with AI-generated images. BMC Med Educ. 2025, 25:1027. 10.1186/s12909-025-07592-y
44. Li Z, Jiang J, Chen K, et al.: Preventing corneal blindness caused by keratitis using artificial intelligence . Nat Commun. 2021, 12:3738. 10.1038/s41467-021-24116-6

45. Sajeev S, Prem Senthil M: Classifying infective keratitis using a deep learning approach. Proceedings of the 2021 Australasian Computer Science Week Multiconference. Proc 2021 Australas Comput Sci Week Multiconf. 2021, 20:1-4. 10.1145/3437378.3437388
46. Maehara H, Ueno Y, Yamaguchi T, et al.: The importance of clinical experience in AI-assisted corneal diagnosis: verification using intentional AI misleading. Sci Rep. 2025, 15:1462. 10.1038/s41598-025-85827-0
47. Taki Y, Ueno Y, Oda M, Kitaguchi Y, Ibrahim OM, Aketa N, Yamaguchi T: Analysis of the performance of the CorneAI for iOS in the classification of corneal diseases and cataracts based on journal photographs. Sci Rep. 2024, 14:15517. 10.1038/s41598-024-66296-3
48. Kuo MT, Hsu BW, Yin YK, et al.: A deep learning approach in diagnosing fungal keratitis based on corneal photographs. Sci Rep. 2020, 10:14424. 10.1038/s41598-020-71425-9
49. Tiwari M, Piech C, Baitemirova M, et al.: Differentiation of active corneal infections from healed scars using deep learning. Ophthalmology. 2022, 129:139-46. 10.1016/j.ophtha.2021.07.033
50. Liu Y, Jain A, Eng C, et al.: A deep learning system for differential diagnosis of skin diseases . Nat Med. 2020, 26:900-8. 10.1038/s41591-020-0842-3
51. Wu CT, Lin TY, Lin CJ, Hwang DK: The future application of artificial intelligence and telemedicine in the retina: a perspective. Taiwan J Ophthalmol. 2023, 13:133-41. 10.4103/tjo.TJO-D-23-00028
52. Tappeiner C: Artificial intelligence in ophthalmology: acceptance, clinical integration, and educational needs in Switzerland. J Clin Med. 2025, 14:6307. 10.3390/jcm14176307
53. Ratti E, Morrison M, Jakab I: Ethical and social considerations of applying artificial intelligence in healthcare-a two-pronged scoping review. BMC Med Ethics. 2025, 26:68. 10.1186/s12910-025-01198-1
54. Nguyen T, Ong J, Masalkhi M, et al.: Artificial intelligence in corneal diseases: a narrative review . Cont Lens Anterior Eye. 2024, 47:102284. 10.1016/j.clae.2024.102284
55. Selvaraju RR, Cogswell M, Das A, Vedantam R, Parikh D, Batra D: Grad-CAM: visual explanations from deep networks via gradient-based localization. Int J Comput Vis. 2020, 128:336-59. 10.1007/s11263-019-01228-7
56. Marouf AA, Mottalib MM, Ridi SS, Jafarullah O, Rokne J, Alhajj R: Eye-XAI: an explainable artificial intelligence approach for eye disease detection using symptom analysis. BMC Med Inform Decis Mak. 2025, 25:433. 10.1186/s12911-025-03253-8
57. Topol E: Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again . Basic Books, New York; 2019.