Review Article

A review of artificial intelligence applications in anterior segment ocular diseases

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ABSTRACT

Background: Artificial intelligence (AI) has great potential for interpreting and analyzing images and processing large amounts of data. There is a growing interest in investigating the applications of AI in anterior segment ocular diseases. This narrative review aims to assess the use of different AI-based algorithms for diagnosing and managing anterior segment entities.

Methods: We reviewed the applications of different AI-based algorithms in the diagnosis and management of anterior segment entities, including keratoconus, corneal dystrophy, corneal grafts, corneal transplantation, refractive surgery, pterygium, infectious keratitis, cataracts, and disorders of the corneal nerves, conjunctiva, tear film, anterior chamber angle, and iris. The English-language databases PubMed/MEDLINE, Scopus, and Google Scholar were searched using the following keywords: artificial intelligence, deep learning, machine learning, neural network, anterior eye segment diseases, corneal disease, keratoconus, dry eye, refractive surgery, pterygium, infectious keratitis, anterior chamber, and cataract. Relevant articles were compared based on the use of AI models in the diagnosis and treatment of anterior segment diseases. Furthermore, we prepared a summary of the diagnostic performance of the AI-based methods for anterior segment ocular entities.

Results: Various AI methods based on deep and machine learning can analyze data obtained from corneal imaging modalities with acceptable diagnostic performance. Currently, complicated and time-consuming manual methods are available for diagnosing and treating eye diseases. However, AI methods could save time and prevent vision impairment in eyes with anterior segment diseases. Because many anterior segment diseases can cause irreversible complications and even vision loss, sufficient confidence in the results obtained from the designed model is crucial for decision-making by experts.

Conclusions: AI-based models could be used as surrogates for analyzing manual data with improved diagnostic performance. These methods could be reliable tools for diagnosing and managing anterior segment ocular diseases in the near future in remote areas. It is expected that future studies can design algorithms that use less data in a multitasking manner for the detection and management of anterior segment diseases.

KEYWORDS

artificial intelligence, deep learning, machine learning, anterior eye segments, corneal disease, keratoconus, cataract, refractive surgery, pterygium, keratitis

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INTRODUCTION

Artificial intelligence (AI) is a new topic in computer science that imitates human cognition and behavior [1]. Machine learning (ML) and deep learning (DL) are important branches in this growing scientific field. Recently, AI has shown great potential for use in medical research owing to its ability to process data [2]. In ophthalmology, researchers have investigated the use of AI in posterior segment diseases, particularly retinal diseases [3].

Currently, anterior segment diseases with a risk of permanent eye impairment have encouraged researchers to use AI models [4, 5]. Timely diagnosis and appropriate treatment are important to prevent vision loss [6]. Routine clinical practices may be time-consuming and result in poor decision-making. Therefore, by designing tools based on AI methods, diagnosis and management can be performed with greater accuracy, less time, and lower cost [6, 7]. Despite various studies on the application of AI in ophthalmology, challenges remain that have been overlooked by researchers [8].

To our knowledge, few studies have compared different applications of AI in anterior segment diseases [3, 9]. This narrative review aims to assess the applications and diagnostic performance of AI in anterior segment entities, including keratoconus, corneal dystrophy, corneal grafts, corneal transplantation, refractive surgery, pterygium, infectious keratitis, cataracts, and disorders of the corneal nerves, conjunctiva, tear film, anterior chamber angle, and iris.

METHODS

The English-language literature published from April 1999 to August 2022 was searched via the PubMed/MEDLINE, Scopus, and Google Scholar databases using the following keywords for AI and anterior segment ocular diseases: "artificial intelligence," "deep learning," "machine learning," "neural network," "anterior eye segment," "corneal disease," "keratoconus," "dry eye," "refractive surgery," "pterygium," "infectious keratitis," "anterior chamber," and "cataract." The extracted articles were first reviewed by title and abstract, then the full texts of relevant articles were examined for parameters related to the detection and management of anterior segment disease.

RESULTS

We compared the relevant articles based on the application of AI-based models in the diagnosis and treatment of anterior segment ocular diseases. Furthermore, we prepared a summary of the diagnostic performance of AI-based methods for these purposes (Table 1). AI-based models based on DL and ML can analyze data obtained from corneal imaging modalities with an acceptable diagnostic performance (Table 1). Currently, complicated and time-consuming manual methods are available for diagnosing and treating eye diseases. AI methods could save time and prevent vision impairment in eyes with anterior segment diseases. In the Discussion section below, the retrieved studies concerning AI-based models for diagnosing and treating anterior segment ocular diseases are outlined.

DISCUSSION

Keratoconus

Keratoconus (KCN) is a bilateral, non-inflammatory, asymmetric ectatic corneal disorder that can cause corneal irregularity, increased aberrations, and even vision loss [3]. As KCN is a progressive disease, timely diagnosis could save vision [3, 55]. Imaging modalities used for the diagnosis of KCN include placido disc-based corneal topography, three-dimensional corneal tomography, anterior segment optical coherence tomography (AS-OCT), and biomechanical assessment [56].

The diagnostic accuracy of corneal imaging methods based on AI models has been evaluated in some studies. Feedforward neural networks, convolutional neural networks (CNN), support vector machine (SVM) learning, multilayer perceptron (MLP), and decision tree classification (DT) are effective in differentiating keratoconic eyes from normal eyes [3]. Kamiya et al. [10] found that CNN using six color-coded maps obtained from AS-OCT could distinguish a healthy cornea from that of KCN with an accuracy of 99.1% and could also evaluate KCN severity. In another study, Lavrik and Valentin [11] detected KCN with a high accuracy (99.3%) using a CNN (KeratoDetect, Keratoconus Detection Algorithm). In addition, AI can predict the results of KCN treatment. Valdes-Mas et al. [13] predicted postoperative visual quality based on corneal shape changes using an artificial neural network (ANN).

Table 1. Summary of studies on the diagnostic performance of artificial intelligence-based models in anterior segment ocular entities

Author (Year of Publication)	Instruments	Number of Eyes and/or Images	AI algorithms	Diagnostic performance (%)
Keratoconus				
Kamiya et al. (2019) [10]	AS-OCT	239 normal eyes 304 eyes with KCN (108 eyes grade I, 75 eyes grade II, 42 eyes grade III, and 79 eyes grade IV)	CNN	Accuracy: 99.1 Sensitivity: 98.4 Specificity: 100
Lavric et al. (2019) [11]	Pentacam	1,500 normal eye 1,500 eyes with KCN	KeratoDetect CNN	Accuracy: 99.3
Yousefi et al. (2018) [12]	AS-OCT	3,156 eyes with valid Ectasia Status Index	Unsupervised ML	Sensitivity: 97.7 Specificity: 94.1
Valdes-Mas et al. (2014) [13]	-	288 eyes with KCN	ANN MLP	Mean Absolute Error: 95
Issarti et al. (2019) [14]	Pentacam	312 normal eyes, 77, 220, and 229 eyes with KCN suspect, mild KCN, and moderate KCN, respectively	Feedforward NN	Accuracy: 96.6 Sensitivity: 95.6 Specificity: 97.8
Ruiz Hidalgo et al. (2017) [15]	Pentacam	131 eyes	SVM and binary classification	Accuracy: 98.9 Specificity: 99.1
Xu et al. (2022) [16]	Pentacam	430 normal eyes, 231 unaffected eyes from asymmetric KCN, and 447 eyes with KCN	KerNet and index derived AI models (XGBoost, LGBM, LR and RF)	KerNet on validation set -Accuracy: 94.12 -AUC: 99 Index derived AI models: -Accuracy: 84.02 – 86.98 -AUC: 94.4 – 96.8
Herber et al. (2021) [17]	Pentacam	116 normal eyes 318 eyes with KCN	LDA and RF algorithms	The overall accuracy for: - LDA: 71.0 - RF: 78.0
Hazarbassanov et al. (2022) [18]	AS-OCT and Pentacam	6,961 eyes	Unsupervised ML (FPA-K-means)	Accuracy: 96.03 Precision: 96.29
Firat et al. (2022) [19]	Pentacam	341 normal 341 eyes with KCN	AlexNet (SVM)	Accuracy: 98.53 Sensitivity: 98.06 Specificity: 99.01
Corneal Transplantation				
Treder et al. (2019) [20]	AS-OCT	Eyes post-DMEK surgery 1,172 AS-OCT images (609: attached graft; 563: detached graft) for training and testing	DT	Accuracy: 96 Sensitivity: 98 Specificity: 94
Hayashi et al. (2020) [21]	AS-OCT	31 eyes with rebubbling 31 eyes with no rebubbling 469 images	DNN	AUC: 96 Sensitivity: 96.7 Specificity: 91.5
Abou Shousha et al. (2020) [22]	OCT	3,900 normal eyes 3,900 eyes with graft rejection 12,000 OCT images	DCNN	AUC: 99 Accuracy: 100
Mangana et al. (2022) [23]	-	220 images of post-keratoplasty anterior pole eyes	AutoML	Accuracy: 99.5 Sensitivity: 95.8 Specificity: 95.5
Elsawy et al. (2021) [24]	AS-OCT	879 eyes 158,220 AS-OCT images (45,900; 16,740; 64,800; and 30,780 images of healthy eyes, eyes with FECD, KCN, and eyes with DES, respectively)	MDDN	AUC: 99 F1 scores: 90
Refractive Surgery				
Lopes et al. (2018) [25]	Pentacam	2,980; 71; and 182 eyes with stable LASIK, PLE, and KCN, respectively	RF, CNN, Bayers network, SVM	AUC: 97 Accuracy: 94.2 Sensitivity: 96.6 Specificity: 98.8
Yoo et al. (2019) [26]	Pentacam	153 eyes (1, 108, and 42 eyes with PLE, KCN, FFKCN, respectively) 10,561 images	Ensemble classifier based on ML (SVM, ANN, RF, LASSO [a feature of NN], AdaBoost)	AUC: 98.1 Internal Accuracy: 94.1 External Accuracy: 93.4

Continued Table 1. Summary of studies on the diagnostic performance of artificial intelligence-based models in anterior segment ocular entities

Saad et al. (2016) [27]	OPD-Scan	114 post-LASIK stable eyes 62 eyes with FFKCN	DF	AUC: 97 Sensitivity: 63 (for FFKCN) Sensitivity: 100 (for KCN) Specificity: 82
Yoo et al. (2020) [28]	Slit lamp, Pentacam	18,480 healthy eyes	A multiclass XGBoost model	Accuracy: 81
Khamar et al. (2020) [29]	OCT	76 eyes (22, 22, 15, and 1 eyes after LASIK, SMILE, PRK, and transepithelial PRK refractive surgeries, respectively)	DT	AUC: 79 Sensitivity: 86.4 Specificity: 71.9
Pterygium				
Zulkifley et al. (2019) [30]	Slit lamp	60 normal eyes 60 eyes with pterygium	CNN	Accuracy: 81.1 Sensitivity: 95 Specificity: 98.3
Wan Zaki et al. (2018) [31]	Slit lamp	2,692 normal eyes 325 eyes with pterygium	SVM	Accuracy: 91.2 Sensitivity: 88.7 Specificity: 88.3 AUC: 95.6
Hung et al. (2022) [32]	Slit lamp	61 normal eyes 176 eyes with pterygium	DL, MLP	Accuracy: 91.7 Sensitivity: 91.7 Specificity: 91.7 F1 score: 84.6
Xu et al. (2021) [33]	Slit lamp	190 normal eyes 162 eyes with pterygium 1,220 images	PyCharm – EfficientNet-B6	Accuracy: 94.68 AUC: 93.7 Sensitivity: 90.06 Specificity: 97.32
Jais et al. (2021) [34]	-	93 eyes with pterygium	RapidMiner – SVM	Accuracy: 94.44 Specificity: 100 Sensitivity: 92.14
Infectious Keratitis				
Saini et al. (2003) [35]	-	106 eyes with corneal ulcer (either bacterial or fungal keratitis)	ANN	Accuracy: 90.7 Specificity (bacterial): 100 Specificity (fungal): 76.4
Wu et al. (2018) [36]	Confocal microscopy	378 images	DT, KNN, LR, SVM	AUC: 86 – 98 Accuracy: 81.7 – 99.1 Sensitivity: 78.5 – 98.5 Specificity: 87.4 – 98.9
Liu et al. (2020) [37]	Confocal microscopy (fungal keratitis)	1,213 images (994 abnormal images and 219 normal images)	CNN	Accuracy: 100 Sensitivity: 99.9 Specificity: 100
Kuo et al. (2020) [38]	Fundus photography and slit lamp microscopy	288 images (fungal keratitis)	DenseNet algorithm (a representative CNN based on DL)	Accuracy: 70 Sensitivity: 71 Specificity: 68
Essalat et al. (2022) [39]	Confocal microscopy	4,001 eyes: 897; 1,391; 1,004; and 743 eyes with fungal keratitis, acanthamoeba keratitis, NSK, and normal eyes, respectively	CNN (DenseNet161)	Accuracy: 93.55 Precision: 92.52 Recall: 94.77 F1 score: 96.93
Ghosh et al. (2022) [40]	Slit lamp	66 eyes with fungal keratitis 128 eyes with bacterial keratitis (779 and 1,388 images from eyes with fungal and bacterial keratitis, respectively).	CNN (VGG19, ResNet50, and DenseNet121)	Precision and sensitivity respectively: - VGG19: 88. 70 - DenseNet121: 61. 85 - RestNet50: 57. 85
Natarajan et al. (2022) [41]	Slit lamp	177 images from eyes with herpes simplex viral stromal necrotizing keratitis and 130 images from eyes with culture-proven non-viral keratitis (43 bacterial and 87 fungal keratitis).	CNN (DenseNet and ResNet)	AUC: 73 Accuracy: 72 Sensitivity: 69.6 Specificity: 76.5

Continued Table 1. Summary of studies on the diagnostic performance of artificial intelligence-based models in anterior segment ocular entities

Anterior Chamber Angle and Iris				
Xu et al. (2019) [42]	AS-OCT	4,036 AS-OCT images, with corresponding 1,943 and 2,093 open and close angle gonioscopy grade, respectively	Modified ResNet-18	AUC: 93.3 Accuracy: 89.1 – 98.4
Fu et al. (2019) [43]	AS-OCT	2,113 OCT images (7,375 open-angle and 895 angle-closure glaucoma)	VGG-16 (CNN)	AUC: 96 Sensitivity: 90 Specificity: 92
Fu et al. (2020) [44]	AS-OCT HD-OCT	4,135 images by AS-OCT and 701 images by HD-OCT (7,475 open-angle and 895 angle-closure glaucoma)	MLDN	Accuracy: 91.2 – 91.8 Sensitivity: 87.4 – 93.0 Specificity: 90.8 – 95.1
Shi et al. (2019) [45]	UBM	540 eyes with open-angle and angle-closure 540 UBM images	Inception v3 CNN	AUC: 99 Accuracy: 97.2 Sensitivity: 96.3 – 98.2 Specificity: 98.1 – 99.1
Dimililer et al. (2016) [46]	-	50 normal eyes 50 eyes with iris tumor 100 images of two databases (MilesResearch and EyeCancer)	BPNN	Accuracy: 95.7
Liu et al. (2022) [47]	AS-OCT	116 normal eyes 171 eyes with primary angle-closure glaucoma 5,166 images	DLLSS and MPSS	-
Shon et al. (2022) [48]	Visual field test	9,212 eyes with primary open-angle glaucoma	CNN	AUC: 86.4 Sensitivity: 42 Specificity: 95
Cataract				
Xu et al. (2020) [49]	Fundus camera	8,030 fundus images: 2,212; 1,871; 2,272; and 1,675 fundus images of eyes with no cataract, eyes with mild, moderate, and severe cataract, respectively	AlexNet + VisualDN (CNN)	Accuracy: 86.2 Sensitivity: 79.8 – 95.0 Specificity: 83.3 – 88.4
Zhang et al. (2019) [50]	Fundus camera	1,352 images (487, 317, 124, 154, 135, and 135 images of eyes with no cataract, eyes with slightly mild, mild, medium, slightly severe, and severe cataracts, respectively)	SVM + FCNN	Accuracy: 92.66 Sensitivity: 99.4
Jiang et al. (2018) [51]	Slit lamp	6,090 slit lamp images of pseudophakic eyes	TempSeq-Net (CNN)	AUC: 97 Accuracy: 92.2 Sensitivity: 81.0 Specificity: 91.4
Ahn et al. (2022) [52]	AS-OCT, Optical biometry	2,332 anterior segment images	v4 CNN and ResNet (DNN)	-
Shimizu et al. (2021) [53]	Slit lamp	18,596 images	ML	Accuracy: 87.8 Sensitivity: 99.6 Specificity: 96
Junayed et al. (2021) [54]	Fundus camera	2,067 normal images 2,679 cataract images	CataractNet (CNN)	Accuracy: 99.13 Specificity: 99.17 F1 score: 99.07

Abbreviations: AS-OCT, anterior segment optical coherence tomography; KCN, keratoconus; CNN, convolutional neural network; ML, machine learning; ANN, artificial neural networks; MLP, multilayer perception; NN, neural networks; SVM, support vector machines; AI, artificial intelligence; LGBM, a machine learning model called light gradient boosting machine; LR, linear regression; RF, random forests; AUC, area under the curve; LDA, Linear discriminant analysis; FPA-K-means, a forward propagation acceleration; DMEK, descemet membrane endothelial keratoplasty; DT, decision tree; DNN, deep neural networks; DCNN, deep convolutional neural networks; AutoML, automated deep learning; FECD, fuchs endothelial dystrophy; DES, dry eye syndrome; MDDN, multi-disease deep learning diagnostic network; F1 score, the F1 score is a combination of precision and recall; LASIK, laser-assisted in situ keratomileusis; PLE, post-LASIK ectasia; FFKCN, forme fruste keratoconus; LASSO, least absolute shrinkage and selection operator; OPD-scan, Placido-aberrometer systems (Nidek, Gamagori, Japan); DF, Discriminant function; SMILE, small incision lenticule extraction; PRK, photorefractive keratectomy; DL, deep learning; KNN, k-nearest neighbor; NSK, non-specific keratitis; HD-OCT, high-definition optical coherence tomography; MLDN, Multipath lightweight deep network; UBM, ultrasound biomicroscopy; BPNN, back propagation algorithm in neural network; DLLSS, deep learning supersampling; MPSS, manually plotted SS; FCNN, fourier convolution neural network.

Corneal Dystrophy

Corneal dystrophy is a genetic, non-inflammatory, and bilateral disease [57]. The differences between an edematous cornea and a normal cornea can be identified using OCT images based on DL algorithms [58]. In addition, using high-resolution OCT images, early-stage Fuchs' corneal endothelial dystrophy (FECD) without corneal edema can be distinguished from late-stage FECD with corneal edema. The sensitivity and specificity in the differentiation of the normal cornea from that of FECD (early or late) using this method have been reported as 99% and 98%, respectively [59].

Corneal Nerves

Corneal nerves are altered in some corneal diseases, and AI-based algorithms may be useful for identifying related diseases. In vivo confocal microscopy (IVCM) provides more information about the basal nerves and is superior to manual examinations [1]. The CNN approach with IVCM images and neural segmentation obtained a correlation score of 0.80 between readers and CNN [60]. In one study, nerve properties, including fiber length and tail points, were measured using DL models to diagnose diabetic neuropathy and its severity [61]. The authors compared DL performance with that of a reliable automated analysis program called ACCMetrics (Early Neuropathy Assessment [ENA] group, University of Manchester, Manchester, UK) and found that the DL algorithm had superior performance. The corneal nerve segmentation network (CNS-Net) is another DL-based model that evaluates the automatic segmentation of the sub-basal corneal nerve fiber using IVCM images with an area under the curve (AUC) of 96% [62].

Corneal Grafts

Endothelial cell characteristics can be assessed using AI-based algorithms and specular microscopic images. U-Net is a DL-based model designed by Daniel et al. [63] based on the automatic segmentation of binocular microscopic images for different corneal diseases. They found a good correlation between the research results and the manual interpretation of images. Treder et al. [20] detected graft detachment after Descemet membrane endothelial keratoplasty (DMEK) using AS-OCT images based on the DL method with sensitivity, specificity, and accuracy of 98%, 94%, and 96%, respectively. Evaluation of endothelial cell density (ECD) and hexagonality (HEX) using CNN with Topcon SP-1P (Topcon Co., Tokyo, Japan) binocular microscopic images in the eyes of patients who underwent ultrathin Descemet stripping automated endothelial keratoplasty showed an accuracy of 98.4% [64]. However, the success rates of ECD and HEX determination using Topcon IMAGEnet i-base software have been reported as 71.5% and 30.5%, respectively [64].

Corneal Transplantation

Graft detachment is a complication of endothelial keratoplasty and may require intervention [65]. AI can help in choosing proper cases at the right time; Treder et al. [20] evaluated 1,172 AS-OCT images based on the DL method in the diagnosis of graft detachment after DMEK surgery (accuracy: 96%, sensitivity: 98%, and specificity: 94%). Hayashi et al. [21] designed nine models of deep neural network structures using AS-OCT images and evaluated them to assess rebubbling after DMEK. They reported the highest AUC for the VGG19 model [21]. Therefore, with AI methods, better decisions can be made regarding the treatment and follow-up of these patients.

Refractive Surgery

Although various refractive surgical approaches are effective in improving patients' visual acuity and quality of life, the risk of iatrogenic ectasia has been a concern for both patients and physicians [1]. AI technology may be able to prevent complications and reduce the risk of corneal ectasia. In recent years, platforms have been designed based on AI methods to monitor those at risk of post-laser in situ keratomileusis (LASIK) ectasia (PLE) [56]. Ambrosio et al. [66] evaluated the performance of several AI-based models using Pentacam HR tomography data (Oculus, Wetzlar, Germany). They found that the Pentacam random forest index had an AUC of 99.2%, a sensitivity of 94.2%, and a specificity of 98.8%, and had diagnostic power superior to that of Belin/Ambrosio deviance (AUC: 96%, sensitivity: 87.3%, and specificity: 97.5%).

In addition, AI-based models can predict the appropriateness of corneal refractive surgery. Yoo et al. [26] examined 10,561 eyes that underwent laser epithelial keratomileusis, LASIK, and small-incision lenticule extraction surgery. They found that the XGBoost model derived from the meta-algorithm could predict the suitability of corneal refractive surgery with internal and external accuracy of 94.1% and 93.4%, respectively. In addition, Saad and Gatinel [27] designed a linear diagnostic model using Orbscan II data, which had a high sensitivity and specificity for the diagnosis of PLE. The SCORE Analyzer and the Pentacam InceptionResNetV2 Screening System (PIRSS) models were also generated based on DL models and had accuracies of 95% and 91%, respectively [67, 68].

Conjunctiva and Tear Film

The most important application of AI for the conjunctiva and tear film is the diagnosis of dry eye disease (DED). The fluorescein breakdown time test, tear film interferometry, tear film protein analysis, and meibography are common clinical examinations for DED evaluation [9].

Algorithms based on SVM and MLP can evaluate interference patterns in the lipid layer of tears using the interferometry technique [69-71]. In addition, Koh et al. [72] used a method combining SVM and scale-invariant feature transform with meibography; the length and width of meibomian glands were measured with sensitivity and specificity of 97.9% and 96.1%, respectively. Recently, the multi-disease deep learning diagnostic network (MDDN) method was developed for the automatic diagnosis of several eye diseases, including KCN, DED, and FECD, using 158,220 AS-OCT images [24]. In that study, the MDDN model showed a high level of validity (AUC > 99%) [24]. DED detection is possible by analyzing tear film protein patterns using ANN with an AUC of 93%, a sensitivity of 90%, and a specificity of 90%. In addition, AI-based methods have shown promising results in the automatic grading of conjunctival hyperemia using the conjunctival segmentation algorithm [73-75].

Pterygium

Pterygium is an ocular surface disease that causes excessive growth of the conjunctiva toward the cornea [3]. Various AI-based methods have been reported for the differentiation of healthy eyes from those with pterygia. Zulkifley et al. [30] used Pterygium-Net for the detection and localization of pterygia. Pterygium-Net is a DL model that utilizes three layers of CNN with three layers of fully connected networks with a high diagnostic ability (accuracy: 81.1%, sensitivity: 95%, and specificity: 98.3%) and a low failure rate of 0.053 for pterygium localization. In addition, Wan Zaki et al. [31] used SVM and ANN to distinguish healthy eyes from those with pterygia based on images taken from the anterior surface of the eye. Both algorithms had an average accuracy of 91.2%; however, SVM, with a sensitivity of 88.7% and a specificity of 88.3%, and AUC of 95.6%, may be more effective for detection of pterygia.

Infectious Keratitis

Infectious keratitis (IK) is an important cause of blindness, with a prevalence of 1.5–2 million people worldwide [76]. Timely diagnosis and proper follow-up can reduce serious eye problems and the need for corneal transplantation [56]. The current reference standard methods for the diagnosis of IK are corneal scraping, microscopy, staining, and culture [3]. Confocal microscopy is a noninvasive and non-contact imaging method used to detect fungal IK [36]. Recently, AI-based models involving image processing methods have been developed to identify IK. Saini et al. [35] evaluated the success rate of ANN in classifying IK in corneal ulcer classifications. They reported that the ANN algorithm has a higher accuracy than that of physicians' predictions (accuracy: 90.7% versus 62.8%). The robust binary pattern, or ARBP, is another new model that can distinguish fungal hyphae by processing confocal microscopic images of IK-affected corneas and healthy corneas (accuracy: 99.74%) [36]. Kuo et al. [38] designed a DL software called DenseNet algorithm to distinguish fungal from non-fungal keratitis, with 71% sensitivity and 68% specificity. These models may be useful for tele-diagnosis of IK in remote areas where a corneal specialist is unavailable.

Anterior Chamber Angle and Iris

Glaucoma may not be detected in its early stages, and early detection is vital for preventing vision loss [4]. Gonioscopy is the reference standard for the evaluation of angle-closure glaucoma; however, it has limitations, such as subjective interpretation and poor reproducibility [77]. AS-OCT, high-frequency ultrasound biomicroscopy (UBM), and Scheimpflug imaging, as with the Pentacam, serve as effective tools for challenging gonioscopic circumstances [77].

DL-based methods have been designed for the automatic detection of primary angle-closure glaucoma (PACG) using images obtained from AS-OCT. The OCT image processing method categorizes images based on related features. Xu et al. [42] designed three CNN classifiers with an analysis of 3,396 AS-OCT images for the diagnosis of PACG. Their results showed that the ResNet-18 classifier had the best performance (AUC: 92.8%) [42]. VGG-16 multilevel and multi-context deep network algorithms were developed in the process of analyzing 8,270 images and had good diagnostic accuracy (Table 1) [43, 44].

UBM also produces high-quality images of the anterior chamber angle [3]. Shi et al. [45] designed the Inception v3 software, which is a type of CNN algorithm for the classification of the anterior chamber angle using UBM images. They classified the images into one of three categories: open-angle, narrow-angle, and angle-closure. The sensitivity and specificity of this algorithm were 98.04% and 99.09% for open-angle, 96.30% and 98.13% for narrow-angle, and 98.21% and 99.05% for angle-closure, respectively [45]. It appears that CNN has an acceptable success rate in classifying glaucoma images.

Studies have shown that AI-based methods can be useful for diagnosing iris diseases [3]. Dimililer et al. [46] designed an intelligent eye tumor detection system (IETDS) based on the two conventional 3-layer back propagation neural networks (BPNN) with 4,096 input neurons. The IETDS could accurately detect different types of iris tumors using the BPNN1 and BPNN2 back-propagation neural networks (accuracy: 95.7%). BPNN1 uses resized original images to detect eyes with or without tumors, and BPNN2 uses the preprocessed image in IETDS to increase the detection ratio [46].

Cataracts

Cataracts are one of the main causes of blindness worldwide [9]. They are usually diagnosed using a slit lamp examination, and the lens opacities classification system III and the Wisconsin cataract grading system are the two main cataract grading systems [78, 79].

AI-based models can aid in automatic cataract recognition and grading using images obtained by slit-lamp microscopy and fundus photography. Using fundus images, Zhang et al. [50] developed a new cataract grading method using residual networks (ResNet18), gray-level co-occurrence matrix (GLCM), SVM classifiers, and fully connected neural network (FCNN) DL-based models. This method achieved an average accuracy of 92.66%, which was at least 1.75% higher than that of existing methods [50]. The AlexNet and VisualDN models were designed based on CNN by processing 8,030 fundus images for cataract diagnosis and grading (AUC: 86.2%) [49]. In addition, Jiang et al. [51] demonstrated a model based on deep CNN using slit lamp images to predict the progress of posterior capsule opacification with an accuracy of 92.2% (Table 1).

Limitations of Artificial Intelligence

Despite the several advantages of using AI in ophthalmology, some limitations have been reported that create a serious challenge. These include higher accuracy in the training set than in the test set, which is called "overfitting" [1, 80]; unfavorable results due to the use of irrelevant or inappropriate inputs, called "rubbish in and rubbish out" [1]; and the lack of transparency of decision-making and data analysis methods by the model, which is identified as a "black box" [1, 80].

The use of data collected from different groups is an important challenge in the future of AI. Data collection for training different AI-based models has been performed for particular populations, races, and ethnicities [8]. Therefore, this could create a significant challenge during the testing phase. Furthermore, choosing a model with high diagnostic power may be challenging when faced with a heterogeneous population. Therefore, it is necessary to validate a large dataset from a heterogeneous population that reflects real-world settings while observing medicolegal issues and ensuring data security [1,4]. Although there is a large amount of worldwide data available to design various AI-based models, data validity is an important issue [8, 80]. Data should be verified by a specialist for quality and specific details related to the ocular structure, and manual data sorting is time-consuming. In addition, standardization and classification of data for the anterior segment are more difficult than those for the posterior segment because of the transparent nature of the cornea and the differences in image magnification and contrast. This issue becomes more challenging when models with large datasets are required [1].

Because many anterior segment diseases can cause irreversible complications and even vision loss, sufficient confidence in the results obtained from the designed model is crucial for decision-making by experts. Automation bias occurs when an expert relies on the output of a model for diagnosing a disease and does not look for other clinical evidence [81]. To fully trust the results of a model and avoid automation bias [82], models should be periodically retrained with new and different data to reduce the possibility of errors. This issue is more important in anterior segment diseases and may become a significant challenge in the future.

Although this review provides information for eye care practitioners by summarizing studies of AI applications in anterior segment ocular diseases, it has some limitations. One drawback is the lack of a systematic search and meta-analysis on validity results concerning the diagnostic performance of each AI-based method for each anterior segment disease. A systematic review and meta-analysis of articles reporting the validity of a particular AI-based model may provide more robust and conclusive results. The lack of a grey literature review is another limitation. The use of AI is growing rapidly, and there could be unpublished data with useful information that was not presented here. Review articles addressing these limitations could pave the way for future AI applications in treating and managing anterior segment ocular diseases and could provide robust results to confront existing challenges in this regard.

CONCLUSIONS

Diagnosis of corneal diseases and monitoring responses to management remain major challenges in ophthalmology. However, corneal imaging modalities and data processing algorithms can be useful. AI-based models can be used even in areas that do not have access to ophthalmologists with a teleophthalmology approach. The diagnosis of many anterior segment diseases requires accurate examination; however, multitasking models can be used simultaneously with clinical examination. In the future, new technologies based on AI will make the diagnosis and treatment of anterior segment diseases easier and safer using combined models with different datasets.

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