• Intelligent Ophthalmology •

Artificial intelligence-aided diagnosis and treatment in the field of optometry

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Abstract

● With the rapid development of computer technology, the application of artificial intelligence (AI) to ophthalmology has gained prominence in modern medicine. As modern optometry is closely related to ophthalmology, AI research on optometry has also increased. This review summarizes current AI research and technologies used for diagnosis in optometry, related to myopia, strabismus, amblyopia, optical glasses, contact lenses, and other aspects. The aim is to identify mature AI models that are suitable for research on optometry and potential algorithms that may be used in future clinical practice.

● **KEYWORDS:** artificial intelligence; myopia; strabismus; amblyopia; optometry

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INTRODUCTION

Optometry is an interdisciplinary field that combines modern optical technology with ophthalmology and uses principles and technologies of modern optics to overcome visual obstacles. It is a medical specialty that blends classic traditional practices and modern high-technology characteristics. Modern optometry is also closely related to ophthalmology. The strategic combinations in optometry have opened an avenue for a holistic and comprehensive approach to ophthalmic clinical services[1]. Various ocular health problems concern optometry, including visual problems during rehabilitation from eye diseases, visual quality of modern surgical and non-surgical ametropia correction, and exploration of the etiology and mechanisms of functional eye diseases (*e.g.*, myopia)[2].

With the rapid development of capable algorithms and increasing computing power, medical artificial intelligence (AI) has experienced an explosive growth in recent years. AI allows to extract features from unexpected sources and draw connections that humans overlook or cannot detect[3]. In ophthalmology and optometry, which are important branches of clinical medicine, several image and non-image data resources are available to constitute a good foundation for AI applications. Although research on AI was initially focused on ophthalmology[4], more studies are being devoted to applied AI in optometry for the prevention and correction of conditions such as myopia, strabismus, and amblyopia. In this review, we summarize and analyze recent research achievements of AI-aided technology in optometry related to myopia, strabismus, amblyopia, optical glasses, contact lenses, surgical treatment of refractive error, and other visual corrections.

SEARCH METHODS

A systematic literature search was performed on PubMed and the Web of Science. We aimed to retrieve studies on the application of AI to optometry. As keywords, we considered all combinations of optometry, refractive error, ametropia, myopia, hyperopia, astigmatism, amblyopia, strabismus, low vision, glasses, orthokeratology (OK), contact lens, and refractive surgery with artificial intelligence, machine learning (ML), deep learning (DL), convolutional neural network

Table 1 The application of AI in the prediction, screening and classification of myopia

Authors, year	Modalities	Sample size	Databases	Algorithms	AUC (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
Lin *et al*[10], 2018	Medical records	-	High myopia	RF	80.2-88.8	-	-	-
Yang *et al*[11], 2020	Original data	-	Myopia	GBRT/SVM	97.0	93.0	94.0	94.0
Li *et al*[12], 2022	Cycloplegic autorefraction data	-	Myopia	RF	-	>80.0	-	-
Wu *et al*[13], 2022	Fundus images	1854	High myopia	CNN/TL	89.5-96.9	85.3-92.4	72.5-92.2	91.5-98.1
Yang *et al*[14], 2020	Ocular appearance images	2350	Myopia	DCNN	92.7	-	81.1	86.4
Choi *et al*[15], 2021	OCT	690	High myopia	CNN	99.0	100.0	-	-
Sogawa *et al*[16], 2020	OCT	910	MM	CNN	97.0-100.0	67.6-96.5	90.6-100.0	94.2-100.0
Hemelings *et al*[17], 2021	Fundus images	1200	PM	CNN	98.7	-	-	-
Du *et al*[18], 2021	Fundus images	7020	PM	EfficientNet	88.1-98.2	92.1	37.8-87.2	94.5-98.3
Lu *et al*[19], 2021	Fundus images	1000	PM	CNN	99.5	97.4	93.9	98.2
Tan *et al*[20], 2021	Fundus images	226686	High myopia and MM	CNN	91.3-97.8	-	88.0-95.2	72.9-91.4
Ye *et al*[23], 2021	OCT	2342	PM	CNN	92.7-97.4	-	73.9-92.8	84.8-94.0
Kim *et al*[25], 2021	OCT	860	PM	SVM	82.8-86.8	84.5-91.5	77.5-80.0	88.1-93.6
Wan *et al*[26], 2021	Fundus images	758	The risk of high myopia	DCNN	99.7	98.2	95.2-100.0	97.9-100.0
Lu *et al*[27], 2021	Fundus images	16428	PM	DL	99.3	97.7	97.7	97.2
Li *et al*[21], 2022	OCT	5505	Myopic vision- threatening conditions	CNN	96.1-99.9	-	90.0-100.0	90.5-96.5
Li *et al*[22], 2022	Fundus images	36515	PM	DCNN	97.0-99.8	93.0-96.9	90.8-93.3	98.7-99.6
Park *et al*[24], 2022	OCT	367	PM	CNN	95.0-98.0	86.0-95.0	85.0-93.0	88.0-96.0
Wang *et al*[28], 2023	Fundus images	10347	MM and PM	CNN/TL	95.0-100.0	93.2-99.8	90.8-96.8	93.3-99.9

AUC: Area under the curve; RF: Random forest; TL: Transfer learning; GBRT: Gradient boosting regression tree; SVM: Support vector machine; CNN: Convolutional neural network; DCNN: Deep convolution neural network; PM: Pathological myopia; MM: Myopic maculopathy; OCT: Optical coherence tomography; DL: Deep learning; Original data: Students' individual activity, their own eye condition, parental heredity, individual physiology, eye habits, environment, diet and so on.

(CNN), and decision tree. No limitations regarding the publication date were applied to the search.

ARTIFICIAL INTELLIGENCE APPLICATION IN MYOPIA

Worldwide, myopia is a leading cause of visual impairment characterized by uncorrected refractive errors[5-6]. In 2020, approximately 161 million people had moderate to severe vision impairment or blindness due to uncorrected refractive errors, which are the leading cause of vision impairment[6]. Sixty years ago, 10%–20% of the Chinese population had myopia. Nowadays, up to 90% of teenagers and young adults wear glasses, becoming the rule instead of the exception in settings such as Chinese universities[7]. Moreover, the risk of children developing high myopia has become a great concern among parents[8], with thousands seeking care at optometric and ophthalmic clinics annually around China. This may lead to a substantial healthcare burden that the current infrastructure might struggle to handle. As a greater proportion of young individuals develop high myopia, there is a higher risk of developing visual impairment and blinding complications, including retinal detachment, glaucoma, macular degeneration, and macular neovascularization[9].

AI can be used to accurately identify individuals at early risk to provide personalized treatments and simplify the allocation of medical resources. Table 1 mainly reviews the application of AI in the prediction, screening and diagnosis of myopia.

For the accurate prevention and control of myopia, AI models can predict development trends based on genetic factors, living environment, and eye habits in adolescent myopia patients through regular routine refractive examination and big data comparisons. In 2018, Lin *et al*[10] proposed a big data and ML approach to predict the onset of high myopia among Chinese school-aged children at specific future dates. This study provided evidence for transforming clinical practice, health policy-making, and precise individualized interventions regarding the practical control of myopia in school-aged patients. Yang *et al*[11] provided a systematic solution that included feature selection, data cleaning, and model training. A series of protective and risk factors for myopia were screened, and a risk prediction model based on a support vector machine (SVM) was obtained for accurately predicting the occurrence of myopia in the future. Li *et al*[12] investigated risk factors for myopia progression in primary school students and established a prediction model by applying ML to longitudinal cycloplegic autorefraction data. AI models can accurately predict the development of myopia in children. Wu *et al*[13] developed an AI system that could predict optical coherence tomography (OCT)-derived high myopia grades based on fundus images. This system may reduce the costs of patient follow-ups and is suitable for application in less developed areas, where only fundus images but not OCT scans can be acquired. Yang *et al*[14] applied an AI system to myopia screening using ocular appearance images and achieved a high screening accuracy, enabling remote monitoring of the refractive status in children with myopia. Choi *et al*[15] verified and evaluated a DL model for screening high myopia using spectral-domain OCT. An AI model based on ResNet50 showed comparable diagnostic performance to retinal specialists.

In addition to myopia screening, AI has been applied to pathologic myopia. In 2020, Sogawa *et al*[16] developed an AI model to accurately distinguish OCT images without and with myopic macular lesions, such as myopic choroidal neovascularization and retinoschisis. Hemelings *et al*[17] applied a CNN to establish a high-myopia AI model and automatically segmented and graded related lesions, obtaining an area under the curve up to 0.9867. Du *et al*[18] developed an AI algorithm to identify the features of myopic maculopathy for its automatic classification. The algorithm achieved high sensitivity and specificity for identifying specific myopic maculopathy lesions. Lu *et al*[19] developed DL algorithms and AI models for automatic pathologic myopia identification, myopic maculopathy classification, and "plus" lesion detection on retinal fundus images. Tan *et al*[20] developed and tested retinal-photograph-based DL algorithms for detecting myopic maculopathy and high myopia. They also used blockchain technology for data transfer and model transfer and testing between sites and across two countries. Li *et al*[21] developed an AI system that could identify the four vision-threatening conditions in high myopia: retinoschisis, macular hole, retinal detachment, and pathological myopic choroidal neovascularization. Li *et al*[22] designed a dual-stream deep CNN that perceived features from original images and corresponding processed images by color histogram optimization for classifying no myopic maculopathy, tessellated fundus, and pathologic myopia. Ye *et al*[23] developed a CNN-based AI system for the detection and classification of myopic maculopathy in patients with high myopia using OCT macular images. Their system achieved a sensitivity equal to or even better than that of junior retinal specialists. Park *et al*[24] developed an AI algorithm that used three-dimensional OCT volumetric images to automatically diagnose patients with pathologic myopia. The model was developed using transfer learning based on four pretrained CNNs, namely, ResNet18, ResNext50, EfficientNetB0, and EfficientNetB4. The model based on EfficientNetB4 showed the best performance in identifying pathologic myopia. Kim *et al*[25] proposed an SVM classifier with radial basis function kernel using a dataset of posterior globe tomographic measurements to predict the presence of pathologic myopia. Only six features were used in their model to achieve 91.47% accuracy and an area under the curve of 0.865. Wan *et al*[26] used deep convolution neural network (DCNN) to grade the risk of developing high myopia. The input images were automatically classified into three categories: normal fundus images (class 0), low-risk high myopia images (class 1), and high-risk high myopia images (class 2). According to the results of fivefold cross-validation, the average accuracy reached 98.15%. Lu *et al*[27] designed various AI systems to detect pathologic myopia and myopic macular lesions according to a recent International Photographic Classification System based on color fundus images. Their performance was comparable to that of general ophthalmologists and retinal specialists. Wang *et al*[28] developed an AI model for the detection and classification of myopic macular lesions based on fundus images. Its performance was comparable to that of experts and could assist ophthalmologists by reducing the workload and saving time during large-scale myopia screening and long-term follow-ups.

Overall, AI can be applied to myopia in various ways. Currently, AI research is mainly focused on the classification and prediction of myopia. However, these efforts have not yet translated into clinically relevant and viable solutions. Deeper collaborative research should be conducted in combination with the development of robust datasets toward implementations in clinical practice.

ARTIFICIAL INTELLIGENCE APPLICATION IN STRABISMUS

Strabismus is a clinical condition in which the visual axis deviates in either eye. It can be caused by monocular abnormalities in both eyes or by abnormalities in the optic nerve muscles that control the eye movements or various mechanical restrictions. Strabismus affects approximately 0.8%–6.8% of the world's population and appears by the age of 3y in 65% of the affected individuals[29-31]. Strabismus impairs the quality of life of preschool children and is a major cause of binocular vision impairment and visual function abnormalities[32]. Therefore, early strabismus diagnosis is necessary for its prevention. Conventional methods for strabismus diagnosis, such as the alternate prism cover test and Hirschberg and Krimsky tests, require the judgment of a professional ophthalmologist, thus being time-consuming and expensive[33-34]. Recently, automated strabismus screening using digital images has become a research hotspot to aid ophthalmologists in diagnosing strabismus faster, more cost-effectively, and more accurately. Table 2 lists AI applications in strabismus diagnosis.

Zheng *et al*[35] developed and evaluate DL algorithms that screen referable horizontal strabismus in children's primary gaze photographs. The DL algorithm's performance (with an accuracy of 0.95) in diagnosing referable horizontal strabismus

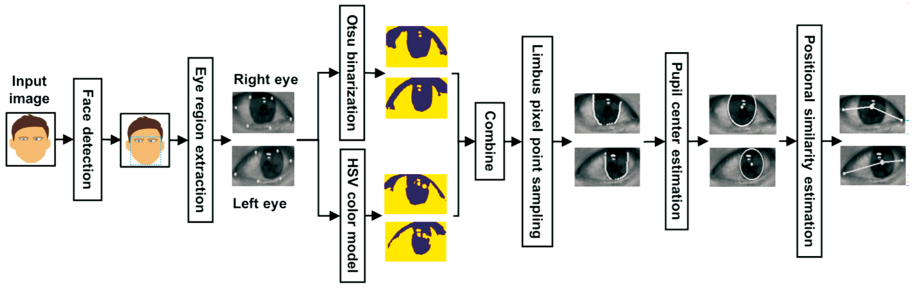

Figure 1 The flowchart of the proposed method[39] A frontal facial image is sent to the face detection model to identify the face region and the detected face region is subsequently used to extract the eye region through the facial landmark detector. Otsu's binarization and the color model are applied to the extracted eye region image, and the results from two methods are used to form a new image. The pixel points located at the limbus are sampled and used to estimate the pupil center. Finally, the positional similarity of the iris on both eyes is computed for strabismus screening.

Table 2 Summary of studies focused on computer-aided strabismus diagnosis

Authors, year	Modalities	Sample size	Databases	Algorithms	AUC (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
Mao *et al*[38], 2021	Nikon D5300	5797	Corneal light-reflection images	CNN	99.8	99.0	99.1	98.3
Huang *et al*[39], 2021	-	60 (30 strabismus, 30 normal)	Low-light and ambient-light images	CNN	-	-	-	-
Zheng *et al*[35], 2021	Nikon D800	7530 (3330 strabismus, 4200 orthoptic)	Primary gaze images	DCNN	99.0	95.0	94.0	99.3
de Figueiredo *et al*[37], 2021	Nikon S8200	110 strabismic	Nine gazes images	CNN	42.0-92.0	-	-	-
Chen *et al*[36], 2018	Tobii X2-60	42 (17 strabismic, 25 normal)	Eye-tracking, gaze deviation images	CNN	95.20	95.2	94.1	96.0

AUC: Area under the curve; CNN: Convolutional neural network; DCNN: Deep convolution neural network.

was better than that of the resident ophthalmologists (with accuracy ranging from 0.81 to 0.85). Chen *et al*[36] used eye tracking data and a CNN to identify strabismus. First, an eye tracker was used to record the eye movements of the participants. A gaze deviation image was then constructed to represent the subjects' eye tracking, and a CNN trained on the large ImageNet dataset was used to extract features from the gaze deviation image for strabismus recognition, achieving an accuracy of 95.2%. de Figueiredo *et al*[37] developed a mobile application to evaluate eye movements. The application showed an overall accuracy of 42%–92%, and it established a convenient and quick tool to accelerate the clinical diagnosis of strabismus.

Despite the available developments, further exploratory research and validation are required. Mao *et al*[38] constructed an AI system consisting of three DL models for strabismus diagnosis, angle evaluation, and operation planning based on corneal light-reflection photographs. The system was trained and validated using a retrospective development dataset. On the retrospective test sets, the system detected strabismus with a sensitivity of 99.1%, specificity of 98.3%, and area under the curve of 0.998. Huang *et al*[39] used a CNN face detection model and detector of 68 face marker points for eye region extraction from frontal face images (Figure 1). The deviation in the positions on both sides was compared for strabismus screening by calculating the distance from the center of the pupil to the inner and outer canthus. The algorithm determined that the deviation of iris position on both sides was significantly smaller in normal subjects than in strabismus patients (P<0.001).

ARTIFICIAL INTELLIGENCE APPLICATION IN AMBLYOPIA

Amblyopia is the loss of best-corrected visual acuity in one or both eyes caused by abnormal visual experiences during visual development, presenting as a non-organic pathology on ocular examination. Amblyopia is the leading cause of visual impairment in children worldwide, affecting 1%–6% of that population[40-41]. If left untreated, amblyopia can lead to complete blindness. In addition, amblyopia treatment is limited by age (visual maturity). Therefore, early screening for amblyopia risk factors is essential for successful recovery[42]. Amblyogenic risk factors include refractive error, anisometropia, strabismus, ptosis, media opacities, and form deprivation[43-44]. Photographic screening is an effective method for the objective screening of refractive errors and amblyopia. The use of AI in the clinical diagnosis of amblyopia can greatly improve its efficiency and accuracy. Table 3 lists AI applications in amblyopia diagnosis.

Murali *et al*[45] embedded DL algorithms in an Android smartphone to implement the Kanna facial photo screener that identified amblyogenic risk factors. The AI algorithm was highly accurate in detecting strabismus and refractive errors. The researchers then tested the Kanna screener with 654 people under 18 years of age[46]. Hence, the Kanna screener was highly accurate in recognizing amblyogenic risk factors and may be suited for use in smartphones. The screener was compared

Table 3 Summary of studies focused on computer-aided amblyopia diagnosis

Authors, year	Modalities	Sample size	Databases	Algorithms	F-score (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
Murali *et al*[45], 2020	Android smartphone	54	Low-light and ambient-light images	CNN	73.2	88.2	88.2,	75.6
Murali *et al*[46], 2021	Android smartphone	654	Low-light and ambient-light images	CNN	85.9	90.8	83.6	94.5

CNN: Convolutional neural network.

Table 4 Summary of studies focused on computer-aided optical glasses and contact lens diagnosis

Authors, year	Modalities	Sample size	Databases	Algorithms	AUC (%)	IoU	R^2	MAE	RMSE
Zhang *et al*[50], 2019	Clinical infornation and optometry parameters	1467	Lens fitting	ML	-	-	0.93/0.95	-	-
Fan *et al*[48], 2021	Clinical infornation and optometry parameters	1037	Corneal refractive therapy lenses	ML	-	-	-	≥0.386	≥0.556
Fan *et al*[49], 2022	Clinical infornation and optometry parameters	1271	Lens fitting	SVM	-	-	≥0.730	≥0.263	≥0.373
Fang *et al*[52], 2023	Clinical infornation and optometry parameters	91	Predict treatment effect of ok	ML	94.9	-	-	-	-
Tang *et al*[53], 2021	Corneal topographical maps	6328	Identify the corneal treatment zone	FCN/CNN	-	0.90±0.06	-	-	-

AUC: Area under the curve; IoU: Intersection over union; MAE: Mean absolute error; RMSE: Root mean squared error; ML: Machine learning; SVM: Support vector machine; FCN: Fully convolutional networks; CNN: Convolutional neural network.

with other tools for screening amblyogenic risk factors. The results showed that the Kanna screener outperformed the other automated solutions.

ARTIFICIAL INTELLIGENCE APPLICATION IN OPTICAL GLASSES AND CONTACT LENS

OK is an effective treatment to slow the progression of axial length elongation in myopic children by flattening the central cornea while steeping the mid-peripheral cornea to mitigate relative peripheral hyperopia[47]. Given its effectiveness in controlling the progression of myopia, OK is widely used worldwide. However, various complications may be associated with wearing OK lenses. The conventional method for fitting lenses requires skills and experience in repeated lens trials to determine the appropriate lens parameters, consequently being time-consuming. In addition, repeated lens trials may increase the risk of ocular surface injury and cross-risk infections. Recently, many studies have explored ML algorithms to improve the accuracy and feasibility of selecting OK lens parameters to minimize the number of lens trials and improve efficiency while maintaining accuracy. Table 4 lists AI applications in the prescription of optical glasses and contact lenses.

Fan *et al*[48] proposed an ML-based strategy for prescribing the returning zone depth and landing zone angle for corneal refractive therapy lenses. The first corneal refractive therapy trial lens is conventionally selected based on a sliding card provided by a manufacturer. Although this approach requires only two parameters, namely, flat keratometry and spherical reduction, the sliding card is designed using corneal parameters of Western adolescents instead of Chinese subjects. Furthermore, the card does not consider the eccentricity and anterior chamber depth. Fan *et al*[48] retrospectively analyzed the clinical case files of 1037 Chinese myopic adolescents with good lens fitting. Three models were adopted, including calculation, ML, and linear regression models, to estimate the values corresponding to the returning zone depth and landing zone angle. The optimized ML model exhibited the highest performance among the evaluated methods.

Fan *et al*[49] then constructed an ML-based approach for estimating the aligning curvature of a vision shaping treatment lens to improve their previous calculation method. The ML models were compared with the previous calculation method, and the final parameters of the ordered lenses were evaluated. The linear SVM and Gaussian process ML models achieved the best performances. The ML model can provide practitioners with an efficient method for estimating the alignment curve curvatures of vision shaping treatment lenses and reducing the probability of cross-infection originating from trial lenses, which is especially useful during pandemics, such as that for coronavirus disease (COVID-19). Zhang *et al*[50] get an OK lens fitting model according to enrolled 750 OK lens wearers (1467 samples) to evaluate basic optometry examination data and effective optometry prescriptions. This OK lens fitting model seems promising for efficient, fast, and accurate prescriptions of glasses. The effectiveness of OK in controlling myopia progression is well-known[51], but it is not equally effective in all patients. Fang *et al*[52] used an ML-assisted model to predict the clinical effects of OK. The model included ocular parameters and clinical characteristics of 91 OK wearers, including age, baseline axial length, pupil diameter, lens wearing time, time spent outdoors, time spent near work, white-to-white distance, anterior corneal flat keratometry, and posterior corneal astigmatism. The decision analysis curve showed that the model was sufficiently good to guide lens fitting. In addition, the calibration plots showed excellent overall agreement between the predictions, while the 2-year outcomes showed a correlation between the prediction and actual observations. Tang *et al*[53] proposed an AI algorithm to identify the boundary and the center of reshaped corneal area (*i.e.*, treatment zone). These AI models showed equal performance to expert clinicians in assessing OK zones and

Table 5 Summary of studies focused on computer-aided surgical treatment of myopia

Authors, year	Surgery type	Sample size	Databases	Algorithms	AUC (%)	Accuracy (%)	R^2	MAE	RMSE
Saad *et al*[60], 2010	LASIK	143	Forme fruste keratoconus	Linear discriminant model	98.0	-	-	-	-
Lopes *et al*[59], 2018	LASIK	3693	Corneal ectasia after surgery	SVM, ANN, RF	99.2	-	-	-	-
Cui *et al*[62], 2020	SMILE	865	Nomogram	ANN	-	93.0	-	-	-
Xie *et al*[57], 2020	Refractive surgery	6465	Screening potential candidates for refractive surgery	CNN	-	94.7	-	-	-
Yoo *et al*[61], 2020	LASIK, LASEK, SMILE	18480	To select the refractive surgery technique	ML	-	≥78.9	-	-	-
Park *et al*[68], 2021	SMILE	3034	Nomograms of sphere, cylinder, and astigmatism axis	ML	-	≥23.6	≥0.9922	-	≥0.1166
Kim *et al*[69], 2022	LASIK, LASEK, SMILE	2009	Myopic regression after surgery	CNN	≥73.0	≥71.7	-	-	-
Francis et *al*[70], 2023	LASIK, SMILE, PRK	539	Corneal stiffness after surgery	ML	100	-	-	≥6.24	-
Shen *et al*[64], 2023	ICL	6297	Vault	RF	≥71.8	≥80.2	≥0.285	-	≥159.026
Xu et *al*[65], 2021	ICL	137	Vault	ANN	-	-	0.98	-	-
Kamiya *et al*[66], 2021	ICL	1745	Vault	SVR, RF	-	-	-	≥94.8	-
Kang *et al*[67], 2021	ICL	3739	Vault ICL size	GB	-	≥67.4	-	≥106.88	≥140.14

LASIK: Laser-assisted *in situ* keratomileusis; LASEK: Laser epithelial keratomileusis; SMILE: Small incision lenticule extraction; PRK: Photorefractive keratectomy; ICL: Implantable contact lens; AUC: Area under the curve; MAE: Mean absolute error; RMSE: Root mean squared error; ML: Machine learning; SVM: Support vector machine; ANN: Artificial Neural Network; RF: Random forest; LR: Linear regressor; GB: Gradient boosting; SVR: Support vector regressor.

centers. A cross-sectional study found that AI may improve the accuracy, efficiency, and reliability of measurements recorded using hICA in various light environments for the normal human eyes[54]. Overall, such AI systems can automate and facilitate the assessment and reduce interindividual subjectivity during follow-ups.

ARTIFICIAL INTELLIGENCE APPLICATION IN SURGICAL TREATMENT OF REFRACTIVE ERROR

Optometrists often use nonsurgical methods to treat visual problems, including prescription of optical glasses and contact lenses, visual training, and drug delivery. Alternatively, surgical methods practiced by refractive surgeons include various corneal refractive interventions such as laser-assisted in situ keratomileusis, small incision lenticule extraction, photorefractive keratectomy, and lens implantation in phakic eyes, such as implantable collamer lense (ICL)[55].

With the extensive development of corneal refractive surgery, the demand for minimizing the risk of post-operative complications has increased, including AI research on screening for the risk of ectasia after corneal refractive surgery and guiding the selection of the corneal refractive surgery type[56-58]. Table 5 lists AI applications in the surgical treatment of myopia.

Lopes *et al*[59] collected Pentacam examination results of 3693 patients after laser-assisted *in situ* keratomileusis in five centers and evaluated various ML models, including regularized discriminant analysis, SVM, naïve Bayes classification, neural networks, and random forest (RF). The RF algorithm provided the highest accuracy in predicting corneal ectasia after corneal refractive surgery, establishing the Pentacam RF index, which achieved an area under the curve of 0.992 (sensitivity of 94.2%, specificity of 98.8%, and cut-off of 0.216). That index was significantly higher than the Belin-Ambrósio deviation index. Using Orbscan II tomography, Saad and Gatinel[60] designed a linear discriminant model with high sensitivity (93%) and specificity (92%) for detecting dilation after laser-assisted in situ keratomileusis. Xie *et al*[57] developed a screening system for refractive surgery based on an Inception-ResNet-V2 model and a large dataset containing 6465 corneal tomography images. The model achieved an overall detection accuracy of 95% (95% confidence interval, 0.888–0.978) on an external test set, being comparable to the performance of senior ophthalmologists as refractive surgeons (92.8% accuracy; 95% confidence interval, 0.912–0.944). Yoo *et al*[61] used data from 18 480 subjects to train an interpretable ML model based on extreme gradient boosting (GB) for selecting the corneal refractive surgery type. When tested on internal and external validation sets, the accuracy of the model was 81.0% and 78.9%, respectively, and the inference interpretation was consistent with knowledge of ophthalmologists. Cui *et al*[62] used data from 865 subjects to train a nomogram prediction model of small incision lenticule extraction based on an artificial neural network and compared the model predictions with surgeons' evaluations. The efficacy of the network was significantly higher than that of the surgeons. The post-operative corrective error of 93% of the subjects in the ML group was within 0.50d, compared with 83% in the surgeon group.

Corneal refractive surgery is an effective method to correct myopia, but the amount of correction is limited by the corneal thickness. For patients with high myopia, especially very high myopia, and those who cannot undergo corneal refractive surgery because of insufficient corneal thickness or abnormal morphology, lens implantation in phakic eyes may be the only surgical option. Implantation can correct a wide range of refractive errors, with myopia reaching 18 diopters (D) and astigmatism reaching 6 D, all of which can be completely corrected, providing satisfactory visual effects and enhanced quality of life[63]. Research on AI-assisted lens implantation in phakic eyes has been mainly focused on predicting the vault after ICL using ML and selecting the ICL size through the vault. Common algorithms include linear regressors, RF, SVM, GB, AdaBoost, extreme GB, and light GB machines. Shen *et al*[64] collected and summarized the data of 3536 patients (6297 eyes) who underwent ICL surgery. They tested the ML models of decision tree, RF, AdaBoost, GB, extreme GB, and support vector regression and found that the RF, GB, and extreme GB algorithms accurately predicted the vault after receiving ICLs, achieving accuracies of 82.8%, 81.5%, and 80.2%, respectively. Based on the vault prediction, models for ICL size prediction were established. The prediction accuracies of the RF, GB, and extreme GB algorithms for ICL size were 82.2%, 81.5%, and 81.8%, respectively. Xu *et al*[65] established a model to predict the vault and choose the ICL size based on the data from 74 subjects (137 eyes) who received ICL. Using linear regression analysis, they found that the vault was related to the ICL size, anterior chamber depth, angle-to-angle distance, white-to-white distance, and lens thickness. They also analyzed a neural network, finding that adding input variables improved the prediction performance. When the 11 considered variables were included in the neural network, fitness was close to 1 (R^2=0.98). The studies by Kamiya *et al*[66] and Kang *et al*[67] were similar. They used various ML models to predict the vault and ICL size, Korean data for training and internal validation, and Japanese data for external validation, obtaining promising results. Kamiya *et al*[66] included 1745 subjects who received ICL in Japan and South Korea and used support vector regression, GB regression, RF, and linear regression to predict the vault. Using the mean absolute prediction error, calculated as the absolute value of the actual post-operative vault minus the predicted vault, the RF algorithm achieved the best prediction. Followed by GB, linear, and support vector regression, they observed a higher predictability of the vault with their ML algorithm than with the manufacturer nomogram. In the predictive results of training with Korean data and testing with Japanese data as external validation, the RF algorithm also provided the lowest error and highest percentage of eyes within 50–200 μm of the target vault. Kang *et al*[67] used the stacking ensemble technique based on extreme GB and a light GB machine to pre-operation ocular data from two eye centers and then predicted the postoperative vault. Their proposal outperformed similar ML models, with a lower average absolute error of vault prediction after receiving ICL (106.88 μm and 143.69 μm in internal and external validations, respectively). Good performance was also obtained in the prediction of ICL size (accuracies of 75.9% and 67.4% for internal and external validation, respectively)[68-70].

ARTIFICIAL INTELLIGENCE APPLICATION IN THE DESIGN OF CONTACT LENSES AND LOW VISION

The design of a complex lens involves several uncertain variables. Supporting the best lens design to reduce wearing discomfort is essential. In addition, customizable treatment for correcting higher-order aberrations is a current research hotspot in lens design. Yen *et al*[71] combined a neural network and genetic algorithm to optimize the spherical aberration, coma aberration, and modulation transfer function of contact lenses. They aimed to apply optical design and optimization to select the parameters of contact lenses and support optical designers in the improvement of contact lenses (myopia with 5.5 D and astigmatism with 1.75 D) after routine optimization using available optical software. When implementing the proposed optional weight neural network-genetic algorithm, the performance could be adjusted by changing the weight of the fitness function. This method simplified the selection of parameters for optical system optimization. Low vision AI-aided device fitting is closely related to visual rehabilitation needs. Dai *et al*[72] have established a FCNN model for AI-aided device fitting. The accuracy of this AI model is about 80%.

CONCLUSION

Eyecare problems related to optometry are diverse and include visual problems during eye disease recovery, visual quality after surgical or non-surgical refractive corrections, and etiological investigation of functional eye diseases such as myopia[73]. The considerable economic growth in China has resulted in better quality of life. To cope with the demand for quality eyecare, an increase in the number of optometric professionals and standardization of comprehensive eyecare services are planned. However, there is a general shortage of optometrists in China. Compared with the proportion of optometrists to population in the United States, the shortage of optometrists in China reaches approximately 200 000. To overcome this problem, many sub-degree or diploma programs in optometry are available. Graduates from bachelors and diploma programs are more numerous and can overcome the shortage of optometrists. However, these graduates may not have the necessary knowledge and skills to provide comprehensive eyecare services[74].

AI technology can support optometry services. With the rapid development of computer science and technology, the application of AI in medical research has become a hot topic, especially in ophthalmology[75-79]. Just a few years after pioneering demonstrations of medical AI algorithms that achieve expert-level disease detection from medical images, the landscape of medical AI has matured considerably[3]. With the assistance of AI, computers can be used to identify and analyze data to replace manual work in applications such as automatically identifying the corneal fluorescein staining morphology after wearing OK lenses and automatically analyzing and classifying optometry data. Compared with manual methods, computerized identification and analysis can take less than a second, greatly improving the efficiency and reducing costs[80]. On the other hand, judging whether a medical image is abnormal is mostly based on a quantitative analysis of size, shape, color, and quantity, while hidden features may be overlooked. This is because humans may fail to find relations between such features and the analysis results. In addition, hidden features contained in images may far outnumber low-dimensional features such as size, shape, and quantity, and some of them can be neither seen by humans nor quantitatively analyzed. With the help of ML technology[81], several images can be provided as samples to a computer to learn and automatically extract high-dimensional features, thus finding internal relations between the images and results.

AI research on optometry includes the application of big data in the collection of massive clinical data and images, and the application of medical big data to AI to guide or assist doctors in clinical decision-making by exploiting supercomputing and data mining in cloud computing. AI may alleviate the pressure owing to the shortage of optometrists and heavy workload, and it can lead to optimal services for clinical and scientific research by using existing data resources. For optometry, different data modalities involving image and non-image samples are available. Therefore, we believe the development of AI in optometry will include methods considering multimodal medical data and approaches integrating DL in image processing, non-image big data processing, and novel formulations.

However, there are still some limitations in AI-aided diagnosis and treatment in the field of optometry. First of all, in most studies, the effectiveness of the model lacks external validation. It raises the question of whether the AI model still has the research effect in further popularization and application. Second, because of the differences in the size, format and shooting mode of images output by different devices, it is difficult to directly apply the model developed for one device to another device with similar functions, and it is necessary to further develop and train the compatibility of the model with images to solve such problems. Finally, if the relationship between input and expected output materials is complex, the system will probably not build a AI model. In some rare cases, some unexpected mistakes may occur in the AI model, so in clinical practice, the AI-aided model still needs the supervision of clinicians, and it can't run independently without the attention of doctors.

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