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REVIEW ARTICLE

Insights into artificial intelligence in myopia management: from a data perspective

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Abstract

Given the high incidence and prevalence of myopia, the current healthcare system is struggling to handle the task of myopia management, which is worsened by home quarantine during the ongoing COVID-19 pandemic. The utilization of artificial intelligence (AI) in ophthalmology is thriving, yet not enough in myopia. AI can serve as a solution for the myopia pandemic, with application potential in early identification, risk stratification, progression prediction, and timely intervention. The datasets used for developing AI models are the foundation and determine the upper limit of performance. Data generated from clinical practice in managing myopia can be categorized into clinical data and imaging data, and different AI methods can be used for analysis. In this review, we comprehensively review the current application status of AI in myopia with an emphasis on data modalities used for developing AI models. We propose that establishing large public datasets with high quality, enhancing the model's capability of handling multimodal input, and exploring novel data modalities could be of great significance for the further application of AI for myopia.

Keywords Myopia · Data modality · Artificial intelligence · Machine learning · Deep learning

Key messages

What is known:

- AI is increasingly used in myopia management and a few reviews have summarized its application scenarios.
- No study has focused on the data modalities available in myopia and the appropriate AI methods for each type of data

What is new:

- AI has been applied to most parts of the clinical practice of myopia management and is mainly built on three types of data: clinical data, FP and UWF FP, OCT.
- Establishing large public datasets with high quality, improving the capability of handling multimodal input, and exploring novel data modalities are potential future directions.

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Introduction

Myopia, which is defined as a spherical equivalent (SE) ≤ −0.5 diopters (D), is a substantial global health issue. The global prevalence of myopia is estimated to be 49.8% (4.758 billion) of the world's population, of which 9.8% (938 million) will suffer from high myopia by 2050 [1]. In some Asian countries, more than 80% of high school students are myopic [2–8], and a greater proportion of young individuals develop high myopia (spherical equivalent (SE) ≤ −6.0

diopters) [9], which further results in a higher risk of developing visually impairing and blinding complications [10, 11]. Although the causes of this pandemic remain unknown, strategies for coping with the myopia pandemic such as early identification, regular follow-up, and timely intervention of high-risk groups of myopia, are essential and are gaining more social attention [12].

In recent years, artificial intelligence has been advancing at an unprecedented rate, showing great potential for the automated analysis of medical information and images. In the field of ophthalmology, due to the wide application of various imaging technologies in eye diseases, many studies have applied AI methods to different ophthalmology diseases, such as diabetic retinopathy (DR) [13–16], age-related macular degeneration (AMD) [17, 18], cataract [19], dry eye syndrome (DES) [20], and glaucoma [21–23]. For myopia, research efforts are still relatively insufficient compared to other subspecialties, even though AI has shown the potential to address urgent needs in the field of myopia.

The clinical tasks of managing myopia include early screening, risk stratification, progression prediction, timely and individualized intervention, and ongoing management [24, 25]. Relevant data modalities produced during the process can be classified into two categories: clinical data and imaging data. As a concept in AI, machine learning (ML) is deeply entwined with statistics and is powerful for working with numerical or categorical data [26]. Commonly used ML techniques in myopia include support vector machine (SVM), linear regression, random forest (RF), naive Bayes, k-nearest neighbor (KNN), and extreme gradient boosting (XGBoost) [27]. As a subset of ML, deep learning (DL) has performed well in many image-based applications, such as object recognition and semantic segmentation [28]. Convolutional neural networks (CNNs) are the foundation of image-driven applications in myopia and the use of recurrent neural networks (RNNs) is still at an early stage. The abundant datasets with adjunctive AI analysis have led to improvements in myopia management.

As an emerging research field, there are currently only few reviews summarizing the application scenarios of AI in myopia [29–32], and none has focused on the data modalities available and the AI methods appropriate for each type of data, which is insufficient as data continue to grow in variety and quantity. Therefore, in this review, we examine how AI methods have been applied in analyzing different data modalities generated from clinical practice in myopia.

Method of literature review

We conducted a comprehensive literature review using two databases (i.e., PubMed and IEEE Xplore) in August 2022 and March 2023. Our search terms included a combination of relevant keywords, such as "myopia" and "artificial intelligence" and Boolean operators to ensure a comprehensive search. We also reviewed the reference lists of relevant articles to identify additional studies that may have been missed in our initial search. Our review is focused on the use of AI in the risk identification, screening, detection, classification, and treatment of myopia. Accordingly, we considered research articles that utilized AI for these purposes to be appropriate for inclusion in our review and have incorporated relevant studies in this article.

Clinical practice of myopia management

When facing a patient with myopia in the clinic, clinician considerations usually follow the sequence of risk factor identification, the examination process, selection of treatment strategies, and ongoing management [33], as shown in Fig. 1.

Myopia has been traditionally viewed as a consequence of the sophisticated interaction of lifestyle, genetics, and environmental factors. Therefore, detailed history taking is routinely conducted at the very beginning, and risk factors for a given individual are identified. Then, simple clinical tests such as cycloplegic and/or noncycloplegic refraction, best-corrected visual acuity, binocular vision and accommodative tests, anterior eye health evaluation, and corneal topography are taken for all visits. Measurement of axial length is optional, and currently, there is no established standard for normal or accelerated axial elongation. For patients who need further examination, especially those with a high degree of refraction, fundus imaging and examination are performed if indicated. After all the examinations, for patients who may result in low vision and blindness, selection of treatment strategies should be considered and in an individual way. For those possessing multiple risk factors, it will be helpful to predict the prognosis and carry out regular follow-up.

During the whole process, a large amount of meaningful data is generated. Since the key components of developing an AI application can be concluded as "MDT," that is "Model, Data and Target"[34, 35], the abundant datasets make it possible for AI to assist in many tasks of myopia management based on each type of data modality.

Artificial intelligence on clinical data in myopia

At nearly all steps of the clinical practice mentioned above, a considerable amount of clinical data is generated. These data can include basic ophthalmologic information, such as cycloplegic and noncycloplegic refraction, axial length (AL), corneal curvature radius (CR), best-corrected visual acuity (BCVA), and intraocular pressure (IOP); behavioral and environmental data, such as eye habits, reading

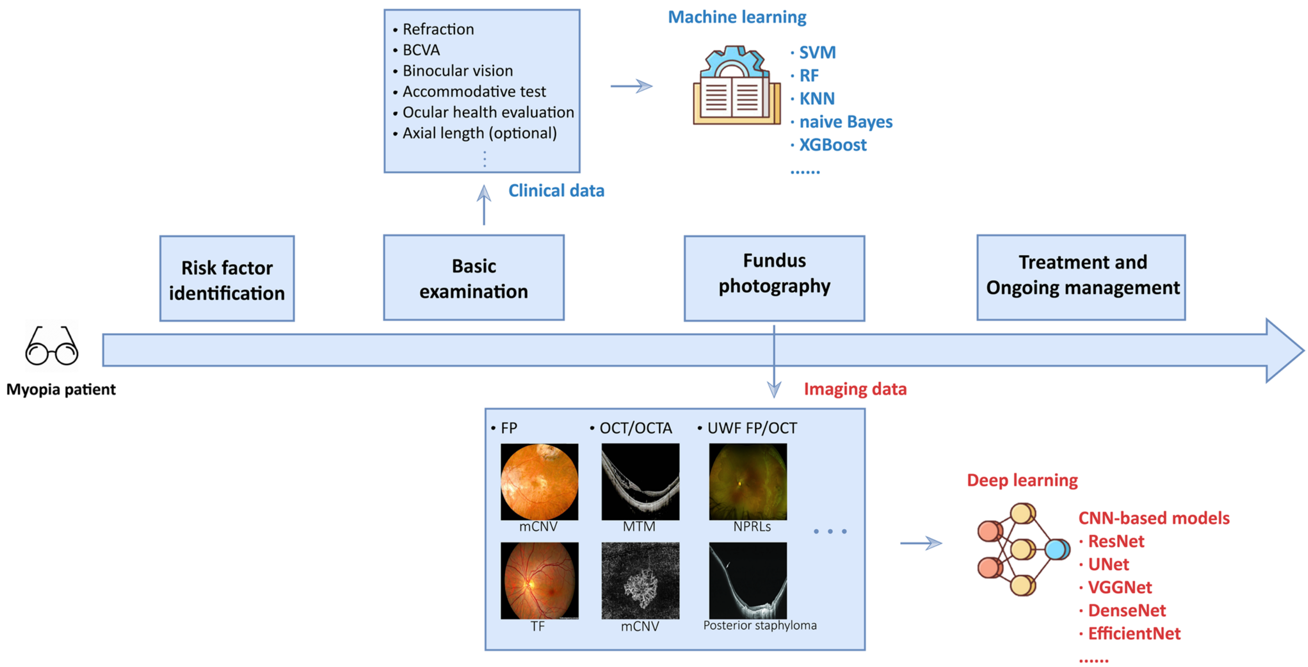

Fig. 1 The procedure of clinical practice on myopia. *SVM* support vector machine, *RF* random forest, *KNN* k-nearest neighbor, *mCNV* myopic choroidal neovascularization, *TF* tessellated fundus, *MTM* myopic traction maculopathy, *NPRLs* notable peripheral retinal lesions, *FP* fundus photography, *OCT* optic coherence tomography, *OCTA* optic coherence tomography angiography, *UWF* ultra-widefield

distance, illumination conditions, and outdoor activity; and personal information related to diseases, such as demographics, heredity, and psychological state. All of the basic ophthalmologic information is numerical data, which is a data type expressed in quantitative numbers. For others, most of them are categorical data, a collection of information that is divided into groups and can take on numerical values, although meaningless. In brief, all of these clinical data can be expressed in a numeric form, which is different from imaging data generated from fundus examination.

Considering the size, especially for a complex disease such as myopia where numerous codependent factors are involved in the causes, epidemiology, diagnostics, and progression, it is almost impossible to manually analyze the clinical data. Therefore, ML methods, with the capability of handling large amounts of data in a nonlinear way and extracting large numbers of potential predictive parameters, even when it outnumbers observations [36], are suitable for applications in myopia (Table 1). Applications based on this type of data mainly include prognosis prediction, refractive surgery assistance, and remote monitoring.

Prognosis prediction

By constructing risk models with various variables in this data modality, many studies have determined the capability of ML methods for prognosis prediction. The random forest model is shown to predict the onset of high myopia at 18 years of age as early as 8 years in advance at a clinically acceptable accuracy by using long-term refraction data [37]. Comprehensively assessing the physiological elongation of axial length, a key indicator for high myopia, by SVM and GBRT, instead of mydriatic optometry can be used to predict myopia progression [40]. Additionally, the probability produced by these models can help persuade patients for further referral [39].

Refractive surgery

ML methods have been applied to eye parameters obtained from advanced instruments to screen candidates for refractive surgery [46], detect corneal ectasia susceptibility [47], and distinguish healthy corneas from diseased one [48, 49]. One of the earliest studies on AI applications in myopia focused on using ML methods and data collected by the GALILEI Dual Scheimpflug Analyzer to automate the detection of subclinical keratoconus, which is a contraindication for refractive surgery [50]. Additionally, different ML models trained on medical records of myopia patients have been reported to improve the accuracy of intraocular lens (IOLs) power selection, which is crucial for reducing postoperative refraction errors, especially in highly myopic eyes that have undergone cataract surgery. The integration of AI into IOL power calculation formulas, such as Hill-RBF3.0 and Kane,

Table 1 Summary of artificial intelligence (AI) research in myopia based on clinical data

Research	ML model	Data modality	Application	Results	Year
Lin, H. et al. [37]	Random forest	Refraction data	Prognosis prediction (Predicting the onset of myopia)	Predicting the onset of high myopia at 18 years of age as early as 8 years in advance (AUC ranged from 0.802 to 0.886)	2018
Rampat, R. et al. [38]	XGBoost	Wavefront aberrometry data	Prognosis prediction (predicting subjective refraction)	MSE ranges from 0.094 to 0.301 diopters for different vector	2020
Tang, T. et al. [39]	Robust linear regression	Clinical data	Prognosis prediction (estimating the physiological elongation of axial length)	R-square: 0.87	2020
Yang, X. et al. [40]	GBRT + SVM	Clinical data	Prognosis prediction (predicting the myopia situation of grade 6 students)	Accuracy: 0.93; Precision: 0.95; Sensitivity equals 0.94; F1 score: 0.94; AUC: 0.98; Specificity: 0.94	2020
Li, S.M. et al. [41]	Random forest	Clinical data	Prognosis prediction (selecting risk factors and building prediction model for myopia progression)	Determine 6 key variables, with a combined weight of 77%, and the accuracy of the prediction model is over 80%	2022
Hou, X. et al. [42]	Three ML algorithms	Serum metabolic profile	Prognosis prediction (predicting progression of myopic retinopathy)	XGBoost showed good prediction accuracy (AUC 0.897) and had well-fitted calibration curves	2023
Ye, B. et al. [43]	SVM	Behavioral and environmental data	Monitoring (differentiating indoor and outdoor locations)	The accuracy and AUC were 92.43% and 0.96	2019
Mrochen, M. et al. [44]	Not mentioned	Behavioral data	Monitoring (automatic recognition of the activities performed by children with myopia)	ML algorithms can provide the identification of the type of visual activity	2020
Wei, L. et al. [45]	XGBoost	Demographics and biometrics data	Refractive surgery (predicting the actual postoperative refraction)	MAE is 0.33–0.35, MSE is 0.18–0.19, and is better than Barrett Universal II formula	2020
Xie, Y. et al. [46]	InceptionResNetV2	Pentencam system	Refractive surgery (classifying corneal types for patients wanting to undergo refractive surgery)	Total detection accuracy of 94.7%, comparable to that of senior refractive surgeons	2020
Lopes. et al. [47]	Random forest	Pentencam system	Refractive surgery (detection of corneal ectasia susceptibility)	The AUC is 0.992, being statistically higher than the Belin/Ambrósio deviation (AUC = 0.960)	2018
Ruiz, Hidalgo. et al. [48]	SVM	Pentencam system	Refractive surgery (automatically identifying corneal patterns)	KC versus normal discrimination task: accuracy 98.9%, sensitivity 99.1%, specificity 98.5%. forme fruste versus normal task: accuracy 93.1%, sensitivity 79.1%, specificity 97.9%	2016
Kovacs, I. et al. [49]	Neural network	Pentencam system	Refractive surgery (discriminating healthy corneas from patients with unilateral keratoconus)	Automated classifiers trained on bilateral data of index of height decentration had higher accuracy than the unilateral single parameter in discriminating fellow eyes of patients with keratoconus from control eyes (AUC equals 0.96 versus 0.88)	2016

Table 1 (continued)

Research	ML model	Data modality	Application	Results	Year
Smadja. et al. [50]	Decision tree	Scheimpflug Analyzer System	Refractive surgery (automatizing the detection of subclinical keratoconus)	Between normal and keratoconus: 100% sensitivity and 99.5% specificity; Between normal and forme fruste keratoconus: 93.6% sensitivity and 97.2% specificity	2013
Kim, J. et al. [51]	ResNet50, XGBoost	Preoperative data and fundus images	Refractive surgery (predicting the presence of myopic regression at 4 years of follow-up examination postoperatively)	The AUC of predicting myopic regression of more than 0.5 D is 0.753	2022
Cui, T. et al. [52]	A double hidden layer ANN	Clinical data	Refractive surgery (predicting SMILE nomogram)	The machine learning technique performed as well as surgeon in safety, but significantly better than surgeon in efficacy	2020
Cheng, H. et al. [53]	\	Preoperative data	Refractive surgery (comparing new AI IOL power selection methods (Kane and Hill-RBF2.0) with other traditional formulas)	The Kane, H1-MWK, and H1-WK methods were equally accurate in eyes with high to extreme myopia	2021
Omoto, M. et al. [54]	\	Preoperative data	Refractive surgery (investigating the prediction accuracy of AI IOL power selection methods)	The prediction accuracy using AI (Hill-RBF3.0 and Kane) showed excellent prediction accuracy	2022
Fang, J. et al. [55]	Logistic regression	Clinical data	Treatment (predicting the treatment effect of ortho-k)	The C-statistic of the predictive model was 0.821	2022
Fan, Y. et al. [56]	Four ML algorithms	Clinical data	Treatment (estimating the alignment curve (AC) curvature in orthokeratology lens fitting for vision shaping treatment (VST)	The R-squared values for the output AC1K1, AC1K2 and AC2K1 values were 0.91, 0.84, and 0.73, respectively	2022
Kaya, C. et al. [57]	RT	Horizontal and vertical EOG signal data	Others (classifying individuals who have refractive disorders or not)	Sensitivity: 95.5%; specificity: 96%; classification accuracy: 90.91%	2018
Ahn, H. et al. [58]	FcNN, XGBoost, TabNet	Clinical data	Others (identifying patients who would benefit from corneal topography)	sensitivity of predicting which patients needed corneal topography is 90.5–96.4%	2022

ML, machine learning; *AUC*, area under the receiver operating curves; *MAE*, mean absolute error; *MSE*, mean square error; *SVM*, support vector machine; *RT*, reduced-error pruning tree; *EOG*, electrooculogram; *SMILE*, small incision lenticule extraction has shown to produce more accurate prediction results compared to traditional formulas, including Barrett Universal II, Haigis, and SRK/T [53, 54].

Monitoring

Environmental risk factors, such as working at a close range (< 20 cm) and excessive continuous close working time (> 30 min), are considered to be factors relevant to the development of myopia, and increasing effective outdoor exposure time is an independent protective factor against myopia. However, it is difficult to monitor them widely in the public. Various smart wearable devices have been developed for monitoring working distance or outdoor exposure time, such as RangeLife [59], FitSight [60], and Cloud clips [61]. Through the data collected by wearable devices, an SVM model has been trained for distinguishing indoor and outdoor locations [43]. It may further combine with Internet apps, encouraging children to spend more time outdoors [60].

Artificial intelligence on imaging data in myopia

Fundus examination, which is recommended annually in high myopes, provides a visualization of both the central and peripheral retina under dilation and generates a considerable amount of imaging data. Among the different imaging methods, fundus photography (FP) and optical coherence tomography (OCT) are most commonly used for the assessment of myopia-related fundus changes.

By fundus examination, optic disc tilt and arc-shaped spots can be found in simple high myopia. For the fundus of pathologic myopia, a severe form of high myopia, posterior staphyloma, myopic traction maculopathy (MTM), myopic choroidal neovascularization (mCNV), dome-shape macula (DSM), and high myopia-related optic neuropathy can be seen, with a high specificity. These pathologic changes usually lead to irreversible damage to the retina, choroid, and other tissues, which will seriously affect the visual function of patients, but may present insidiously. Thus, timely imaging as well as accurate interpretation with the help of AI is important in detecting early complications and monitoring progression [62].

Fundus photography-based applications

FP is routinely ordered in a wide variety of ophthalmic conditions [63, 64]. It documents the retina, macula, optic nerve, and main retinal blood vessels in our eyes by using a highly specialized camera with high-powered lenses designed to visualize the pattern of the back of the eye [65]. It is often referred to as retinal fundus photography (RFP), highlighting the fact that an ophthalmologist's primary goal is typically to identify the appearance of the retina.

Based on this data modality, several studies have reported the use of machine learning methods for myopia and associated complications, as shown in Table 2. Unlike prognosis prediction, which is based on clinical data, the prediction task based on FP images mainly aims at predicting refractive error with ResNet [66], a famous CNN model used for feature extraction, which is surprising given that this was not a task thought to be possible manually. This might be useful for studying possible morphological changes in myopic eyes and can also help in epidemiologic research of myopia from large fundus image datasets where refraction labels are unavailable. In addition, fundus images can be investigated by fully convolutional networks (FCNs), a model modified from CNNs, and the semantic segmentation, or pixelwise classification, of these myopia-related fundus changes is possible [67]. For different types of myopic maculopathy, CNN-based models have been exploited to perform the classification task according to the META-PM classification system [68, 69]. In addition to private datasets, the utilization of a public dataset for training UNet + + to detect pathologic myopia and highlight the areas of lesions is also possible [70].

Traditional fundus cameras only capture images at an angle of 30 to 60° [78]. Therefore, combined with UWF imaging techniques, a novel form of FP, namely UWF fundus images (UWF-FP), enables ophthalmologists to observe the peripheral retina without pupillary dilation [79], with up to a 200° view of the ocular fundus in a single exposure. The employment of artificial intelligence in this data modality has achieved promising results, such as detecting glaucomatous optic neuropathy [80], identifying lattice degeneration [81], and even screening anemia [78]. For myopia, UWF-FP enables ophthalmologists to screen notable peripheral retinal lesions (NPRLs), the clinically significant peripheral retinal lesions that are more frequently seen in myopic eyes than normal eyes [82]. If kept untreated, patients with NPRLs will likely result in rhegmatogenous retinal detachment (RRD), an important cause of visual loss [83]. Based on the peripheral retinal information provided by UWF-FP, a customized CNN network [77] has achieved satisfying accuracy in automatically identifying the NPRLs. Similar to FP, UWF-FP can also be used by CNN-based models to predict refractive error, with an MAE of predicted spherical equivalent (SE) equal to 1.1150D [71]. Although surprisingly, this accuracy is inferior to the result of Varadarajan et al. [66], which is based on FP. This might result from the difference in the quality and quantity of the training and validation datasets. Further comparison of the performance of AI applications between FP and UWF-FP is needed.

Table 2 Summary of artificial intelligence (AI) research in myopia based on FP

Research	ML model	Data modality	Application	Results	Year
Varadarajan, A.V. et al. [66]	ResNet	Fundus images	Prediction (estimating refractive error)	MAE for estimating spherical equivalent: 0.56–1.81 diopters	2018
Shi, Z. et al. [71]	A customized CNN network (MDNet)	UWF fundus image	Prediction (predicting refractive error)	The MAE of predicting SE can reach 1.1150D, with RMSE equals 1.4520D	2022
Foo, L. et al. [72]	DenseNet121	Fundus images and clinical data	Prediction (predicting the 5-year risk of high myopia)	The image models (AUC: 0.91–0.95), clinical models (AUC 0.90–0.97) and mixed models (AUC 0.97–0.98) achieve clinically acceptable performance	2023
Wan, C. et al. [73]	DCNNs	Fundus images	Classification (categorizing patients by estimated risk of high myopia)	AUC of external validation: 0.9964–0.9968	2021
Du, R. et al. [68]	Efficient Net	Fundus images	Classification (identifying the different types of MM lesions)	Accuracies: 87.53–97.50%, AUC: 0.881–0.982, sensitivity: 0.370–0.872, specificity: 0.945–0.983	2021
Lu, L. et al. [69]	ResNet, FPN-based Faster R-CNN	Fundus images	Classification (automatically identifying pathologic myopia and classifying MM as well as “plus” lesions)	AUC: 0.979–0.995, Sensitivity: 0.684–0.978, Specificity: 0.970–0.995, Accuracies: 0.967–0.994	2021
Li, J. et al. [74]	Dual-stream DCNNs	Fundus image	Classification (identifying pathologic myopia, tessellated fundus, and no MM eyes)	AUC: 0.970–0.998, Sensitivity: 81.1–98.8%, Specificity: 95.9–99.6%	2022
Sun, Y. et al	A deep network with feature fusion framework	Fundus image	Classification (identifying the different types of MM lesions)	Five-grade accuracy on a private data-set:0.8921; AUC on PALM dataset: 0.99	2023
Shao, L. et al. [67]	ResNetFCN	Fundus images	Segmentation (semantic segmentation of tessellated fundus and quantitatively assessing the FTD)	Not mentioned	2021
Li, M. et al. [75]	MyopiaDETR	Fundus images (iChallenge-PM dataset)	Segmentation (diagnosing the lesion area of normal myopia, high myopia and PM)	Reaching AP_{50} of 86.32% on the iChallenge-PM dataset	2023
Tan, T. et al. [76]	ResNet101	Fundus image	Detection (identifying myopic macular degeneration and high myopia)	AUC: 0.969–0.978 for myopic macular degeneration, 0.913–0.973 for high myopia	2021
Li, Z. et al.[77]	CNN-based models	UWF fundus image	Detection (automatic identification of NPRLs)	AUC of 0.999, with sensitivity and specificity of 98.7% and 99.2% respectively	2019
Hemelings, R. et al. [70]	UNet++	Fundus images (PALM dataset)	Detection and segmentation (identifying pathologic myopia and semantic segmentation of myopia-related fundus changes)	AUC for PM detection: 0.9867; Dice and F1 metrics for semantic segmentation of lesions: 0.93 and 0.98 on optic disc, 0.80 and 0.91 on retinal atrophy, and 0.80 and 0.70 on retinal detachment	2020

AUC, area under the receiver operating curves; *MAE*, mean absolute error; *RMSE*, root mean square error; *PALM*, a public fundus images dataset; *PM*, pathologic myopia; *FTD*, fundus tessellated density; *MM*, myopic maculopathy; *UWF*, ultra-widefield; *NPRLs*, notable peripheral retinal lesions; *SE*, spherical equivalent

Optical coherence tomography-based applications

To analyze the fundus changes associated with myopia, OCT is another widely used method. It is carried out for detecting myopia-related vision-threatening conditions, such as retinal detachment, pathological mCNV, macular hole, and retinoschisis [84]. The characteristics of OCT enable ophthalmologists to see a myriad of pathologies in the anterior and posterior segments of myopic eyes, including the cornea, sclera, anterior chamber, vitreous, choroid, retina, and optic nerve, which can only be seen in enucleated eyes before [85].

Based on OCT, deep learning has been extensively studied for the detection of AMD [86] and glaucoma [87]. Regarding myopia and associated complications, 12 studies reported the use of CNN-based models (Table 3). It can help ophthalmologists identify myopic maculopathy in patients with high myopia [88] and the presence of pathologic myopia [89]. Four vision-threatening conditions associated with myopia can also be automatically detected with InceptionResNetV2 [84]. Since OCT images contain layer information, which is its unique characteristic, studies have demonstrated the potential for segmenting and analyzing the choroidal sublayers by using U-Net [90] and mask R-CNN [91], and further utilization of this in myopia is expected. It can also be helpful in automatic screening for high myopia [92] and estimating uncorrected refractive error [93].

Apart from applications that produce actual outputs, there are other ways to use AI methods in myopia. The ATN classification and grading system is a widely applicable clinical diagnostic criterion for myopic maculopathy [102]. While atrophy (A) can be judged based on FP only, determining the categories of traction (T) and neovascularization (N) requires FP together with OCT images. Apparently, OCT examination is much more difficult to adopt than FP. Therefore, a study built a multibranch ResNet with FP and OCT images to achieve ATN grades based on FP only, and the performance was superior to that of ophthalmologists who are not retinal specialists [101].

Limitations and prospects

Despite the reported effective implementation of AI in the clinical practice of myopia, problems and roadblocks remain. Prior to the general adoption of AI, critical technical and clinical restrictions must be overcome.

Establishment of a solid data foundation

The quality and quantity of data are extremely important to the applications of AI. The majority of the aforementioned AI applications in myopia use datasets collected by ophthalmologists during their clinical practice, which are usually on one or a few population groups exclusively. This might result in poor generalizability [103] and makes it difficult to determine whether the poor performance is attributable to spectrum bias [104, 105]. The disparity of imaging systems, discrepancy in imaging and postprocessing protocols, and lack of computing power also hinder the implementation of these algorithms into clinical practice. People who are in low-resource environments are frequently undercounted because it can be challenging to obtain medical attention and thus capture their data [106].

In this sense, public ophthalmological datasets are essential and provide an equal platform for comparing the outcomes of AI models in ophthalmology. There are some popular public datasets established by ophthalmologists from multiple centers for other ophthalmopathies, but none of them focus on myopia alone [106]. AI research in myopia might consider the feasibility of utilizing these public datasets in the future. The establishment of a large-scale public myopia dataset is also possible with novel AI technologies. A generative adversarial network (GAN) can be used in the generation of a large number of random and diverse images, and You et al. [107] determined its application on FP and OCT images in ophthalmology, offering a new way to enlarge datasets. Federated learning [108] and swarm learning [109] have emerged as potential methods to cope with privacy problems, providing a decentralized and secure method of data management.

Handle multitasks with multimodal data

The complexity of clinical manifestations in diseases and the diversity of data obtained through different examination modalities present a challenge in AI applications. In myopia, current AI models are typically designed for specific data modalities and purposes, resulting in high accuracy in distinguishing between "disease-free" and "diseased" cases, but poor performance in more complex tasks such as distinguishing between multiple diseases [48]. This challenge arises from the fact that some pathological changes in myopia can also occur in other ophthalmic conditions. One approach to address this is to exclude patients with comorbidities or group together a range of diseases. Alternatively, multimodal medical data fusion techniques can be employed by extracting relevant features from images and processing them with AI algorithms [94, 100]. These features are not limited to geometric measurements but may also include characteristic lesion regions [110]. Additionally, image data can be processed to obtain a virtual score, which can be predicted together with clinical data by AI algorithms [72]. While new developments in this area continue to emerge, it is important to note that multimodal data do not consistently outperform unimodal data, as demonstrated in a study on diabetic retinopathy staging [111].

Table 3 Summary of artificial intelligence (AI) research in myopia based on OCT

Research	ML model	Data modality	Application	Result	Year
Li, Y. et al. [84]	InceptionResNetV2	OCT images	Classification (identifying four vision-threatening conditions)	The AUC is high for all conditions (0.961–0.999); provide interpretable diagnosis results with heatmaps	2022
Yoo, TK. et al. [93]	ResNet50	OCT images	Prediction (estimating uncorrected refractive error)	MAE of SE prediction: 2.66D For detecting high myopia: AUC is 0.813 and accuracy is 71.4%	2021
Lu, H. et al. [94]	Five ML algorithms	OCT images	Prediction (predicting axial length)	Accuracy: 0.94, AUC: 0.95 (in binary classification); Accuracy: 0.88, AUC: 0.94 (in multiclass classification)	2022
Cahyo, D.A.Y., et al. [95]	U-Net	SS-OCT images	Segmentation (volumetric choroidal segmentation)	IoU: 0.92, accuracy: 0.99	2020
Li, J. et al. [96]	U-Net	EDI-OCT images	Segmentation (analyzing the choroidal sublayer)	Accuracy: 0.987, dice coefficient: 0.959	2021
Chen, H.J. et al. [91]	Mask R-CNN	OCT images	Segmentation (segmenting and quantifying the choroid)	The error of the automatic choroidal boundary segmentation: 6.72 ± 2.12 μm for inner and 13.75 ± 7.57 μm for outer. The mean dice coefficient: 93.87% ± 2.89%	2022
Mao, J. et al. [97]	The RU-net and transfer learning system	OCT images	Segmentation (segmentation of blood vessel)	Accuracy: 98.24%, sensitivity: 71.42%, specificity: 99.37%, precision: 73.68%, F1 score: 72.29	2023
Choi, KJ. et al. [92]	Three CNN models (ResNet50, InceptionV3, VGG-16)	SD-OCT images	Detection (identifying high myopia)	AUC: 0.86–0.90	2021
Sogawa, T. et al. [98]	Nine CNN models (VGG16/19, ResNet50, Inception V3, InceptionResNetV2, Xception, DenseNet121/169/210)	SS-OCT images	Detection (identifying images with and without myopic macular lesions)	AUC: 0.970–1.000, accuracy: 67.6–96.5%, sensitivity: 90.6–100%, specificity: 94.2–100%	2020
Ye, X. et al. [88]	ResNet101	OCT images	Detection (identifying MM in high myopia)	AUC: 0.927–0.974	2021
Du, R. et al. [99]	DarkNet-19	SS-OCT images	Detection (identifying the presence of mCNV, MTM, and DSM with soft labels)	The AUC in mCNV, MTM, and DSM models were 0.985, 0.946, and 0.978. The AUPR were 0.908, 0.876, and 0.653 respectively	2022
Park, S.J. et al. [89]	Four CNN models (ResNet18/50, EfficientNetB0/B4)	OCT images	Detection (identifying the presence of pathologic myopia)	Accuracy: 95%, sensitivity: 93%, specificity: 96%, AUC: 98%	2022
Kamiya, K. et al. [100]	SVR, GBR, RFR, LR	OCT images	Refractive surgery (prediction of phakic intraocular lens vault)	Significantly better predictability of the pIOL vault than conventional nomogram	2021
Wu, Z. et al. [101]	Multi-branch ResNet-34	FP images and OCT images	Others (estimating ATN grades)	AUC: 0.895–0.969, average accuracy: 85.3–94.2%	2022

SS-OCT, swept-source OCT; *EDI-OCT*, enhanced depth imaging OCT; *SD-OCT*, spectrum-domain OCT; *AUC*, area under the receiver operating curves; *AUPR*, the area under the precision-recall curve; *SE*, spherical equivalent; *IoU*, intersection over union; *MAE*, mean absolute error; *RMSE*, root mean square error; *pIOL*, phakic intraocular lens vault; *mCNV*, myopic choroidal neovascularization; *MTM*, myopic traction maculopathy; *DSM*, doom-shape macula; *MM*, myopic maculopathy; *ATN*, the atrophy, traction, and neovascularization classification and grading system

Explore the potential of novel data modalities

Novel forms of OCT images, such as UWF optical coherence tomography (UWF OCT) and OCT angiography (OCTA), can be seen in the clinical practice of myopia. UWF OCT, instead of the traditionally used 3D-MRI, can be helpful for better visualization of the posterior staphyloma in myopic eyes [112–114], which is "an outpouching of the wall of the eye with a radius of curvature less than the radius of curvature of the surrounding eye wall" [115] and usually results in poorer vision and more anatomical anomalies [116]. OCTA is very helpful for detecting retinal microvasculature in a noninvasive and depth-resolved way [117], thus providing a way of detecting mCNV with high sensitivity and specificity. Based on UWF OCT and OCTA, AI research is still restricted to improving the quality of images, such as image reconstruction [118, 119] and denoising [120], and there is currently a dearth of research exploiting the possibility of developing DL models to detect posterior staphyloma or mCNV.

Conclusions

The advent of AI is expected to transform the management of myopia. The findings of this review suggest that AI has been applied to most parts of the clinical practice of myopia and is built mainly on three types of data: clinical data, FP, and UWF FP, OCT. Image-driven AI applications account for the majority. However, compared with other ophthalmic diseases, AI research in myopia is still in its early stages, and these results are far from clinically viable. It is necessary to establish large public datasets with high quality and improve the capability of handling multimodal input. Exploring novel data modalities, designing advanced algorithms, and finding additional application scenarios could also be of great significance.

Abbreviations AL: Axial lengths; AMD: Age-related macular degeneration; AI: Artificial intelligence; BCVA: Best-corrected visual acuity; CNNs: Convolutional neural networks; CR: Corneal curvature radius; DES: Dry eye syndrome; DR: Diabetic retinopathy; DSM: Dome-shaped macula; FCNs: Fully convolutional networks; FP: Fundus photography; GAN: Generative adversarial network; IOP: Intraocular pressure; KNN: K-nearest neighbor; mCNV: Myopic choroidal neovascularization; ML: Machine learning; MTM: Myopic traction maculopathy; NPRLs: Notable peripheral retinal lesions; OCT: Optical coherence tomography; OCTA: Optical coherence tomography angiography; PM: Pathologic myopia; RF: Random forest; RFP: Retinal fundus photography; RNNs: Recurrent neural networks; RRD: Rhegmatogenous retinal detachment; SVM: Support vector machine; SE: Spherical equivalent; SMILE: Small incision lenticule extraction; UWF FP: Ultra-wildfield fundus photography; UWF OCT: Ultra-wildfield optical coherence tomography

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Declarations

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