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RECEIVED 12 February 2025

ACCEPTED 03 April 2025

PUBLISHED 23 April 2025

CITATION

He X, Wang Y, Zhang X, Chi W and Yang W
(2025) Artificial intelligence in pathologic
myopia: a review of clinical research studies.
Front. Med. 12:1572750.
doi: 10.3389/fmed.2025.1572750

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Artificial intelligence in pathologic myopia: a review of clinical research studies

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Myopia is a significant global health challenge, with the incidence of pathologic myopia (PM) on the rise. PM-related fundus diseases have become a leading cause of irreversible blindness. Early detection and treatment are crucial for the prevention and control of myopia. Recent advancements in artificial intelligence (AI), particularly in machine learning and deep learning algorithms, have shown promising results in the field of PM in ophthalmology. This review explores the latest developments in AI technology for managing PM, emphasizing its role in screening and diagnosis, grading and classification, and predictive assessment. AI has shown significant potential for clinical application in PM management, enhancing its intelligent, precise, and efficient practices.

KEYWORDS

artificial intelligence, pathologic myopia, diagnosis, classification, prediction

1 Introduction

Myopia, a prevalent global condition, is characterized by focused light in front of the retina due to the eye's extended axial length (AL) or changes in the refractive medium (e.g., cornea and lens) or abnormal accommodation of the eye, leading to blurred vision (1). Myopia can progress to high myopia (HM) and pathologic myopia (PM). HM is defined as a significant lengthening of the AL of the eye with a refractive error usually at or above -6.00 D. Typically, the AL of the eye is more than 26.5 mm. In comparison, PM is defined as structural changes in the eye due to excessive elongation of AL, resulting in severe visual impairment and complications such as posterior scleral staphyloma, lacquer cracks, choroidal neovascularization, macular hemorrhage, and myopic maculopathy (MM). PM emerges with characteristic fundus lesions, indicating a more advanced stage compared to HM, which highlights a significantly higher disease-related risk (2). With advances in ophthalmic technology, significant breakthroughs have been achieved in the diagnosis and treatment of PM. Advanced imaging tools such as color fundus photography (CFP) and optical coherence tomography (OCT) have revealed new pathologic features such as leopard-shaped fundus and myopia-associated MM. At the same time, new treatments for these lesions and their complications have shown remarkable results. For example, anti-VEGF therapy has been shown to be effective in treating macular neovascularization triggered by PM, while vitreoretinal surgery has emerged as an effective means of managing traction macular detachment. Posterior scleral reinforcement has been proposed as a treatment option to address the problem of increasing axial growth, and its effectiveness and limitations have been clinically.

The prevalence of myopia, particularly in East and Southeast Asia, presents a major health challenge. Predictions suggest a significant rise in HM by 2050, with the prevalence of myopia in the world population from 22.9% to 49.8% (3–5). The widespread occurrence of myopia (30%–50%), especially PM (1%–3%), underlines the urgent need for effective management strategies to reduce its heavy societal impact (6). Early detection and regular monitoring are essential for managing PM, emphasizing the gap between growing diagnostic needs and limited medical resources, posing a significant public health challenge.

In the realm of managing such challenges, AI emerges as a pivotal tool, encompassing machine learning (ML) and deep learning (DL) which employ deep neural networks (DNNs) to solve complex problems. Convolutional neural networks (CNNs), a specific type of DNN, are adept at processing image data, making them particularly useful in ophthalmology. The capability of AI to analyze vast amounts of data offers unprecedented support in diagnosing, grading, and predicting ocular diseases (7). Its application in PM, through accurate analysis and interpretation of fundus images, marks a significant advancement in ophthalmology, potentially revolutionizing PM management (8–13). The China Alliance of Research in High Myopia (CHARM), a large-scale research project planned to cover more than 100,000 Chinese patients, aims to investigate the diagnosis, progression, and genetic factors of HM (14). AI applications for myopia have now been identified and synthesized by many researchers, but there is not a complete narrative of AI applications for PM. Complications of PM bring serious health hazards and economic burdens to patients and society, so it is urgent to fully recognize the application of AI in PM.

This review delves into the application of AI technology in PM, highlighting significant research breakthroughs and their value in clinical practice. AI is transforming PM management through a stepwise approach:

1. Screening and Diagnosis: AI-powered image analysis automates early detection of PM lesions, significantly improving diagnostic sensitivity compared to manual review.
2. Grading and Classification: Building upon diagnostic findings, AI further quantifies lesion features to objectively classify disease stages.
3. Predictive Assessment: By integrating longitudinal data and lesion characteristics, AI models generate personalized progression risks, enabling proactive interventions.

This pipeline (Figure 1)—from detection to stratification to prognosis—demonstrates AI's capability to address the full clinical spectrum of PM.

Abbreviations: AUC, area under the curve; PM, pathologic myopia; HM, high myopia; MM, myopic maculopathy; PPA, peripapillary atrophy; AL, axial length; DCA, diffuse chorioretinal atrophy; mCNV, myopic choroidal neovascularization; CPF, color fundus photograph(y); OCT, optical coherence tomography; UWF, ultra-widefield; AI, artificial intelligence; DL, deep learning; ML, machine learning; CNN, convolutional neural network.

2 Retrieval methods

On 31 January 2025, we conducted a thorough search of the PubMed database and WOS Core Collection. We reviewed the latest research on AI in the field of PM. Our focus was on screening and diagnostic methods, classification and grading systems, and prediction models for disease progression. We used search terms including “artificial intelligence”, “machine learning”, “deep learning”, “ensemble learning”, “reinforcement learning”, “transfer network”, “neural network”, “supervised learning”, “computer vision system”, “computational intelligence”, “evolutionary computation”, “large language model”, “pathologic myopia”, “high myopia”, “myopic maculopathy”, and “progressive myopia”.

Inclusion criteria: The inclusion criteria were as follows:

1. AI technology application: Research studies that utilize AI technology for the diagnosis, grading, and prognostic evaluation of PM.
2. Detailed model development: Research studies that provide a comprehensive description of the AI model construction, including the training and validation processes.

Exclusion criteria: The exclusion criteria were as follows:

1. Non-human research studies: Research studies that involve animal models or *in vitro* experiments rather than human subjects.
2. Review, conference papers, and non-peer-reviewed articles: Research studies that are review articles, conference papers, or articles that have not undergone peer review.
3. Clinical research articles unrelated to AI or PM.

After collecting the relevant literature, we manually screened the titles and abstracts to match the research, and the screening process details are provided in Figure 2.

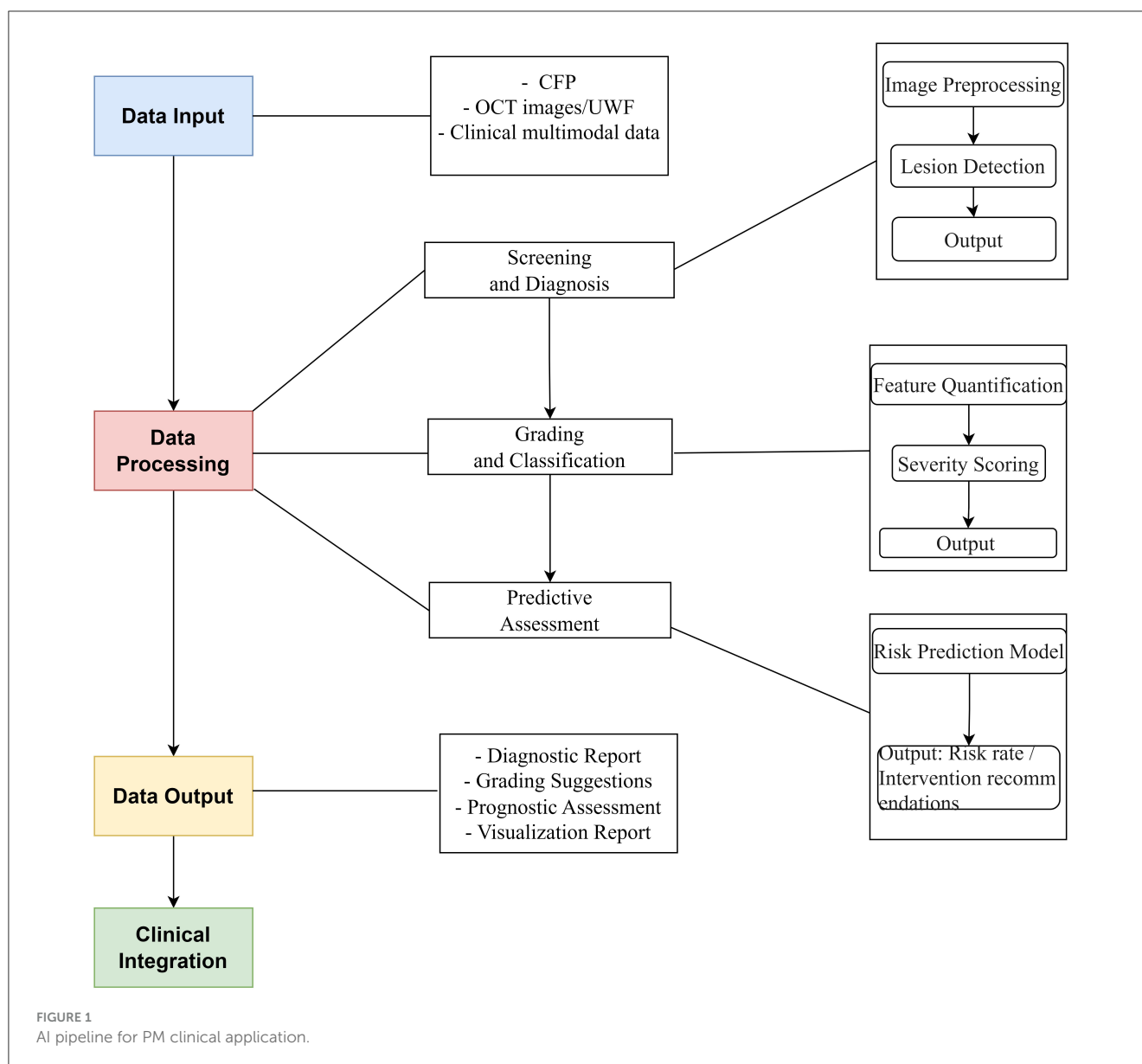
Analyzing the latest AI research findings in the field of PM and categorizing them based on their content, the application of AI in managing PM is prominently showcased in three primary aspects: screening and diagnosis, grading and classification, and predictive modeling for assessing PM progression.

3 Applications of AI in screening and diagnosis of PM

Early identification and accurate diagnosis of PM are crucial for the effective prevention and management of its complications (15). Table 1 lists AI applications in the diagnosis of PM (Literature not listed is not clinical research studies in multiple case centers and could not be included in the table).

3.1 AI screening and diagnosis of fundus images for PM

AI plays a pivotal role in enhancing the capabilities of primary care providers in detecting and managing PM by automating the screening process and facilitating timely referrals. This advancement is further supported by the



development of imaging technologies ranging from CFP and OCT to ultra-widefield (UWF) imaging (16), which has dramatically improved the understanding of myopic fundus lesions (17). The target population for this task is at-risk individuals in the general population, especially adolescents and children, as they are at a critical period in the development of myopia.

3.1.1 Color fundus photography

Research initiatives have successfully used various AI models (e.g., EfficientNet) based on CFP to diagnose common retinal diseases such as PM, glaucoma, and diabetic retinopathy with high accuracy (18–21). The multi-disease diagnostic tool PADar has been developed for primary eye screening, demonstrating the

potential of AI to increase the rate of early diagnosis of PM in the primary care setting (22).

Developing an automatic, accurate, and non-invasive screening system for PM patients through AI can significantly conserve time and resources for both clinicians and patients. CNNs, specialized in processing lattice-structured data, have demonstrated superior performance in the automatic screening and diagnosis of PM. The pre-processed fundus photographs were feature extracted by the CNN model and categorized into normal fundus images and pathologic myopic fundus, achieving the best AUC of 0.9845 (23). However, the problem of overfitting cannot be avoided, and data augmentation mode was matched to the image dataset, achieving an accuracy increase of 2.85% (24). DL models, such as the PM-AI system (25) and MyopiaDETR (26), not only effectively detect the location of lesions but can also suggest the presence of myopic choroidal neovascularization (mCNV) (27–30). MM

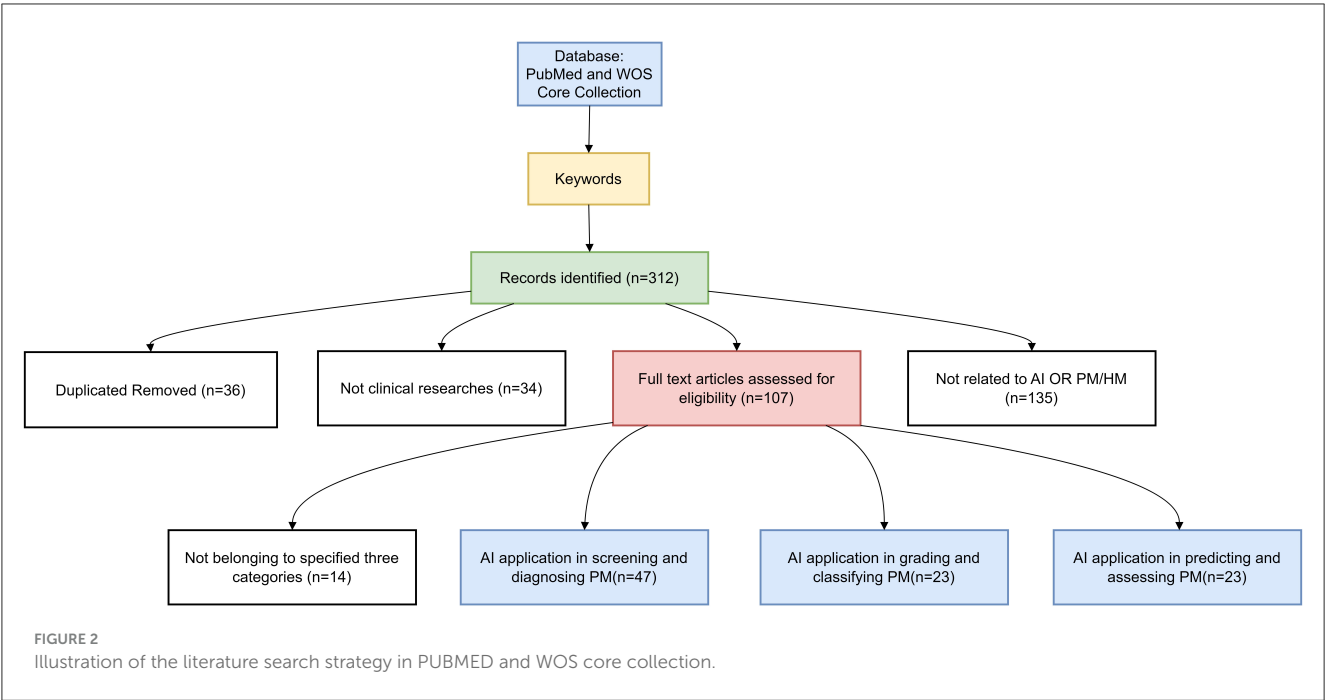


TABLE 1 The application of AI in the screening and diagnosis of PM/HM.

Authors	Modalities	Sample size	Algorithms	AUC (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
Zhu et al. (16)	CFP	2,400	DL	>95.0	95.6	96.1	99.6
Gu et al. (18)	CFP	4,795	DL	–	93	85	94
Rauf et al. (20)	CFP	–	CNN	98.5	–	–	–
Ren et al. (22)	CFP	1,156	DL	–	–	98.17	93.06
Wang et al. (25)	CFP	7,606	CNN/TL	95.0–100.0	93.2–99.8	90.8–96.8	93.3–99.9
Tan et al. (26)	CFP	226,686	CNN	97.3	–	95	86.9
Lu et al. (28)	CFP	17,330	DL	99.3	97.7	97.7	97.2
Qian et al. (29)	CFP	4,603	DL	–	–	80.1	94.6
Li et al. (30)	CFP	36,515	DCNN	97.0–99.8	93.0–96.9	90.8–93.3	98.7–99.6
Zhang et al. (31)	CFP	1,391	DL	99.9	96.8	83.1	95.6
Choi et al. (32)	OCT	690	CNN	99	100	–	–
Ye et al. (33)	OCT	2,342	DL	92.7–97.4	–	–	–
Li et al. (34)	OCT	5,505	CNN	96.1–99.9	–	90.0–100.0	90.5–96.5
Li et al. (39)	OCT	720	DL	–	–	92.4	99.8
Xu et al. (40)	OCT	800	DL	99.5	–	–	–
Zhang et al. (27)	UWF	2,644	DCNN	–	93	90.7	95.2
Mao et al. (46)	UWF	317	DL/TL	–	98.2	71.4	99.4

is a series of macular lesions associated with PM, characterized by macular atrophy, lacquer cracks, choroidal neovascularization, and posterior staphyloma. DL models show great potential in screening the diagnosis of MM (31–33). Furthermore, self-supervised learning is integrated with DL to make a more precise diagnosis (34).

3.1.2 Optical coherence tomography and ultra-widefield images

Fundus imaging presents significant challenges for PM. The evolution of modalities for ophthalmic imaging provides a solid foundation for entering the era of healthcare intelligence. Choi et al. (35) comparatively assessed the ability of three DL models

to screen for HM using OCT imaging, with ResNet 50 performing the best. Innovations such as the application of models like Inception ResnetV2 and ResNeSt101 (36) for detecting fundus complications (retinoschisis, macular hole, retinal detachment, and mCNV) affirm the value of CNNs in achieving high diagnostic accuracy (37). Anatomically, Ota-Itadani et al. (38) used DL on 3D OCT imaging to detect and classify lamina cribrosa defects, assisting in early screening for PM.

The advent of UWF technology has also solved many of the challenges of PM imaging (30). UWF OCT improves the imaging of mCNV, the vitreoretinal interface, and the progression of myopic traction maculopathy (17).

These advancements underscore the transformative potential of AI in the management of PM, highlighting AI's role in refining diagnostic methodologies through enhanced image analysis and the integration of novel technologies.

3.2 AI applications of imaging markers and multimodal data analysis for PM

The applications of AI in employing imaging markers and bioinformation for the diagnosis of PM have shown significant advancements. Choroidal thickness and the degree of peripapillary atrophy (PPA) at the optic disc are recognized as effective indicators for assessing PM-related lesions (39–41).

Utilizing AI for precise segmentation and data collection on choroidal characteristics greatly aids in disease diagnosis. Recent research using DL algorithms has demonstrated a high degree of accuracy in distinguishing between the choroidal thickness measured automatically and manually, highlighting AI's capability in achieving detailed analysis with high agreement levels (42–44). Research studies utilizing mask region CNN models have automated the process of segmenting the choroidal region in OCT images of myopic patients, enabling the assessment of myopia severity based on choroidal thickness (45). Innovations such as the Boundary Enhancement Module and the utilization of parallel branches in AI architecture have aimed to improve segmentation accuracy by enhancing boundary features from varied perspectives (46). DL has also facilitated the automatic quantification of the vascular structure of the choroid, allowing the extraction of valuable metrics such as choroidal thickness, area, volume index, and vessel density through automated segmentation (47, 48), while thinner choroidal thicknesses tend to be associated with elongation of AL over 2 years (49). Furthermore, DL models have been employed successfully for noise reduction in OCT-scanned images, achieving the automated three-dimensional reconstruction and segmentation of intrachoroidal cavitation (50). AI applications extend to enhance the accuracy of segmenting high myopic choroid, with U-Net-based sequence models showing promising results (51). Although UWF imaging is primarily used to capture images of the peripheral retina, its 200° panoramic field of view and high resolution also make it possible to display details of the posterior pole clearly. The analysis of UWF imaging has revealed an association between the severity of mCNV and increased retinal blood vessel density and branching, highlighting AI's potential to provide foundational data for PM screening and diagnosis (52). Moreover, AI-measured lacquer crack

extension is proved to be related to the progression of mCNV that a larger initial LC area or a faster rate of LC expansion may predict earlier CNV onset (53).

Advancements in AI have enhanced the segmentation accuracy of the optic disc and PPA (54). Measurement of vascular parameters and PPA area with a DL model confirms pathologic mechanisms in the development of PM (55). Through the integration of vision transformer and CNNs in model development, modern algorithms, based on UWF imaging, significantly outperform classical models in segmenting the optic disc and PPA (56). Its ability to handle complex backgrounds and fuzzy boundaries, multi-scale feature extraction, feature fusion, and boundary information processing enable transformers to more accurately segment PPA, fundamentally aiding ophthalmologists in diagnosing and managing conditions related to PM. However, incorporating transformers typically requires larger training datasets, so a lightweight image segmentation network named simple CNN-UNet is proposed for precise segmentation of the optic disc (57). In response to the limitations of retinal atrophy such as unclear boundaries and irregular shapes, ARA-Net-segmented retina has been proposed to detect retinal atrophy in various area sizes (58).

AI significantly enhances the diagnosis of PM by integrating more biological data alongside the direct screening and identification of distinctive fundus images. Zhang et al. (59) developed the PM-BMII, a computer-aided diagnostic framework that smartly merges diverse biomedical data from various sources, such as genetic, demographic, clinical information, and imaging data, improving the diagnostic accuracy of ~4.2–46.3% of PM. Furthermore, AI's capability to discern correlations between multiple potential factors and HM enriches our understanding, as evidenced by Zhang et al.'s (60) discovery of a significant link between increased serum vitamin A levels and HM prevalence. The role of AI extends beyond diagnostic advancement to enhancing healthcare service quality and the efficacy of medical interventions. A comparative research by Fang et al. (61) highlighted the superior educational effectiveness of an AI-driven PM auto-recognition system over traditional teaching methods in improving students' diagnostic accuracy and learning efficiency, showcasing the impact of AI in medical education.

The deployment of AI in the diagnosis of PM presents multiple advantages, such as convenience, speed, and medical resource conservation, alongside ensuring accuracy and enhancing management efficiency. Its automated screening and diagnostic capabilities play a pivotal role in early detection, raising awareness, and mitigating complications. This not only improves the ophthalmologist's ability to deliver timely and personalized interventions but also improves the overall patient experience through more accurate diagnostic results. Consequently, AI's contributions are vital in preserving visual health and alleviating societal burdens.

4 Applications of AI in grading and classification of PM

The application of AI in grading and classifying PM is indispensable for determining the severity of damage, the risk of complications, and its impact on visual acuity. This categorization

TABLE 2 The application of AI in the grading and classifying of PM/HM.

Authors	Modalities	Sample size	Algorithms	AUC (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	MM grading methods
Wan et al. (55)	CFP	758	DCNN	99.6–99.7	98.2	–	–	–
Huang et al. (56)	OCT	2,837	CNN	96.1–99.8	–	91.7–97.8	98.3–99.1	–
Hemelings et al. (57)	CFP	1,200	CNN	98.6	–	–	–	–
Lu et al. (28)	CFP	16,428	DL	99.3	97.7	97.7	97.2	–
Du et al. (58)	CFP	7,020	DL	88.1–98.2	92.1	37.8–87.2	94.5–98.3	–
Zheng et al. (59)	CFP	4,642	DL	96.0–99.2	83.6	64.7–96.9	–	–
Sogawa et al. (60)	OCT	910	CNN	97.0–100.0	67.6–96.5	90.6–100.0	94.2–100.0	–
Lu et al. (65)	CFP	32,010	DL	99.5	97.4	93.9	98.2	META-PM
Wu et al. (66)	OCT	1,853	DL	89.5–96.9	85.3–94.2	–	–	ATN
He et al. (67)	OCT	3,945	DL/TL	98.6	96	–	–	ATN
Wan et al. (69)	CFP	1,750	DL	96.6	–	92.3–100.0	98.1–100.0	
Tang et al. (71)	CFP	1,395	DL	99.8	–	–	–	META-PM
Zhu et al. (70)	CFP	4,252	ALFA-Mix+	–	89.6	86.4	97.2	META-PM
Zhang et al. (80)	CFP	2,159	DL	99.5	95.4	95.4	98.9	META-PM

ALFA-Mix+: an active learning algorithm based ALFA-Mix.

is essential to develop specific treatments, ranging from monitoring the progression in mild cases to preventing complications in severe conditions. The target population for this task is patients who have been diagnosed with PM, which facilitates clinicians to regularly track the progress of PM, assess the effectiveness of treatment, and make timely adjustments to the treatment plan. Table 2 lists AI applications in the grading and classification of PM.

4.1 General advances in AI for grading and classification of PM

In general, many advances have been made by many researchers in AI for PM grading and classification. Wan et al. (62) have successfully utilized a DL model for intelligent risk grading of HM in fundus images. The model's ability to automatically classify fundus images into normal fundus, low-risk HM, and high-risk HM categories demonstrates its superiority over traditional assessments by ophthalmologists, with sensitivity and specificity close to 100%. In another research, Huang et al. (63) employed the ResNet-34 architecture to enhance the grading of traction retinopathy in highly myopic eyes across five categories, achieving significant accuracy in identifying varying severities of traction retinopathy. To optimize current automated diagnostic tools, Wang et al. (18) applied lightweight classification models such as MobileNetV3 and ShufflenetV2, which offer the benefits of shorter diagnosis times along with reduced storage and parameter requirements. Hemelings et al. (64) combined PM classification with lesion segmentation for PM complications using 2D fundus images and the transformer architecture, leading to a reduced false-positive rate for PM cases. Furthermore, the recent contributions of Lu (31) and Du et al. (65) in employing the International Classification System (META-PM) for PM identification and classification have

been notable. While Du R's research is primarily aimed at predicting the risk of developing HM in children, Lu L's research focused more on identifying and classifying PM, with a particular emphasis on pathologic retinal changes.

4.2 Advances in AI for grading and classifying MM

Advances in AI have significantly improved the grading and classifying of MM, a major complication of PM that substantially affects vision quality. MM refers to characteristic degenerative changes in the macula, including chorioretinal atrophy, Fuchs spot, lacquer cracks, posterior staphyloma, and optic disc changes. A CNN model was designed for automatic extraction and quantification of features of the posterior scleral wall from OCT images, which were finally presented as 3D-MRI images (66). The classification of MM is crucial, given its implications on treatment and prognosis. Zheng et al. (67) utilized the EfficientNet model applied to fundus photographs of MM, achieving notable sensitivity and specificity. By exploiting SS-OCT imaging, Sogawa et al. (68) found that DL models could precisely diagnose MM, distinguishing it from non-degenerate conditions. In addition, Du et al. (69) investigated novel imaging biomarkers within the optic disc region of fundus images through ML and radiomics, uncovering features that effectively differentiate between varying degrees of MM severity. Tessellated fundus (TF), well-defined choroidal vessels at the posterior fundus pole, is associated with the development and progression of MM. The choroidal area per unit area exposed on fundus photographs can be used as an assessment metric for deep learning models, reflecting the severity of MM (70–73). Quantified FT was found to migrate toward the macula

TABLE 3 The application of AI in the predicting of PM/HM.

Authors	Modalities	Sample size	Algorithms	AUC (%)	Accuracy (%)	Projected content
Zhao et al. (72)	Refraction records	88,250	–	96.5–99.7	–	Spherical equivalent (SE)/high myopia onset
Yoo et al. (73)	OCT	936	DL	81.3	71.4	Uncorrected refractive error
Wang et al. (74)	Clinical and imaging information	967	–	87	–	Visual acuity
Chen et al. (75)	Clinical and imaging information	660	–	85–89	–	Myopic maculopathy Risk
Lu et al. (76)	OCT	710	ML	93.4–95.6	84.7–94.4	Axial length
Li et al. (77)	blood tests	20,870	ML	79	72	Occurrence of retinal detachment
Lin et al. (78)	Refraction records	132,457	RF	80.2–88.8	–	Myopia development
Foo et al. (79)	CFP	9,456	DL	90.0–99.0	–	The 5-year risk of high myopia
Li et al. (80)	Medical records	612 530	ML	99	–	Myopic progression
Guan et al. (81)	Medical records	1,285,609	RF	95.7	97.1	High myopia onset

as myopia progressed by DL techniques, which has potential applications for predicting HM and its complications.

Currently, the META-PM and ATN (A—atrophy; T—traction; N—neovascularization) grading systems are the primary methods for MM assessment. Lu et al. (74) utilized these systems to train DL algorithms for grading retinal fundus images, achieving an accuracy comparable to that of expert evaluations. Based on the META-PM system, DL models were automatically extracted from fundus images of diffuse chorioretinal atrophy (DCA) regions from fundus images, which were quantitatively graded into four classes based on size, density, and ocular biology (75). It has been shown that the presence of DCA and its association with visual function impairment is linked to a reduction in choroidal perfusion and stromal composition (76). However, challenges remain, such as the algorithm's inability to detect posterior staphyloma or accurately diagnose “PLUS” lesions. Wu et al. (77) investigated myopic macular lesions using the ATN system, employing CNNs (ResNet) and MB-ASPP techniques for finer subgroup classifications. This DL approach demonstrated high accuracy, as reflected in the AUC values for A, T, and N classifications. He et al. (78) employed macular OCT images from the ATN system, developing two algorithms, where the latter, utilizing transfer learning, showed improved performance. A gated attention mechanism network (GAMNet) achieves 93.3% accuracy in classifying myopic tractional macular degeneration (79). Ye et al. (36), adopting the ResNet 501 architecture across five distinct models, achieved differentiation of various MM features such as macular choroidal atrophy and myopic tractional maculopathy among others. The ensemble model made by combining different deep learning models performs better on MM classification (80). Comparative research studies of AI models by Wan et al. (81), Zhu et al. (82), and Tang et al. (83) showcased advancements in MM detection and classification, employing techniques such as VOLO-D2 models and the DeepLabv3+ network for lesion segmentation and classification. On the basis of the above META-PM grading, Meng et al. (84) proposed to grade HM by combining the visual

index of contrast sensitivity function (CSF) and fundus features, emphasizing the non-negligible role of functional indexes, which help to identify the hidden visual damage in early stage (84). These research studies have enhanced our understanding of myopic retinopathy onset signs and provided innovative approaches for monitoring myopia progression.

5 Applications of AI in predicting and assessing PM

The application of AI in predicting and assessing PM is essential for identifying individuals at the highest risk and accurately forecasting future trends early in the disease (Table 3). AI's capability in DL-based classification has demonstrated considerable potential in ophthalmic research for the early prediction and assessment of PM.

5.1 AI prediction for risk assessment of PM

In the realm of risk assessment for PM, AI methods have been deployed to gauge prospective risk and predict the tendency toward progressive myopia in patients with HM. Zhao et al. (85) employed random forest and gradient boosting decision tree (GBDT) models to predict refraction and the likelihood of developing HM using a refractive data span of 15 years. This approach aids in the early identification and prevention of myopia. Yoo et al. (86) extracted structural features from the posterior segment of OCT images and utilized ML to predict uncorrected refraction, which reduces the risk of overlooking problems associated with PM or HM. Similarly, machine learning models for predicting long-term visual acuity in patients with high myopia have also achieved good results using fundus imaging information (87). In addition, machine learning based on SS-OCT can make predictions about the progression of MM after 10 years based on relevant predictors

such as longer AL or thinner choroidal thickness (88). Although AL and choroidal thickness are important predictors of PM, they have no discriminative ability sufficient for prediction. Kim et al. (89) utilized a support vector machine (SVM) to accurately measure the relative tomographic elevation of posterior sclera on OCT images, increasing accuracy by 10% compared to that which only measured AL and choroidal thickness. Lu et al. (90) developed classifiers to predict ocular AL using OCT scanning, while Li et al. (91) continuously monitor and predict retinal detachment in patients with HM using the conditional probability algorithm based on blood parameters designed, with an AUC of ~ 0.96 . AI prediction for myopia risk in visually developing children.

Regarding the assessment of myopia risk in visually developing children, it is crucial to predict refractive changes during this critical period to manage the prevalence of HM and PM adequately. Multiple machine learning algorithms were constructed to confirm the correlation between BMI and HM with an AUC of 85%, with implications for the etiologic progression of HM (92). Lin et al. (93) used random forest on large datasets, alongside factors such as age and spherical lenses, to forecast HM incidence over 8 years. Foo et al. (94) combined DenseNet-121, a deep neural network model, with random forest to evaluate fundus images and clinical data, assessing the likelihood of children developing HM within 5 years. Li et al. (95) aggregated data from various cohorts to predict myopia progression and the risk of HM using ML, achieving an AUC of 0.99. Guan et al. (96) explored risk factors for HM through ML, with random forest showing notable accuracy. Clark et al. (97) introduced “polygenic scoring” (PGS) to predict myopia in children by assessing genetic susceptibility through DL and examining refractive error across different European populations. Ota-Itadani et al. and Liu et al. have further illustrated the potential of AI in PM research, focusing on structural abnormalities in PM patients. Liu et al. (98) and Kang et al. (99) observed optic disc and peripapillary atrophy (PPA) changes related to refractive errors in school-aged children, suggesting the PPA to optic disc area ratio as an early indicator of myopia progression. Tiny retinal vascular changes in children with HM can also be recognized by AI, such as a decrease in arterial branching angle and vascular arteriovenous ratio, which can help identify trends in HM earlier (100, 101).

5.2 AI prediction for treatment outcomes in PM

AI has demonstrated its potential to effectively predict treatment outcomes and efficacy in patients with PM. For instance, Zhou et al. (102) applied AI algorithms to calculate lens power during intraocular lens (IOL) implantation in highly myopic eyes, achieving high prediction accuracy. Notably, AI models such as XGBoost, Hill-RBF, and Kane excelled in cases with an AL exceeding 26 mm. In another research, Guo et al. (103) utilized extreme gradient boosting and support vector regression algorithms to formulate the Zhu-Lu formula, a novel ML approach for predicting post-surgical lens dioptric power in highly myopic patients. Wei et al. (104) developed and compared five ML algorithms based on OCT scans, all of which showed high accuracy

and stability in predicting the optimal corrected visual acuity after cataract surgery in highly myopic patients. Yang et al. (105) and Kang et al. utilized a deep neural network to predict visual acuity in patients with PM and mCNV treated with anti-VEGF, achieving an accuracy rate of over 80%. Sawai et al. (106) investigated the impact of the denoising process on the prediction of PM using single-frame optical coherence tomography angiography (OCTA) imaging, highlighting its role in providing fast and high-quality image analysis. Despite these advancements, the AI-based prediction of PM progression remains in its early stages. To enhance the management of PM and improve patient outcomes, it is crucial to increase scientific research investment, foster interdisciplinary collaboration, and conduct more rigorous clinical trials.

6 Limitations of AI in PM

While AI technology has made significant strides in various fields, its application in the clinical research and treatment of PM faces notable challenges. One such challenge is the poor quality of retinal images, such as artifacts caused by eye movements during imaging, which impede the accurate identification and diagnosis of ocular microscopic lesions. To address this, Cheng et al. (107) proposed the structure-preserving guided retinal image filtering (SGRIF) method, which enhances image quality by simulating the natural attenuation and scattering of the human eye lens, thereby improving contrast and aiding in the automated diagnosis of ophthalmic diseases such as optic disc analysis. Improving image quality in clinical work is the basis for AI in ophthalmology clinical work.

In addition, several overarching issues persist in AI research and application for PM. First, the issue of data heterogeneity deficits and model generalization bottlenecks represents the foundational barrier to advancing AI applications in PM research studies. Research studies have predominantly utilized single datasets, which may lack the size and diversity to represent the global spectrum of PM, thus limiting the models' generalizability. In classification tasks, the limited availability of imbalanced lesion distribution (e.g., “plus” lesions) in the META-PM classification of MM can result in overfitting. Second, lack of algorithm interpretability, particularly in tasks such as lesion localization (e.g., posterior staphyloma) and progression prediction, directly undermines clinicians' trust in AI outputs and their integration into practice. Third, deficiencies in clinical validation frameworks affect the spread and the use of AI for PM in clinical management. Of the included research studies above, overreliance on retrospective single-center data with limited real-world prospective validation limited prospective real-world validation research studies. The impact of variations in imaging equipment and quality remains understudied, despite its critical importance—especially given the heterogeneous image quality in primary care settings (e.g., county/township hospitals), which may limit the generalizability of AI models. Moreover, there is a need for a more in-depth exploration of model parameter tuning to enhance the accuracy of screening, grading, and prediction. While most algorithms struggle with detecting or localizing complications such as posterior staphyloma, some have shown promise in segmenting retinal lesion regions to improve detection rates. Last but not the

least, the application of AI in PM and HM is still in the experimental stage and has not been widely put into clinical use, but some of the research studies mentioned above compared the accuracy of AI with the work of ophthalmic professionals, showing AI was better than or equal to the level of experts. Therefore, the development of AI and the advancement of its use in PM management is a major trend.

7 Conclusion

This review provides a comprehensive review of the recent advancements in using AI technologies to manage PM. It highlights the significant contributions of AI in improving screening and diagnostic processes, as well as in grading, classification, and predictive assessment. Integrating AI has notably enhanced the accuracy and efficiency of PM diagnosis and its complications, surpassing traditional methods. AI enables the segmentation and extraction of retinal lesions, which helps in understanding disease severity and predicting disease progression, crucial for its management. In summary, AI is revolutionizing PM clinical management by enhancing its intelligence, precision, and efficiency.

In summary, AI, through the application of DL and ML, has been effectively utilized in the domain of PM. Despite its demonstrated potential, several challenges remain. These include the need to address the limitations in processing low-quality images, refining disease progression models, and fostering interdisciplinary collaboration to advance research and application.

Looking ahead, the value of AI in the management of PM can be further enhanced by focusing on the following areas: (1) The development of more extensive and diverse multicenter PM datasets that include demographic parameters such as age, gender, and occupation, and increase the representation of rare findings such as “plus lesions”. (2) Researchers should concentrate on enhancing the image processing capabilities of AI models, particularly in improving clarity and noise reduction, while also considering the constraints of equipment in primary healthcare settings during clinical applications. (3) Although AI is not yet fully mature for predicting PM, future research can integrate predictive models with intervention strategies. For example, researchers can provide clinical interventions to patients at different risks and compare them with preclinical patients without interventions to see whether there is any difference in the patients’ prognosis. By training AI models with substantial datasets and diverse cases, researchers can develop personalized prevention and treatment recommendations for PM patients based on their risk profiles.

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Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

XH: Data curation, Writing – original draft. YW: Writing – review & editing, Data curation. XZ: Writing – review & editing, Conceptualization. WC: Writing – review & editing, Conceptualization, Funding acquisition, Methodology. WY: Writing – review & editing, Conceptualization, Funding acquisition, Methodology.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This work was supported by Guangdong Basic and Applied Basic Research Foundation (2025A1515011627).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author(s) declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

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