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REVIEW

Artificial Intelligence in Optometry: Current and Future Perspectives

Anantha Krishnan[1,*], Ananya Dutta[2,*], Alok Srivastava[3,4], Nagaraju Konda[1], Ruby Kala Prakasam[5]

[1]School of Medical Sciences, Science Complex, University of Hyderabad, Hyderabad, Telangana, India; [2]Standard Chartered – LVPEI Academy for Eye Care Education, L V Prasad Eye Institute, Mithu Tulsi Chanrai Campus, Bhubaneswar, Odisha, India; [3]L V Prasad Eye Institute, Hyderabad, Telangana, India; [4]Sri Innovation and Research Foundation, Ghaziabad, Uttar Pradesh, India; [5]Standard Chartered – LVPEI Academy for Eye Care Education, L V Prasad Eye Institute, Gullapalli Pratibha Rao Campus, Hyderabad, Telangana, India

*These authors contributed equally to this work

Correspondence: Ruby Kala Prakasam, Standard Chartered – LVPEI Academy for Eye Care Education, L V Prasad Eye Institute, Gullapalli Pratibha Rao Campus, Kismathpur, Hyderabad, Telangana, 500 086, India, Email ruby@lvpei.org; Nagaraju Konda, School of Medical Sciences, Science complex, University of Hyderabad, CR Rao Road, Gachibowli, Hyderabad, Telangana, 500046, India, Email knr@uohyd.ac.in

Abstract: With the global shortage of eye care professionals and the increasing burden of vision impairment, particularly in low- and middle-income countries, there is an urgent need for innovative solutions to bridge gaps in eye care services. Advances in artificial intelligence (AI) over recent decades have significantly impacted healthcare, including the field of optometry. When integrated into optometric workflows, AI has the potential to streamline decision-making processes and enhance system efficiency. To realize this potential, it is essential to develop AI models that can improve each stage of the patient care workflow, including screening, detection, diagnosis, and management. This review explores the application of AI in optometry, focusing on its potential to optimize various aspects of patient care. We examined AI models across key areas in optometry. Our analysis considered crucial parameters, including model selection, sample sizes for training and validation, evaluation metrics, and the explainability of the models. This comprehensive review identified both the strengths and weaknesses of existing AI models. The majority of image-based studies utilized CNN or transfer learning models, while clinical data-based studies primarily employed RF, SVM, and XGBoost. In general, AI models trained on large datasets achieved higher accuracy. However, many optometry-focused models faced limitations due to insufficient sample sizes—28% of studies were trained on fewer than 500 samples, 18% used fewer than 200 samples, and over half validated their models on fewer than 500 samples, with 38% validating on fewer than 200. Additionally, some studies that used the same data for both training and validation experienced overfitting, leading to reduced accuracy. Notably, 20% of the included studies reported accuracy below 80%, limiting their practical applicability in clinical settings. This review provides optometrists with valuable insights into the strengths and weaknesses of AI models in the field, aiding in their informed implementation in clinical settings.
Keywords: artificial intelligence, optometry, AI application

Introduction

There are 2.2 billion people worldwide affected by vision impairment, includes an estimated 295 million with moderate to severe impairment.[1,2] Over 80% of such cases are in low- and middle-income countries.[3] Additionally, the International Agency for the Prevention of Blindness (IAPB), has highlighted the shortage of eye care professionals around the world. One could speculate that the eye care workforce may struggle to meet the rising demand as the global population continues to grow.

An evaluation across 21 Global Burden of Disease (GBD) regions, covering 123 countries, identified a total of 331,781 optometrists.[4] However, low- and middle-income countries face a significant shortage of optometrists, accounting for 90% of the global burden of visual impairment. In many such areas, over 30% of patients travel more than 100 km to access specialty eye care, highlighting a substantial unmet need for services. Additionally, a study in

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Organization for Economic Cooperation and Development (OECD) countries found that a higher number of optometrists per country was associated with a lower prevalence of blindness.[5]

A global survey done in the year 2023 of the optometry workforce, revealed that high-income countries achieved the recommended optometrist-to-patient ratios of 1:50000, while middle-income countries, as well as low-income countries, fell short of the target ratio.[4] The low optometrist-to-patient ratios in these regions were closely linked to higher rates of blindness and vision impairment. This growing disparity underscores the need for innovative solutions to bridge the gap in eye care services, particularly in regions with insufficient optometry resources.

Artificial intelligence (AI) has the potential to play a crucial supportive role in enhancing the existing optometry workforce by streamlining decision-making processes. The use of AI in eye care can significantly reduce the time required for disease screening, detection, diagnosis, and management, thereby improving the efficiency and accuracy of clinical outcomes. A thematic analysis of AI applications in healthcare decision-making has revealed that AI tools not only enhance clinical decision-making but also improve organizational efficiency and shared decision-making by providing accurate, timely, and personalized information.[6]

Although numerous AI models have been developed, a significant limitation is that many remain commercially unavailable and are confined to research labs. The true potential of these AI models, particularly those developed in academic settings, only becomes evident when they are integrated into clinical practice. Although optometrists generally hold a positive outlook on the use of AI in clinical settings, most are unaware of these models and their functionalities due to their restricted use within research environments and academic publications.[7–9]

The limited translation of AI models into clinical practice stems from various challenges, including regulatory barriers, a lack of clinical validation, high development costs, ethical concerns, and limited clinician awareness and training.[10] These factors collectively hinder the widespread adoption of AI in the field of optometry. Moreover, there is a noticeable gap in studies that specifically address the application of AI from an optometrist-centric perspective, further contributing to the slow integration of these technologies.

This review aims to explore the application of AI within the field of optometry, focusing on how AI can enhance various stages of patient care, such as screening, detection, diagnosis, and management. By providing a comprehensive overview, this study seeks to familiarize clinicians with existing AI technologies and raise awareness of their potential benefits in clinical practice.

In optometry, the clinical decision-making process is typically divided into stages: screening, detection, diagnosis, and management, each corresponding to different phases of patient care. Our detailed review is therefore organized into these four categories. We have consolidated AI models designed for various subtopics relevant to practicing optometrists, including refractive errors, strabismus, amblyopia, ocular surface disorders like dry eye, spectacle prescriptions, contact lenses, low vision rehabilitation, referral pathway assistance, and transcription tools for generating medical reports.

Additionally, this review will discuss the current state of AI model accessibility, addressing the need for more robust clinical validation and the importance of fostering collaborations between AI developers and healthcare providers. By bridging these gaps, we aim to highlight pathways for accelerating the adoption of AI in optometry, ultimately enhancing patient outcomes and streamlining clinical workflows.

Review Protocol

This study is a review of existing literature and did not involve any human or animal subjects. Therefore, ethics approval was not required.

Database and Search Strategy

To obtain comprehensive background information on AI in optometry, a literature search was conducted using PubMed. AI related keywords such as artificial intelligence (AI), machine learning (ML), deep learning (DL), were used when searching. Concurrently, we investigated optometry related keywords including amblyopia, low vision, contact lenses, orthokeratology, strabismus, anterior and posterior segment screening, and refractive error. A combinations of the both AI related and eye care related keywords were used to create a query to retrieve published research articles on the application of AI in optometry from past 10 years (2014 to 2024).

Study Selection

A total of 2627 articles were retrieved using the specified query in PubMed (Table 1). After applying an English language filter, 2603 articles remained. Subsequently, filtering for studies involving human subjects reduced the number of articles to 1567. Of these, only 950 articles were freely available for full-text screening for complete review. Articles with titles referencing terms related to artificial AI and optometry were included in the screening process. Articles that were not related to eye care, optometry, or AI were excluded from further analysis. Since optometrists generally do not provide pharmacological prescriptions or surgical services, studies focused on surgical planning, surgery, and drug-based management of ocular conditions were excluded. During title screening 717 articles were removed, of which 448 article were not eye care related, 267 were not optometry related, and 2 articles were not AI related, resulting in 233 articles for abstract screening. In Abstract screening 151 articles were removed, of which 42 articles were not eye care related, 98 articles were not optometry related, 9 articles were not AI related, 1 article was determined to be of low quality due to absence of information on AI, 1 article was retracted from the journal, resulting in 82 articles for full text screening. In the full text screening 16 articles were removed, of which 3 articles were not eye care related, 6 articles were not optometry related, 7 articles were not AI related. Finally reviewed 66 articles. The review process adhered to PRISMA guidelines, as shown in Figure 1, which visually depicts the key steps involved.

Notes: PRISMA figure adapted from Liberati A, Altman D, Tetzlaff J, et al. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. Journal of clinical epidemiology. 2009;62(10). Creative Commons.[11]

Data Extraction

The data extraction process involved systematically collecting and recording relevant information such as model employed, the specific ocular conditions addressed, and outcomes related to disease management, screening, progression, and innovations in eye care were meticulously gathered. Both quantitative (eg sample size, validation method and data, and accuracy) and qualitative parameters (eg interpretations of AI applications, outcomes, limitation and future prospects) were extracted.

Categorization of Selected Articles

The research articles were categorised based on both the quantitative and qualitative parameters mentioned in Data Extraction, and their association with components of the vision assessment workflow and relevant optometric topics. The components of the vision assessment workflow included screening, assessment, diagnosis, and management, while the relevant optometric topics covered refractive errors, strabismus, amblyopia, contact lenses and spectacle prescription, cornea and dry eye, low vision, and referral pathway assistance (Figure 2). This approach also facilitated a comprehensive evaluation of the differences and similarities across studies, highlighting key advancements and identifying gaps in the field.

Evaluation Parameters

All the AI models discussed in the referenced articles were thoroughly reviewed with attention to several critical parameters. These include model selection, the number of samples used in the training and validation sets, and the validation methods employed in the prototypes to ensure rigorous testing and reliability. Some common validation

Table 1 Query Table

Query	Time Period	No. of Entries
((Artificial Intelligence OR Machine Learning OR Deep Learning) AND (Screening OR Detection OR Prediction OR Diagnosis OR Management)) AND (Refractive Error OR Myopia OR Hypermetropia OR Amblyopia OR Strabismus OR Dry Eye Disease OR Low Vision OR Blindness OR Ortho Keratology OR Contact Lenses OR Spectacle prescription OR Corneal Surface)	2014–2024	2627

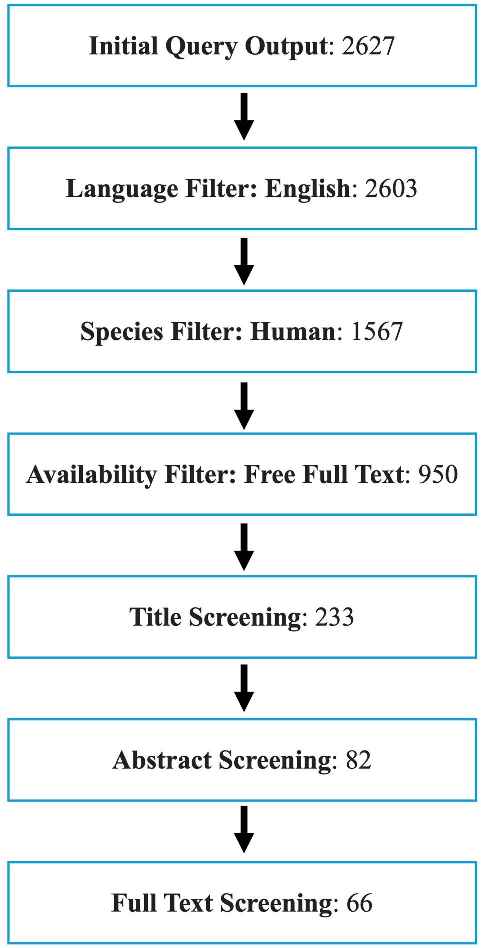

Figure 1 The PRISMA flow diagram outlines the process of selecting research articles for the review. It starts with 2,627 records identified through the initial query and illustrates the sequential filtering of articles at various stages, as depicted in the diagram.

methods include: a. K-fold cross-validation (divides the data into k subsets, trains the model k times, each time leaving out one subset for validation), b. Hold-out validation (splits the data into training and validation sets, using one for training and the other for testing), and c. Leave-one-out validation (similar to k-fold but with k equal to the number of data points, where each point is used once as the validation set). These are not the only methods, and the appropriate methods used in each research study are mentioned in section Application of Artificial Intelligence in Optometry.

We evaluated the AI models using validation metrics such as Accuracy, Sensitivity, Specificity, and Area Under the Curve (AUC). These metrics provide quantitative measures to assess the performance and effectiveness of the AI models.

Accuracy

Represents the proportion of correctly classified instances out of the total number of predictions made. It serves as a broad indicator of a model's performance by showing how often the predictions align with the actual outcomes.[12] While accuracy provides an overall measure of correctness, it must be interpreted carefully in clinical applications, particularly when dealing with imbalanced datasets. This metric is referenced in this article (Tables 2–15)as "A".

Sensitivity

Reflects the model's ability to correctly identify cases of interest out of all the instances where the condition is actually present.[12] A high sensitivity indicates that the model is effective at minimizing missed cases, ensuring that potential instances are reliably flagged for further evaluation. High sensitivity ensures that the AI model reliably flags potential cases for further examination. This metric is referenced in this article (Tables 2–15) as "Se".

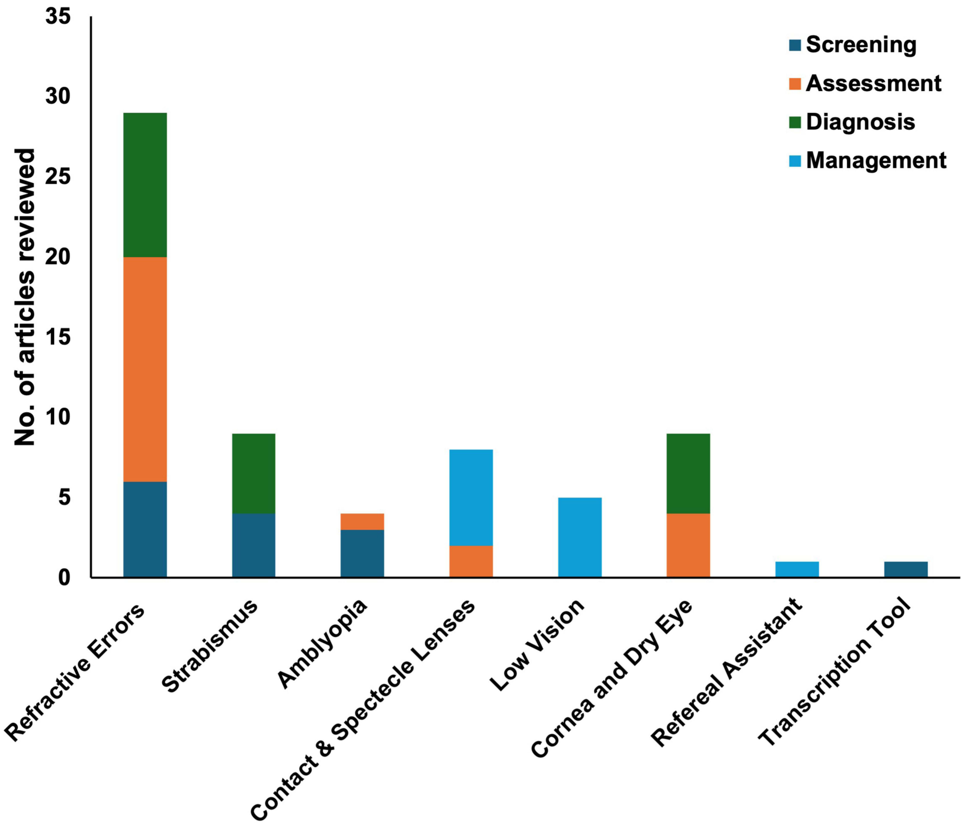

Figure 2 Distribution of articles categorized by optometric topics and components of vision assessment workflow.

Specificity

Reflects the model's ability to correctly identify cases that do not exhibit the condition of interest, effectively distinguishing them from those that do. Specificity is critical to make sure there are no over-diagnosis as it can lead to unnecessary patient anxiety, additional tests, or overtreatment.[12] High specificity ensures that only those genuinely at risk are flagged. This metric is referenced in this article (Tables 2–15) as "Sp".

Area Under the Curve (AUC)

A measure of the model's ability to distinguish between classes, represented by the area under the Receiver Operating Characteristic (ROC) curve, where higher values indicate better classification performance.[12] A high AUC ensures that the model is robust and can distinguish between healthy and diseased eyes effectively. This metric is referenced in this article (Tables 2–15) as "AUC" or "AUROC".

Additionally, we assessed the explainability of the models, an important factor for understanding and trust in clinical applications. There are broadly three types of explainability models a. Black box, these are models who inner working are not interpretable (referenced in this article as "B", Tables 2–15), b. White box, meaning their internal processes are transparent and understandable (referenced in this article as "W", Tables 2–15), and finally c. Grey, whose internal processes are partially interpretable (referenced in this article as "G", Tables 2–15).

We have comprehensively evaluate the AI models, identifying both their strengths and weaknesses, and ensuring they are technically sound, practically and applicable for integration into clinical practice.

Application of Artificial Intelligence in Optometry

We have categorized the articles into following Section 1. Screening, 2. Evaluation, 3. Diagnosis, 4. Management and under which we have the subtopics It must be noted that certain subtopics will be missing under some of the categories due to the fact that relevant studies were not found.

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Screening

Screening is a critical process in eye care, involving the use of large-scale tests to identify the presence of diseases in individuals who appear to be healthy.[13] While these tests do not diagnose conditions, they are essential for evaluating the presence of specific risk factors. Therefore, it is crucial that the screening process is both rapid and accurate, ensuring high sensitivity and specificity.[13]

AI can be used for early detection of individuals who are prone to ocular conditions like refractive errors, amblyopia, strabismus, and ocular surface and dry eye disorders. This will help in simplifying the process of allocation proper services for the individual and save cost and time. Due to high patient influx, optometrists may be compelled to conduct expedited examinations, potentially overlooking subtle visual impairments. A high patient load can contribute to fatigue and increased stress among optometrists, potentially leading to higher error rates and less thorough examinations. In such scenarios AI could assist optometrists by identifying patterns suggestive of latent conditions, offering decision support, and ensuring consistent and accurate interpretations of imaging results, ultimately enhancing screening accuracy and patient outcomes.

This compilation of articles explores the current landscape of AI applications in ophthalmic screenings, focusing on key topics: Refractive errors, Strabismus, Amblyopia, and Referral Pathway Assistance.

Refractive Errors

Refractive errors are one of the leading causes of visual impairments in the world. Early detection of condition like progressive myopia would help prevent the progression and irreversible damage to one's vision. Every healthcare organization in the world advise an early vision screening of school-going children. Table 2, consolidates details on AI tools for screening refractive errors.

AI has shown great potential in improving the screening of refractive errors, as demonstrated by recent studies. One of the biggest issues with early detection of refractive errors such as myopia in remote villages is the absence of clinics. In such cases providing accessibility to individuals to conduct eye examination at home would rapidly improve in detecting early refractive errors. For instance, Yang et al developed a deep learning system (DLS) based on the VGG-Face model to screen for myopia in children.[14] Their goal is to create a high-accuracy, non-invasive screening tool that can effectively detect myopia using images captured by common devices like smartphones, making early diagnosis more

Table 2 AI Tools for Screening of Refractive Errors

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Yang et al[14]	DLS based on VGG-Face. (B)	Myopia in children and high-accuracy screening.	1762	587	Hold-Out Validation	A: 84%, Se: 81.13, Sp: 86.42, AUC: 0.97
2	Choi et al[15]	DL (ResNet 50, Inception V3, and VGG 16). (B)	Screening high myopia and categorize into "normal", "high myopia.	600	600	5-Fold Cross Validation	VI: (A: 100%); HI: (A: 98.89%, AUC: 0.99)
3	Yoo et al[16]	CNN (ResNet50) (B)	Detection of uncorrected refractive error from posterior OCT images	688	248	5-Fold Cross Validation	MM: (Se 82.3, Sp: 68.9, AUC: 0.789); HM (Se: 87.2, Sp: 61.7, AUC: 0.813).
4	Zou et al[17]	FMDLS (B)	Identification of ocular refraction (sphere, cylinder, and cylinder axis)	7086	787	Comparison with clinical cycloplegic refraction	A:89%, Se: 94.1, Sp:88.2, AUC:0.814
5	Li et al[18]	CNN and inceptionResNet2 (B)	Identify vision-threatening conditions in high myopia patients.	4404	1101	Cross validation	A: 96.1–99.9%, Se:90–100, Sp: 90–96.5
6	Rauf et al[19]	CNN-based framework (B)	Detection of pathological myopia	360	40	Hold-Out Validation	A:95%, AUC: 0.9845

Abbreviations: DLS, Deep Learning System; VGG, Visual Geometry Group; CNN, Convolutional Neural Network; FMDLS, Fusion Model-Based Deep Learning System; DL, Deep Learning AUC, Area Under the Curve; VI, Vertical Images; HI, Horizontal Images; MM, Moderate Myopia; HM, High Myopia Explainability; B, Black Box Model; W, White Box Model.

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accessible and efficient. The model achieved an impressive area under the curve (AUC) of 0.93, highlighting the model's accuracy, with a sensitivity (81.13%) and specificity (86.42%) (Table 2. Index 1).[14]

Many times clinics and screening teams are unable to allocate multiple equipment during a screening drive. It is ideal to have a single instrument make multiple measurements. However such devices are rare and not commercially available. AI could however, help make findings based on the patterns of existing measures and images. For example, study by, Choi et al aims to develop deep learning models for accurately screening high myopia using optical coherence tomography (OCT) images.[15] Choi et al employed a combination of ResNet 50, Inception V3, and VGG 16 models to categorize high myopia, achieving near-perfect accuracy with AUC values reaching 0.99, and 100% accuracy for vertical images (Table 2. Index 2).[15] The model seeks to categorize patients into "normal" or "high myopia" groups with high precision, ultimately improving the early detection and management of vision-threatening conditions associated with high myopia.[15]

A similar approach was explored by Yoo et al where they developed a convolutional neural network (CNN) model to measure uncorrected refractive error from posterior segment optical coherence tomography (OCT) images.[16] Utilizing a diverse dataset of 936 eyes from 468 healthy subjects, the model was trained on 688 eyes and validated on 248 eyes using fivefold cross-validation. The ResNet50-based architecture achieved a mean absolute error (MAE) of 2.66 diopters in the test set and demonstrated a Pearson correlation coefficient of 0.588. For detecting moderate myopia (SE ≤ -3.00 D) and high myopia (SE ≤ -6.00 D), the model attained ROC-AUC values of 0.789 and 0.813, respectively, with sensitivities of 82.3% and 87.2%, and specificities of 68.9% and 61.7% (Table 2. Index 3).[16] The model does not account for axial length, which is closely related to refractive error.

However, the AI model still demonstrates potential for improving refractive error assessment, though further validation with larger and more diverse populations is necessary.

Retinal fundus photographs (RFPs) offer extensive insights into the human eye and present a potentially convenient and objective method for evaluating the refractive status of the eye. Zou et al developed a fusion model-based deep learning system (FMDLS) to automatically identify ocular refraction from retinal fundus photographs (RFPs), aiming to replacing traditional cycloplegic retinoscopy.[17] The study retrospectively analysed 7873 high-quality RFPs from 3954 myopic patients. The FMDLS integrated regression models for predicting sphere and cylinder values and classification models for determining the cylinder axis. The FMDLS achieved mean absolute errors of 0.50 dioptres for sphere and 0.31 diopters for cylinder, with strong correlation coefficients of 0.949 and 0.807, respectively. For cylinder axis classification, the system attained an accuracy of 89%, specificity of 94.1%, sensitivity of 88.2%, and an area under the curve (AUC) of 0.814 (Table 2. Index 4).[17] The FMDLS demonstrated reliable agreement with cycloplegic refraction measurements, offering an objective and efficient tool for large-scale refractive assessments.

Apart from early detection of refractive errors, it is imperative to also screen for progression of a condition at multiple visits or screening campaign. Progressive myopia is a condition were the there is a high risk of miss during a screening campaign. This is usually due to either incapability to access previous data on the patient or optometrists not find the pattern of rapid increase of myopia in a short period. This could however be mitigated by implementing predictive models that can find patterns in progression and alert the optometrists. In a study by, Li et al they aimed to identify risk factors for myopia progression in primary school children using machine learning. Li et al utilized a CNN combined with InceptionResNetV2 to identify vision-threatening conditions in high myopia patients, achieving a validation accuracy between 96.1% and 99.9%, with a sensitivity between 90% - 100% and specificity of 90% - 96.5% (Table 2. Index 5).[18] Ultimately aiding in early intervention and management strategies to prevent worsening of the condition.[18]

Similarly, automating the detection of pathological myopia (PM) is vital for efficient screening and reducing the burden on clinical resources. Rauf et al developed a CNN framework for the automatic identification of PM using fundus images from the Pathologic Myopia Challenge (PALM) challenge 2019 dataset, which comprised 400 labelled training images (161 normal, 239 pathological) and 400 unlabelled test images.[19] The best-performing model, named 2C-128N-0D, featured two convolutional layers with 128 neurons each and was optimized using the Adam optimizer with ReLU and Sigmoid activation functions, alongside dropout (0.3) and L2 regularization (0.001) to prevent overfitting. The model was validated using a 10% data split, achieving an area under the curve (AUC) of 0.9845, an accuracy of 95%, and a validation loss of 0.1457 (Table 2. Index 6).[19] This high level of accuracy demonstrates the model's effectiveness in

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distinguishing between normal and pathological cases. However, the study's generalizability is limited by the relatively small and non-diverse sample size. Despite this limitation The CNN-based approach shows significant promise for clinical application in PM detection, offering a non-invasive and accurate diagnostic tool that can enhance early intervention and patient management in optometry.

AI-based models can significantly enhance the accuracy and efficiency of refractive error screening, making them indispensable tools in preventing and managing visual impairments on a large scale. However, currently the AI research is mainly focused on the classification and prediction of myopia. More research warranted to address other refractive error and associated issues such as latent hyperopia, latent myopia, accommodation excess, accommodation insufficiency, etc in children.

Paediatric vision screening identifies children who may be at risk for visual problems, with the objective of referring those in need to an eye care professional for further evaluation and treatment.[20] The main goal of screening in younger children is to detect those who may develop amblyopia, a condition that can lead to permanent vision loss if not addressed. In older children, the focus expands to include identifying risks related to uncorrected refractive errors.[20]

Strabismus

Strabismus, a condition where the eyes do not properly align with each other when looking at an object, can often lead to amblyopia if left untreated, particularly in young children. Early and accurate detection is essential for timely intervention to prevent permanent vision impairment. AI-based approaches have shown significant promise in enhancing the screening process for strabismus. Table 3, consolidates details on AI tools for screening strabismus.

For instance, Chen et al utilized eye-tracking data combined with convolutional neural networks (CNNs) to develop a method for recognizing strabismus, which yielded a high accuracy of 95.2% when tested with the VGG-S model, with a sensitivity of 94.1% and specificity of 96.0%. The AI model demonstrated the effectiveness in detecting subtle eye misalignments (Table 3. Index 1).[21]

Similarly, Huang et al applied image processing techniques to automatically detect strabismus, validating their method on a set of 60 images (30 with strabismus and 30 normal). The average iris positional similarity value was significantly lower in normal images (Mean ± SD: 1.073 ± 0.014) compared to strabismus images (Mean ± SD: 1.924 ± 0.169), with a p-value < 0.001. AI model effectively differentiates between normal and strabismus images based on iris positional similarity (Table 3. Index 2).[22]

The accessibility of strabismus screening will allow for more widespread, timely, and faster screening, especially in settings where specialized equipment may not be readily available to the optometrists. Zheng et al utilized a deep learning model to detect referable horizontal strabismus in children using primary gaze photographs.[18] This model

Table 3 AI Tools for Screening of Strabismus

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Chen et al[21]	CNN (B)	Identify strabismus	41	1 sample used for validation at a time	Leave-One-Out and Cross-Validation	A: 95.2%, Se:94.1, Sp: 96.0
2	Huang et al[22]	CNN with detector for 68 facial landmarks. (B)	Strabismus screening.	Abnormal: 30; Normal: 30	Not Specified	Hold-Out (Train-test Split not specified)	Sig. diff b/w normal and abnormal (p<0.001)
3	Zheng et al[23]	DL (B)	Screening referable horizontal strabismus	5622	1404 with external test data: 277	Five-fold Cross Validation	A: 95%, Se: 94.0, Sp: 99.3, AUC: 0.99
4	Kang et al[24]	U-Net DL model (B)	Strabismus measurement	529	133	Validation to ground truth (clinical validation)	SS: (A: 99.84%, Se: 95.6 Sp: 95.7); LS: (A: 99.92%, Se: 97.47, Sp: 99.9)

Abbreviations: DLS, Deep Learning; SS, Sclera Segmentation; LS, Limbus Segmentation.

achieved an impressive accuracy of 95% with sensitivity of 94.0% and specificity of 99.3% during validation, highlighting the potential of AI tools in clinical settings for early detection and management of strabismus (Table 3. Index 3).[23]

Kang et al developed an automated algorithm combining a U-Net deep learning model with mathematical image processing for detecting facial landmarks and calculate the angles of deviation in the nine cardinal gaze position using photographs of individuals with strabismus.[24] The study utilized a dataset of 529 training images, 133 validation images, and 166 test images, and further validated the algorithm with clinical testing on two patients with cranial nerve palsy. The AI model achieved performance, with sclera segmentation accuracy of 99.84%, Dice Similarity Coefficient (DSC) of 96.88%, and limbus segmentation accuracy of 99.92%, DSC of 95.71% (Table 3. Index 4).[24] These high metrics indicate precise and reliable segmentation, enabling accurate measurement of ocular deviation. However, the algorithm has limitations, including its reliance on two-dimensional images which may introduce measurement errors compared to three-dimensional assessments, challenges in accurately detecting the limbus in patients with small eyes or limited exposure, and the inability to account for patient-specific factors such as age, surgical history, or gaze impairments.

Normal binocular vision requires aligned eyes working together to produce a unified image. Strabismus can emerge at any age and may indicate serious conditions within the orbit, eye, or brain.[25] Amblyopia can frequently result from strabismus, particularly in young children.

Amblyopia

Amblyopia, often referred to as “lazy eye”, is a vision development disorder where one eye fails to achieve normal visual acuity, typically due to poor coordination between the eye and the brain. Also one of the leading cause of visual impairment in children, and early detection is crucial to prevent long-term vision loss.

Accessibility to affordable screening tools can alleviate this problem. In this context, Murali et al aim to develop a deep learning and image processing-based method for screening amblyopia using facial photographs.[20] Their goal is to create an accessible and cost-effective tool that can identify amblyopia risk factors in children, potentially allowing for early diagnosis and treatment without the need for specialized equipment or extensive training. This model, tested and validated on the same dataset of 54 samples, achieved an accuracy of 79.6%, with a sensitivity of 88.2% and a specificity of 75.6%, demonstrating its potential as a useful tool in the early detection of amblyopia (Table 4. Index 1).[26]

A recent study by, Csizek et al explored the potential of an artificial intelligence-based screening method that does not rely on stereoacuity to detect amblyopia and amblyogenic conditions.[27] The study utilized a Perceptron model trained on stereovision test results from 182 samples, demonstrating an AUC of 0.908, significantly outperforming traditional tests like Lang II, Stereo Fly, and Frisby in detecting amblyopia and its risk factors.[27] This AI-based approach showed sensitivity of 96.0% at the optimum ROC point, making it a promising tool for cost-effective and accessible vision screening in children (Table 4. Index 2).[27]

Clark et al employed various AI techniques to automate the identification of amblyopia using colour slope features extracted from images of the eyes.[28] The study investigated the efficacy of Decision Tree Learning, Random Forest, and Artificial Neural Network models on a dataset of 723 patient videos, later reduced to 499 samples. Using a 10-fold stratified cross-validation, the Random Forest model achieved the highest accuracy of 68%, with a sensitivity of 66.67% and a specificity of 45.61%. This approach emphasizes the importance of automated systems in making vision screening more accessible and efficient (Table 4. Index 3).[28]

Transcription Tool

Speech recognition software can transcribe medical dictations into accurate medical notes, streamlining documentation in optometry clinical practice by allowing optometrists to quickly record patient information, diagnoses, and treatment plans, thereby improving efficiency and reducing the administrative burden.

This study aimed to compare the out-of-box performance of three commercially available continuous speech recognition software packages: IBM ViaVoice 98, Dragon Systems NaturallySpeaking Medical Suite, and L&H Voice Xpress for Medicine.[29] Twelve physicians dictated medical records using each software after minimal training, and errors in recognizing medical vocabulary, abbreviations, and general English were analysed. The IBM software outperformed

Table 4 AI Tools for Screening of Amblyopia

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Murali et al[26]	DL (B)	Screening amblyopia risk factors	54	54	Same test and validation data	A: 79.6%, Se: 88.2, Sp: 75.6
2	Csizek et al[27]	Perceptron model (LR) (W)	Screening amblyopia risk factors	182	137	Hold-out validation and cross-validation through 100 independent training sessions	Lang II: (Se: 96.0, AUC: 0.704); Stereo Fly: (AUC: 0.780; Frisby: (AUC: 0.754)
3	Clark et al[28]	DT (B), RF (B), ANN (B)	Identification of amblyopia	499	499	10-fold Cross-Validation	RF (A: 58.37%, Se: 66.67, Sp: 45.61)

Abbreviations: LR, Logistic Regression; DT, Decision Tree; RF, Random Forest; ANN, Artificial Neural Network.

the other two, demonstrating the lowest mean error rate across multiple categories. This robust evaluation highlights the varying accuracy of speech recognition technologies in medical settings, emphasizing the potential for improving documentation efficiency in healthcare (Table 5. Index 1).[29]

Assessment

Effective disease management in healthcare relies heavily on accurate detection of existing conditions and the prediction of future health outcomes. From a public health perspective, AI-driven assessment tools offer the potential to monitor and identify patterns across large populations, which may otherwise be missed. Early detection and prediction of progressive ocular conditions helps in implementation of mitigation strategies, slowing down the progression, prevention of potential vision loss with time.

In this review, we have combined detection and prediction under the unified term "Assessment" due to their significant overlap in the literature. Detection identifies the presence of a condition, while prediction forecasts future events based on current data. These processes are often interdependent, with detection informing predictive models and predictions enhancing further detection efforts. The term "Assessment" captures both processes, providing a cohesive framework for evaluating current conditions and forecasting outcomes, which is essential for effective disease management. Modern machine learning and Artificial Intelligence models have significantly improved the robustness of these predictions, enabling more tailored and effective treatment plans and healthcare strategies.

This compilation of articles explores the current landscape of AI applications in prediction of ophthalmic conditions, focusing on key topics: Refractive errors, Strabismus, Amblyopia, and Contact Lenses & Spectacle Prescription, Low Vision, and Cornea and Dry Eye.

Refractive Errors

Ability to predict the risk of visual impairment in a high risk diseases would help optometrist plan and prevent or slow down the progression with mitigative efforts. However, this requires clinical experience. Quite frequently such conditions are missed in a clinical setting, especially in cases of progressive myopia. In Table 6, we have complied studies that help

Table 5 AI Tools for Transcription

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Devine et al[29]	Continuous speech recognition software packages (B)	Speech to medical report Transcription	Not Specified	Dictation trials performed by 12 physicians	Error comparison between packages	A*: (MER: 6.6% to 8.4%); B*: (MER: 12.0% to 13.9%); C*: (MER: 3.8% to 14.6%)

Notes: A*: IBM ViaVoice 98, B*: Dragon Systems NaturallySpeaking Medical Suite, C*: L&H Voice Xpress for Medicine.
Abbreviation: MER, Mean Error Rate.

predict the onset of refractive errors, vision threatening conditions, prevention, and associated pathologies to refractive errors.

AI works on large data sets to learn prediction by interpreting patterns, and coincidently the field of medicine produces large datasets with multiple features. Augmentation of AI in eye clinics could help assist optometrists in prediction and early detection of vision threatening condition. For examples, Lin et al developed a Random Forest (RF) model to predict the onset of high myopia using an extensive dataset of 517,949 samples.[30] The model was validated using both external and internal datasets, achieving an accuracy ranging from 0.77 to 0.99% for high myopia and 0.20 to 0.79% for other refractive parameters (Table 6. Index 1).[30] Such models are crucial for early intervention strategies, especially in large-scale public health initiatives where early identification can prevent the progression of myopia to more severe levels.[30]

A machine learning-based algorithm combining Support Vector Regression and Gaussian Process Regression was developed to predict spherical refractive error and its progression using age, gender, and spherical power as inputs. Trained on cross-sectional data of 12,780 children and validated using longitudinal data of 81 children, the model achieved a Pearson correlation coefficient of 0.77, a bias of −0.05 D, and limits of agreement of ±0.85 D.[31] This algorithm provides a reliable risk assessment tool for myopia progression, potentially guiding eye care professionals in implementing personalized management strategies (Table 6. Index 2).[31]

Adding to the spectrum of AI-based models, Yang et al developed a predictive model for myopia prevention using a combination of Support Vector Machines (SVM) and Gradient Boosting Regression Trees (GBRT).[32] This model, validated through 5-fold cross-validation with a hold-out validation on a dataset of 1,763 samples with 588 for validation, achieved a robust accuracy of 92.70%, with a sensitivity of 94.0% and a specificity of 94.0% (Table 6. Index 3).[32] Such predictive models are pivotal in preventive eye care, allowing for timely interventions that can mitigate the onset of myopia, especially in younger populations where early action can have long-lasting effects.

Ability to extract refractive status of human eye from reflex images would help in online and remote screening and tele-optometry. Xu et al developed Refractive Error Detection Network (REDNet), combines the strengths of a CNN and Recurrent Neural Networks (RNNs) for predicting refractive errors from photorefraction images. Using a dataset of multiple photorefraction images, REDNet was validated through cross-validation, achieving mean absolute errors of 0.1740 D for spherical power, 0.0702 D for cylindrical power, and 0.1835 D for spherical equivalent. The model demonstrated accuracy of 89.50% for spherical power, 96.70% for cylindrical power, and 89.38% for spherical equivalent (Table 6. Index 4).[33] The AI model showed a sensitivity of 96.97% and 97.19%.

The focus on predictive models extends to more specialized applications, such as Du et al work on automated detection of myopic maculopathy and categorization of different types of lesions in fundus images for detecting pathological myopia (PM). Their deep learning model demonstrated high accuracy (92.1% for PM and 90.2–97.5% for lesion types) using 5-fold cross-validation on a dataset of 3,332 samples. The AI model showed a sensitivity of 84.44% and a specificity of 94.50% (Table 6. Index 5).[34]

Patients with pathological myopia are at high risk of visual impairment due to complications. Kim et al developed a SVM model with a Radial Basis Function (RBF) kernel to predict pathologic myopia using tomographic measurements of the posterior sclera from optical coherence tomography (OCT) scans.[35] The study utilized a dataset of 860 myopic patients, comprising 728 healthy myopia eyes and 132 pathologic myopia eyes. The model was trained on 70% of the data and tested on the remaining 30%, addressing class imbalance with the Synthetic Minority Over-sampling Technique (SMOTE). The SVM model achieved an Area Under the Receiver Operating Characteristic Curve (AUROC) of 0.8712, with 82.5% sensitivity and 91.74% specificity, outperforming conventional indices such as axial length and sub-foveal choroidal thickness (Table 6. Index 6).[35] The AI models were trained on a diverse dataset that included representations of various ethnicities and genders. Male participants constituted 59.30% of the total study population, with a significantly higher proportion in healthy myopic eyes (61.95%) compared to pathologic myopia eyes (44.70%, $p < 0.001$). This machine learning approach offers an objective and quantitative method for diagnosing pathologic myopia in clinical settings, and may help assist optometrists in early detection and referral to ophthalmologists.

To identify risk factors associated with myopia progression in primary school children, Li et al developed a predictive model.[36] By analysing data from the Anyang Childhood Eye Study, the researchers developed a predictive models that

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Table 6 AI Tools for Assessment of Refractive Errors

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Lin et al[30]	RF (B)	Predict the onset of high myopia.	517949	External: 16,114; Internal: 17,113	Cross, External, and Multi-resource	HM: (AUC: 0.77–0.99%); RP: (AUC: 0.20 −0.79%)
2	Barraza-Bernal et al[31]	SVM & GPR (B)	Predict spherical refractive error and its progression using age, gender, and spherical power as inputs	12780	81	Comparison with Myopia Calculator and MyAppia (App)	Pearson correlation coefficient: 0.77, Bias: −0.05 D, Limits of agreement: ±0.85 D
3	Yang et al[32]	SVM and GBRT (B)	Prediction model for myopia prevention	1763	588	Five-fold Cross Validation	A: 92.70%, Se: 94, Sp: 94, AUC: 0.98
4	Xu et al[33]	REDNet (B)	Predicts refractive power	3907	1167	Internal validation using pre-defined datasets	A: 97.13, Se: 96.97, Sp: 97.19, AUC: 0.994
5	Du et al[34]	DL (B)	Detection of MM and categorize different types of lesions in fundus images.	3332	1844	Five-fold Cross Validation	PM: (A: 92.1%); MA: (A: 90.2–97.5%, Se: 84.44, Sp: 94.50)
6	Kim et al[35]	SVM (RBF) (B)	Prediction of pathologic myopia	602	258	Hold-Out Validation	A: 90.31, Se: 82.5, Sp: 91.74, AUC:0.868
7	Li et al[36]	RF (B); ML (B)	Myopia prediction in children.	2466	274	Five-fold Cross validation	A: 80–90%
8	Zhu et al[37]	OMP, RF, KRR, KNN, ETR, MP(B)	Prediction of SER and AL in children.	125	54	Hold-Out Validation	Spherical Equivalent: OMP (R^2 = 0.8997), MLP (R^2 = 0.7839); Axial Length: KR (R^2 = 0.9072), ET (R^2 = 0.7546)
9	Ying et al[38]	XGBoost, RF (B)	Prediction of cycloplegic spherical equivalent refraction (SER) and myopia status	3,876	2,951	External validation using independent dataset	SER Prediction: (A: 93.5%, AUC: 0.984); Myopia Prediction: (A: 95.3%; AUC = 0.987)

10	Wang et al[39]	SVM, RF, LR. (B)	Forecasting long-term visual outcomes and risk of visual impairment in high myopia.	1131	485	10-Fold Cross-Validation	Visual Acuity Prediction: (3 Years: A: 0.682), (5 Years: A: 0.660); Risk Assessment: (5 Years: AUROC:0.870)
11	Oh et al[40]	EfficientNet B3 with Attention Maps (B)	Prediction of axial length from ultra-widefield (UWF) fundus photographs	6,884	1,370	5-Fold Cross-Validation	Within ±1.0 mm (A: 73.7%); Within ±2.0 mm: (A: 95.9%);MAE: 0.744 mm, R^2: 0.815.
12	Hernández et al[41]	RF, GB, EGB, CA (B)	Prediction of subjective refraction (SR) and classification of pathological myopia using wavefront aberrometry and demographics.	1244	518	Hold-Out Validation	AUROC: 0.8712; Spherical Equivalent (M): (MAE Reduction:42.5%); Vertical Astigmatism (MAE: 29.4%): Oblique Astigmatism (J45): (MAE: 41.7%)
13	Zhao et al[42]	RF, XGBoost (B)	Prediction of myopia onset and progression, including high myopia in children and adolescents	70,600	17,650	Hold-Out Validation	XGBoost: (A: 85.4%, AUC: 0.845–0.997)
14	Chen et al[43]	XGBoost, RF (B)	Prediction of 10-year MMD progression in high myopia patients	462	198	Internal and External Validation	Internal Validation: (Se: 0.97, Sp: 0.63, AUROC: 0.84, AUPRC: 0.87); External Validation: (A: 80.0%, AUC = 0.80, Se: 0.97, Sp: 0.63,AUPRC = 0.83 ± 0.01)

Abbreviations: ML, Machine Learning; SVM, Support Vector Machine; GPR, Gaussian Process Regression; GBRT, Gradient Boosted Regression tree; MM, Myopic Maculopathy; HM, High Myopia; RP, Refractive Parameter; PM, Pathological Myopia; RBF, Radial Basis Function; MA, Macular Atrophy; AUROC, Area Under the Receiver Operating Characteristic Curve; REDNet, Refractive Error Detection Network; GB, Gradient Boosting; OMP, Orthogonal Matching Pursuit; EGB, Extreme Gradient Boosting; KRR, Kernel Ridge Regression; KNN, K-Nearest Neighbour; ETR, Extra Tree Regression; CA, Custom Assembly; MP, Multilayer Perceptron; SER, Spherical Equivalent Refraction; AL, Axial Length.

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could inform early intervention strategies, ultimately helping to prevent or slow down the progression of myopia in children.[36] The machine learning model trained on 2466 samples, and validated through Five-fold Cross validation on 274 sample. The model achieved accuracy of greater than 80% on the validation data (Table 6. Index 7).[36]

Accurately predicting how much a child's myopia will worsen over time is challenging. Traditional methods often rely on general observations and may not capture individual variations in myopia progression. Zhu et al developed machine learning models to predict the progression of spherical equivalent refraction (SER) and axial length (AL) in myopic children, aiming to enable early intervention and effective myopia management.[37] The ML utilized a dataset of 179 children aged 6–15 years from a single hospital. The dataset was divided into 125 training and 54 testing samples, with ground truth established through clinical measurements. The ML model employed six regression algorithms Orthogonal Matching Pursuit (OMP), Random Forest (RF), Kernel Ridge (KR) regression, K-Nearest Neighbour (KNN) regression, Extra Tree (ET) regression, and Multilayer Perceptron (MLP) to forecast SER and AL up to grade 6. For SER prediction, the MLP and OMP models achieved the highest accuracy with an R^2 of 0.8997 for grade 6 SER using grades 4 and 5 data (Table 6. Index 8). In AL prediction, the KR and MLP models performed best, with the ET model attaining an R^2 of 0.7546 for grade 6 AL using grades 3, 4, and 5 data (Table 6. Index 8).[37] The study was limited by small sample size from a single hospital, exclusion of left-eye data, and the omission of environmental and genetic factors that may influence myopia progression. Nonetheless, the machine learning-based approach offers a promising tool for accurately predicting myopia progression in children, potentially aiding clinicians in implementing timely and personalized management to prevent severe ocular complications.

Ying et al tackled the challenge of accurately predicting cycloplegic refractive error and myopia status in Chinese children using non-cycloplegic data, addressing the limitations of traditional cycloplegic measurements in large-scale studies.[38] The study analyzed data from 1,938 students (3,876 eyes) in Jinyun and validated the models on 1,476 students (2,951 eyes) in Hangzhou. Utilizing machine learning algorithms such as XGBoost and Random Forest, the models achieved high performance with R^2 values between 0.913 and 0.935 and Mean Absolute Errors (MAE) of 0.393–0.480 diopters for predicting cycloplegic spherical equivalent refraction (SER). For myopia status prediction, Random Forest attained an accuracy of 95.3% and an AUC of 0.987 in the validation set data.[38] The models demonstrated excellent specificity (96.9–97.2%) and maintained robust performance across different age groups (Table 6. Index 9). However, limitations include limited generalizability beyond Chinese students aged 5–18, reliance on specific cycloplegic methods and devices, a cross-sectional design, and reduced accuracy for extreme refractive errors. Despite these constraints, the developed machine learning models offer a reliable and scalable solution for estimating cycloplegic refractive error and myopia prevalence, facilitating large-scale epidemiological studies and supporting public health initiatives to combat the global myopia epidemic.

Forecasting long-term visual outcomes in highly myopic individuals is essential for effective myopia management, yet clinicians often struggle to identify subtle changes in visual acuity over time. Wang et al (2023) addressed this challenge by developing machine learning models, including Support Vector Machines and Random Forest, using a dataset of 1,616 eyes from 967 patients collected at a single centre.[39] The models were validated through 10-fold cross-validation, ensuring robust internal assessment. These models predicted visual acuity at three and five years with R^2 values of 0.682 and 0.660, respectively, while Logistic Regression achieved an Area Under the Receiver Operating Characteristic Curve (AUROC) of 0.870 for assessing the five-year risk of visual impairment (Table 6. Index 10).[39] However, the study's reliance on single-centre data and the absence of external validation limit the generalizability of the findings. Overall the AI models demonstrates potential in managing high myopia by improving prediction accuracy and enabling proactive patient care.

Refractive errors are often linked to the shape of the eye. Myopia is often associated with an elongated eyeball, while hyperopia is associated with a shorter eyeball. Oh et al developed a deep learning model based on EfficientNet B3 to predict axial length from ultra-widefield (UWF) fundus photographs.[40] The study utilised a dataset of 8,254 UWF images from 3,829 patients, the model was trained on 6,884 images and validated on 1,370 images through fivefold cross-validation. The AI model achieved a mean absolute error (MAE) of 0.744 mm and an R^2 value of 0.815 in the test set, with 73.7% of predictions within ±1.0 mm, 95.9% within ±2.0 mm, and 99.2% within ±3.0 mm (Table 6. Index 11).[40] The use of attention maps offers insights into retinal regions influencing axial length predictions. The model reliance on

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data from a single ethnic group it's generalisability is questionable. The downsizing of images to 300×300 pixels may result in the loss of detailed information, potentially impacting prediction accuracy. Despite these limitations, the EfficientNet B3-based model demonstrates significant potential for integrating axial length estimation into routine clinical practice.

Demographics of an individual, combined with refractive errors, have an effect on pathological myopia, as these factors are interrelated. It is thus imperative to consider the demographic details of an individual when predicting pathological myopia. Hernández et al addressed this challenge by developing machine learning ensemble models to predict subjective refraction (SR) using wavefront aberrometry data combined with demographic factors.[41] The study evaluated four models such as Random Forest, Gradient Boosting, Extreme Gradient Boosting, and a custom Assembly (ASB) model—and found that the ASB model outperformed the others. Utilizing a dataset of 860 myopic patients, with 728 eyes classified as healthy myopia and 132 as pathologic myopia, the ASB model achieved a mean absolute error (MAE) reduction of 42.5% for spherical equivalent (M), 29.4% for vertical astigmatism (J0), and 41.7% for oblique astigmatism (J45) compared to a low-cost portable autorefractor. The model demonstrated an AUROC of 0.8712, alongside 82.5% sensitivity and 91.74% specificity, indicating superior classification performance over conventional indices like axial length and sub-foveal choroidal thickness (SCT) (Table 6. Index 12).[41] The AI model's key predictive features include Zernike coefficients for defocus and astigmatism, pupil size, and age, while gender showed minimal influence. However, the study's retrospective design, significant class imbalance, and reliance on a predominantly Korean population limit the generalizability of the findings. Overall, the machine learning ensemble model presents a promising tool for automating the prediction of manifest refraction, potentially reducing the burden on eye care professionals and increasing access to accurate vision correction in underserved areas.

Additionally, prediction requires large and long-standing data to identify patterns that only become apparent over time, especially in developmental pathologies such as myopia. To predict the onset and progression of myopia and high myopia in children and adolescents, Zhao et al developed and validated machine learning models that used 15 years of refractive data from 88,250 individuals at Fudan University's Eye & ENT Hospital.[42] Utilizing Random Forest and XGBoost algorithms, the study achieved accuracy, with XGBoost attaining an R^2 above 0.729 for spherical equivalent (SE) predictions and AUCs ranging from 0.845 to 0.997 for myopia and high myopia onset (Table 6. Index 13).[42] Key predictors identified included age, baseline SE, and annual myopia progression rate. The models performed best in younger age groups (3–14 years) and demonstrated potential for guiding early interventions.

The transparency of an AI model makes the tool valuable for clinical decision making, allowing for targeted interventions in at-risk individuals enhances the uptake of AI by optometrists in general clinical practice. Chen et al developed and validated an interpretable machine learning model to predict the progression of myopic macular degeneration (MMD) over a decade in high myopia patients.[43] Utilizing data from 660 individuals in the Zhongshan High Myopia Cohort and externally validating on 212 patients, the study employed algorithms like Random Forest and XGBoost, with XGBoost achieving the highest performance (AUROC = 0.87) (Table 6. Index 14).[43] Key predictors identified were thinner sub-foveal choroidal thickness, longer axial length, worse best-corrected visual acuity, older age, female gender, and shallower anterior chamber depth. The use of SHAP (Shapley Additive Explanations) enhanced the model's interpretability, enabling clinicians to understand the influence of each factor on MMD progression.[43] Despite limitations such as single-site data and decreased accuracy for long-term predictions, the study highlights the effectiveness of interpretable AI in forecasting ophthalmological conditions, supporting proactive and personalized clinical management.

As these models continue to evolve, their transparency and reliability will be instrumental in bridging the gap between advanced technology and clinical practice.

Amblyopia

Amblyopia, is typically associated with precursor conditions such as anisometropia, strabismus, high refractive errors and sometime issues with optics nerve and brain. This association to precursor factors opens an opportunity to finding patterns that may help predict an onset of amblyopia in individuals. Murali et al conducted a study to evaluate the effectiveness of the Kanna photoscreener, an AI-driven tool designed to identify amblyopia risk factors.[44] The study utilized a deep learning model to analyse images captured by the photoscreener, focusing on critical indicators such as refractive errors, strabismus, and other ocular abnormalities that contribute to amblyopia. The model was validated on a dataset of 654 images, achieving an impressive accuracy of 90.8% using both hold-out and cross-validation techniques, with a sensitivity of 83.6% and a specificity of 94.3% (Table 7. Index 1).[44] This high accuracy highlights the potential to predict amblyopia from its associated risk factor.

Contact Lenses & Spectacle Prescriptions

Specialities such as advance contact lenses and spectacle prescriptions are often under-practiced due to the shear complexity and it's requirement for relatively high skills. This erects an entry barrier for optometry professional and thus impacts patient care. Leveraging the support of AI would however greatly improve in the uptake of this essential practice among fresher professionals. Table 8, elaborates the AI tools available for predicting various parameters relevant during fit assessment for speciality contact lens.

AI's role extends to optimizing corrective measures such as contact lenses and spectacle prescriptions. Fan et al developed a machine learning model to predict critical parameters for corneal refractive therapy (CRT) lenses, achieving an accuracy of 82.1% with Five-fold cross-validation on a small dataset (Table 8. Index 1).[45] This model supports clinicians in fine-tuning prescriptions, thereby improving patient outcomes.

Most speciality contact lenses require high customization based on the unique anatomical and physiological characteristics of the patient, which makes it costly if mistakes are made during fitting. In a related study, Fang et al utilized a logistic regression model with LASSO to predict the treatment effects of orthokeratology (ortho-k) in children.[46] Their model, validated against the gold standard, showed high accuracy in predicting the landing zone angle (LZA) (69.3–86.6%) and return zone depth (RZA) (96.4–97.4%) (Table 8. Index 2).[46] Such predictive models are invaluable in personalizing treatments, ensuring that patients receive the most effective corrective lenses based on their unique anatomical and physiological characteristics.

Cornea and Dry Eye

There is no singular measurement that could determine the presence of dry eye. Corneal health and tear quality are interlinked and problem to one will affect the other. Hence, any changes to the morphology or quality to the tear should be predictive of a potential onset of dry eye. The prediction, evaluation and management of corneal and dry eye conditions are areas where current research is headed. Table 9, elaborates the AI tools available for predicting various morphological, quantitative, and qualitative parameters of cornea and tear.

Dai et al introduced a CNN model with U-Net architecture to evaluate the morphology of Meibomian glands, an essential factor in dry eye disease.[47] The model achieved an impressive Intersection over Union (IoU) of 89.5% and accuracy of 90.8%, validated using both hold-out and cross-validation methods on a small dataset. This AI system is particularly valuable in clinical settings, where detailed morphological assessments are necessary for accurate diagnosis and treatment planning (Table 9. Index 1).[47]

In a more recent study, Garaszczuk et al employed advanced regression models to predict tear osmolarity, an important biomarker for dry eye.[48] Their model achieved a classification accuracy of 83% and a regression accuracy of 78%, demonstrating the potential of AI in providing precise diagnostic insights that can guide targeted treatment strategies (Table 9. Index 2).[48]

Table 7 AI Tools for Screening of Amblyopia

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Murali et al[44]	DL (B)	Detecting amblyopia risk factors.	654	654	Hold-Out and Cross Validation	A: 90.8%, Se: 83.6, Sp: 94.3

Table 8 AI Tools for Screening of Contact Lenses & Spectacle Prescriptions

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Fan et al[45]	ML (B)	Predict the RZD and LZA	64	27	Five-fold Cross Validation	Parameters for CRT lenses: (A: 82.1%)
2	Fang et al[46]	ML (B), LR with LASSO regression (B)	Predict the treatment effect of orthokeratology (ortho-k) in children.	1037	1037	Compared to gold standard	LZA: (A: 69.3–86.6%); RZD: (A:96.4–97.4%)

Abbreviations: RZD, Return Zone Depth; LZA, Landing Zone Angle; LR, Logistic Regression; CRT, Corneal Refractive Therapy; LASSO, Least Absolute Shrinkage and Selection Operator.

Fineide et al developed an AI models to predict tear film instability in dry eye disease (DED) patients using clinical data from 431 individuals.[49] Among various machine learning algorithms, Random Forest achieved the highest accuracy of 99.77%, significantly outperforming baseline models. Key predictors identified included age, Ocular Surface Disease Index (OSDI) scores, meibomian gland metrics, blink frequency, and tear osmolarity (Table 9. Index 3).[49] The AI system has potential to streamline DED diagnosis and enable personalized treatments. However, limitations such as a small, single-site dataset and class imbalance may affect generalizability. Future studies with larger, diverse populations are needed to validate and enhance these predictive models.

El Barche et al addressed the challenge of accurately measuring tear film break-up time (TBUT) for diagnosing dry eye disease (DED) by developing an automated deep learning (DL) algorithm.[50] Utilizing a dataset of 47 slit lamp videos for development and 20 for testing, the study employed a Dual-Task Siamese Network to classify video frames into tear film breakup or non-breakup categories. The approach included postprocessing with a Gaussian filter to smooth predictions and accurately identify TBUT initiation. The algorithm achieved a frame-level Area Under the Curve (AUC) of 0.870 and a strong Pearson correlation coefficient of 0.81 between AI-predicted TBUT and ground truth in the test set (Table 9. Index 4).[50] Validation involved comparing AI measurements with those of an ophthalmologist, demonstrating reliable performance comparable to general ophthalmologists. However, limitations include a small

Table 9 AI Tools for Screening of Cornea and Dry Eye

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Dai et al[47]	CNN with U-Net.(B)	AI system for evaluating the morphology of Meibomian glands (MGs).	40	20	Hold-Out and Cross Validation	U-Net: (A: 90.8%, IoU: 89.5%)
2	Garaszczuk et al[48]	ARM (W)	Predict tear osmolarity.	164	Regression: 33; Classification:41	Hold-Out Validation	Regression (A:78%); Classification (A: 83%)
3	Fineide et al[49]	RF (B), AdaBoost (B), LogitBoost (B), RFC (B)	Evaluation of tear film instability in dry eye disease.	216	215	Ten-fold Cross-Validation	RF: (A: 99.77%); RFC: (A: 100%); AdaBoost: (A: A: 100%); LogitBoost: (A: 100%)
4	El Barche et al[50]	DTSN based on RexNet150 (B)	Automated measurement of tear film break-up time (TBUT) for diagnosing dry eye disease (DED) using video frames	47	20	Comparison with ophthalmologist and ground truth	AUC: 0.870

Abbreviations: IoU, Intersection over Union; ARM, Advanced regression models; RFC, Randomizable Filtered Classifier; DTSN, Dual-Task Siamese Network.

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dataset, potential misclassifications due to residual tear film artifacts, and limited generalizability beyond the study's specific conditions. Despite these constraints, the AI-based method significantly reduces subjectivity and enhances the reliability of TBUT measurements, offering a promising tool for improving diagnostic accuracy and efficiency in clinical settings for managing dry eye disease.

Diagnosis

Rapid diagnosis would help decrease workload and help initiate management protocol quickly. Traditional diagnostic methods rely heavily on the clinical expertise and subjective judgment of optometrists, which can introduce variability and potential human error. Lack of trained professional affects optometry in multi-folds, as the current workforce is understaffed.[3] The integration of AI into the diagnostic process offers a promising solution to these challenges by providing consistent, objective, and accurate assessments that would assist the optometrist in clinic.

Below, we discuss the application of AI in diagnosing refractive errors, strabismus, and cornea and dry Eye.

Eye Refractive Errors

AI has shown tremendous promise in diagnosing refractive errors, particularly in the context of myopia and its associated complications. Table 10, looks in to AI tools that help in diagnosis of refractive error and associated pathologies, mainly pathological myopia.

No exact methodology has been established for diagnosing pathological myopia.[60] The challenges in diagnosing pathological myopia stem from its subtle early stages, variable progression, lack of clear cut-offs, coexistence with other eye conditions, and limited understanding of its underlying causes.[61]

Macular lesions are one of the complications associated with pathological myopia. The presence of macular lesions could be predictive of pathological myopia.[61] Traditionally, macular lesions were assessed using an ophthalmoscope. However, this only allows us to observe the retina directly, making it difficult to evaluate the depth of the lesion thoroughly. Swept-source optical coherence tomography has made it easier to asses these lesions in a 3-D cross-section.

Sogawa et al utilised a deep learning model based on the Visual Geometry Group-16 (VGG-16) architecture to distinguish between individuals with and without myopic macular lesions using swept-source optical coherence tomography (SS-OCT) images.[51] This model was trained and validated on 910 images, achieving an impressive accuracy of 97%, with a sensitivity of 90.6% and a specificity of 94.2% during validation (Table 10. Index 1).[51]

Studies have tried to implement AI in order to diagnose pathological myopia by learning from OCT and fundus images. Hemelings et al employed a convolutional neural network (CNN) to classify pathological myopia and perform semantic segmentation of myopia-induced lesions.[52] The model demonstrated high accuracy in identifying various pathological features, with a particularly strong performance in detecting pathological myopia (98.6%) and retinal detachment (99.0%) (Table 10. Index 2).[52] These findings underscore the potential of AI to provide detailed, lesion-specific diagnostics, which are crucial for targeted interventions.

Studies have tried to define pathological myopia based on myopic maculopathy while some based on myopic refractive error (cutoff values: −6D to −8D).[60] Early diagnosis of high myopia would help in managing the progression. Wan et al developed a CNN-based diagnostic algorithm specifically designed to assess the risk of high myopia.[53] This model, validated with a hold-out validation approach, achieved an accuracy of 98.2%, demonstrating the robustness of AI in identifying high-risk myopia cases (Table 10. Index 3).[53]

Wu et al further explored the diagnostic potential of deep learning by developing a model to diagnose vision-threatening conditions in patients with high myopia.[54] Their model, validated through a hold-out approach, demonstrated high accuracy in detecting atrophy (92.4%), tractional conditions (85.3%), and neovascularization in retina (94.2%) (Table 10. Index 4).[54] This study highlights the versatility of AI in addressing a wide range of myopia-related complications, such as macular atrophy, tractional retinal detachment, and neovascularization associated Pathological Myopia.

Behavioural, environmental, and genetic factors also influence the onset of myopia. Tong et al utilized machine learning (ML) ensemble models to classify myopia and identify its influencing factors among 7,472 students from primary, junior high, and senior high schools in Jiamusi City, China.[55] By integrating visual acuity screening data with

Table 10 AI Tools for Diagnosis of Refractive Errors

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Sogawa et al[51]	DL based on VGG-16 architecture (B)	Diagnosing those with and without myopic macular lesions	910	910	Cross Validation	OCT (A: 97%, Se: 90.6, Sp: 94.2)
2	Hemelings et al[52]	CNN (B)	Classify pathological myopia and perform semantic segmentation of myopia-induced lesions.	2000	400	Hold-Out Validation	PM: (A:98.6%); RD: (A: 99.0%)
3	Wan et al[53]	CNN (B)	Diagnosis algorithm to determine the risk of high myopia	758	100	Hold-Out Validation	A: 98.2%
4	Wu et al[54]	DL (B)	Diagnosing vision-threatening conditions in high myopia	1483	370	Hold-Out Validation	Atrophy (A: 92.4%); Tractional: A: 85.3%); Neo-vascular: A: 94.2%)
5	Tong et al[55]	RF (B), SVM (B), XGBoost (B), AdaBoost (B)	Classification of myopia and identification of influencing factors	5,067	2,172	Hold-Out Validation (70:30 split)	Overall: (AUC: 0.752); Primary: (Se: 41.3, Sp: 69.7, AUC: 0.710); Senior High: Se: 64.3, Sp: 98.0, AUC: 0.722)
6	Manoharan et al[56]	ML (B)	Assess an individual with myopia is "at-risk" or "low-risk" for myopia progression.	149	149	Cross Validation	Se: 89.0, Sp: 94.0, AUC: 0.89–0.90
7	Huang et al[57]	Time-Aware Long Short-Term Memory (T-LSTM) (B)	Predict spherical equivalent (SE) for children and adolescents based on historical vision records	398336	49,042	Hold-Out Validation	T-LSTM: (MAE: 0.103 ± 0.140 D)
8	Ye et al[58]	ResNeSt101 + Focal Loss (B)	Identifies 5 myopic maculopathies	2,342	450	Hold Out validation	Se: 92.8, Sp: 94.0, AUC: 0.927–0.974
9	He et al[59]	(Model A: DNN from ground up) (B); (Model B: Transferred Learned on ImageNet based models (B)	Classification of myopic maculopathy (MM) using optical coherence tomography (OCT) images	2380	680	Hold-Out validation, External validation	DNN model-A: (A: 95%); ImageNet based Model B: (A: 96.4)

Abbreviations: VGG-16, Visual Geometry Group; OCT, Optical Coherence Tomography; ONH, Optic Nerve Head; RD, Retinal Detachment; MAE, Mean Absolute Error.

behavioural, environmental, and genetic factors, the study found that Random Forest model achieved the highest overall performance (AUC = 0.752) and was most effective for primary students (AUC = 0.710), while SVM and XGBoost were optimal for junior and senior high students, respectively (Table 10. Index 5).[55] Influencing factors varied by school period, with genetics playing a major role in primary school, behavioural and environmental factors in junior high, and eye health awareness and outdoor activities in senior high school. SHapley Additive exPlanations (SHAP) analysis highlighted key predictors such as age, parental myopia, and outdoor activity time, while gender had minimal impact. The findings suggest that ML models can enhance school-based vision screenings and support targeted myopia prevention strategies, though further validation with diverse populations is needed to improve generalizability and effectiveness.

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Manoharan et al focused on assessing the risk of myopia progression, developing a machine learning model to predict whether an individual with myopia is "at-risk" or "low-risk" for further progression.[56] Their model, validated against clinical decisions with an AUC ranging from 0.89 to 0.90, with a sensitivity of 89.0% and a specificity of 94.0%. This AI model provides a proactive approach to myopia management, enabling clinicians to tailor interventions based on individual risk profiles (Table 10. Index 6).[56]

Huang et al tried to achieve similar outcomes by developing a Time-Aware Long Short-Term Memory (T-LSTM) model capable of predicting the spherical equivalent (SE) in children and adolescents based on variable-length historical vision records.[57] Using a dataset of 75,172 eyes from 37,586 children, the model achieved a mean absolute error (MAE) of 0.103 ± 0.140 D, which is significantly lower than the clinically acceptable threshold of 0.75 D (Table 10. Index 7).[57]

Ye et al developed a deep learning-based AI system utilizing the ResNeSt101 architecture to identify five types of myopic maculopathies from OCT images. Trained on 2,342 images and independently tested on 450 images, the system showed remarkable performance. For macular choroidal thinning (MCT), it achieved an AUC of 0.927, with a sensitivity of 90.5% and specificity of 88.7%. For Bruch membrane (BM) defects, the AUC was 0.938, with a sensitivity of 88.9% and specificity of 84.8%. In detecting subretinal hyperreflective material (SHRM), the AUC was 0.927, with sensitivity and specificity of 73.9% and 91.3%, respectively. The model excelled in identifying myopic traction maculopathy (MTM) with an AUC of 0.974, sensitivity of 92.8%, and specificity of 90.5%. For dome-shaped macula (DSM), the AUC was 0.955, sensitivity 74.5%, and specificity 94.0% (Table 10. Index 8).[58]

Both methods complement each other, Huang et al's model excels in the prediction of SE trends for early paediatric interventions, while Manoharan et al's model offers simpler risk stratification for clinical decision-making.

He et al developed a deep learning (DL) algorithm to automatically classify myopic maculopathy (MM) using optical coherence tomography (OCT) images, addressing the need for efficient and accurate MM diagnosis in large-scale settings.[59] The study analysed 3,400 high-quality macular OCT images from 2,866 myopic patients across three Chinese hospitals. Two DL models were employed: a deep residual network (ResNet) trained from scratch and a transfer learning (TL)-based model leveraging a multi-source cross-domain TL approach. Validation involved splitting the data into training (70%), validation (20%), and test (10%) sets, supplemented by external validation using 1,000 additional OCT images. TL model achieved a macro AUC of 0.986, accuracy of 96.04%, and a kappa score of 0.940 in the test set, maintaining robust performance in external validation (Table 10. Index 9).[59] Limitations include limited generalizability beyond Chinese populations, reliance on specific OCT devices, a cross-sectional design, and reduced accuracy for extreme refractive errors. Despite these constraints, the DL-based classification system offers a reliable and scalable tool for MM diagnosis, facilitating large-scale screening and supporting clinical decision-making to better manage myopia-related vision impairment.

Together, all these models highlight the potential of leveraging AI-driven methods for both proactive risk stratification and precise diagnostic support. Such tools not only enhance clinical decision-making but also pave the way for more personalized and scalable management of vision-related conditions.

Strabismus

Early diagnosis of strabismus could help is identifying potential amblyopia before it becomes irreversible, thus making alignment screening imperative. Table 11, looks into AI tools that help in diagnosis of misalignments associated with strabismus.

Optometrists who specialise in binocular vision evaluation need to have knee observation to find subtle deviation in eye misalignment in patients. Subtle eye movement disorders may be missed during traditional examinations as these are performed by human individual. de Figueiredo et al utilized a ResNet50 neural network to enhance the objectivity and accuracy of strabismus diagnosis.[62] The model, trained on 8,160 images and validated on 1,440 images using cross-validation with three splits, achieved accuracies ranging from 81.0% to 92.1% (Table 11. Index 1).[62] This study illustrates how AI can improve diagnostic consistency across a diverse patient population, particularly in cases where traditional diagnostic methods may lack precision.

One of the most fundamental and accessible methods of strabismus evaluation is a torch light examination, done by observing the position of corneal reflex. A CNN model capable of diagnosis strabismus have been developed that

Table 11 AI Tools for Diagnosis of Strabismus

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	De Figueiredo et al[62]	ResNet50 neural network (B)	Improve the objectivity and accuracy of strabismus diagnosis.	8160	1440	Cross Validation with 3 splits	A: 81.0% - 92.1%
2	Mao et al[63]	CNN (B)	Diagnosing strabismus based on corneal light-reflection.	Screening:4058; Deviation: 1165; Operation advice: 749	Screening: 870; Deviation: 249; Operation advice: 160	Cross Validation with 3 splits (70%, 15% and 15%)	RT: (A: 99.0%, Se: 99.1, Sp: 98.3); PT: (A: 97.2%, Se: 98.6, Sp: 85.7)
3	Karaaslan et al[64]	DL (Mediapipe) with Image Processing (OpenCV) (B)	Automated detection of strabismus using Hirschberg test	88	88	Validation against ophthalmologist's assessments	Right Eye: (A: 90% ±2° error); Left Eye: (A: 91% ±2° error); Both eyes: 0–45° strabismus measured with <6.6% error.
4	Shu et al[65]	ConvNeXt with GradCAM++ (B)	Early detection of myopia, strabismus, and ptosis	473	473	5-Fold Cross validation with 16 batches.	Myopia: (A: 80%, Se: 73.0, Sp: 76.0); Strabismus: (A:80%, Se: 85.0) Sp: 95.0); Ptosis: (A: 92%)
5	Huang et al[66]	MetaOptNet (ResNet-12) with Image Processing Modules (B)	Strabismus screening	60	30	Hold-Out Validation	Proposed Method: (A: 80.5%, Se: 76.8%, Sp: 84.2%).

Abbreviations: RT, Retrospective test; PT, Prospective test.

analyses corneal light-reflection patterns to identify deviations. The model was validated through both retrospective and prospective tests, achieving an accuracy of 99.0% and 97.2%, respectively (Table 11. Index 2).[63] The model showed a sensitivity of 99.1% - 98.6% and a specificity of 98.3% - 85.7% for both retrospective and prospective tests respectively.

Karaaslan et al addressed the challenge of accurately detecting strabismus by developing an automated method using deep learning and image processing based on the Hirschberg test.[64] The study utilized frontal facial images from 88 patients aged 2–35 years, captured with a 12-megapixel mobile phone camera. By leveraging the Mediapipe library to identify 478 facial landmarks and employing OpenCV for image processing, the algorithm accurately measured corneal reflections and pupil centers to determine strabismus deviations.[64] The method achieved 90–91% accuracy for both eyes with an error margin of ±2 degrees and was validated against clinical assessments by ophthalmologists (Table 11. Index 3).[64] However, limitations include dependency on image resolution, challenges in interpreting 2D images of 3D structures, sensitivity to lighting conditions, and a relatively small, homogeneous dataset. Despite these constraints, the automated Hirschberg test offers a low-cost, efficient screening tool for strabismus, enhancing accessibility and reducing human error in early diagnosis and intervention.

Additional, AI can help diagnose strabismus via teleophthalmology particularly in areas with limited access to specialized eye care. A deep learning model (ConvNeXt) was developed to detect various eye diseases (myopia and ptosis). Including strabismus.[65] The model achieved an accuracy of 80% for both myopia (sensitivity: 84%, specificity: 76%) and strabismus (sensitivity: 73%, specificity: 85%), and 92% for ptosis (sensitivity: 85%, specificity: 95%), demonstrating its robustness in identifying these conditions (Table 11. Index 4). GradCAM++ (Gradient-weighted Class Activation Mapping) was employed to visualize the areas in the input images that most influenced the model's predictions. It was found that the lateral eye regions was most significant for strabismus detection.

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Huang et al developed a strabismus screening method that combines meta-learning with image processing to enhance classification accuracy in scenarios with limited training data.[66] Utilizing MetaOptNet pre-trained on the miniImageNet dataset and a ResNet-12 embedding network, the study extracted high-dimensional features from eye region images. Complementary image processing techniques were employed to derive supplementary features such as position similarity and corneal light reflex (CLR) ratios, which were then integrated with the embedded features using principal component analysis (PCA). A Support Vector Machine (SVM) classifier trained on these combined features achieved a notable accuracy of 80.5%, sensitivity of 76.8%, and specificity of 84.2%, outperforming MetaOptNet (Table 11, Index 5).[66] The inclusion of image processing significantly reduced feature overlap, improving classification outcomes. Although an optimistic start, the AI model still needs a broader dataset and refined image techniques to enhance generalizability.

Cornea and Dry Eye

Dry eye disease (DED) is multifactorial disease that effects the homeostasis of the ocular surface. This is a progressive ocular condition that may start without any noticeable symptoms and erode the corneal and conjunctival surface with time. The loose association between the symptoms and the signs means that individual with observable signs of dry eye may not feel present with any symptoms. As dry eye is multifactor, the number of features that needs to be considered are numerous, posing a challenge to clinicians. Since there is no one specific measurement that can diagnose dry eye with absolute certainty, all the factors must be considered simultaneously before making a diagnosis. Implementing an AI model would however, be very useful in this case as AI models works the best when multiple features are considered. Table 12, consolidates AI models that help diagnose DED and associated conditions by evaluating the morphology of the ocular surface and tear secreting tissues.

DED causes epithelial erosion and is a defining sign, this causes irritation and pain when blinking. This is one of the signs that is consistent with the symptom in DED. Epithelial erosion can be detected using corneal fluorescein staining, thus helping in diagnosis of DED. Feng et al applied a support vector machine (SVM) model to classify and grade corneal fluorescein staining in patients with dry eye disease.[67] Validated on 307 samples through ten-fold cross-validation, the model achieved an accuracy of 82.67%, underscoring its utility in helping clinicians assess dry eye severity with greater precision (Table 12. Index 1).[67]

Meibomian glands secrets the lipid layer of the tear, and is very important for maintaining the stability of the tear on the cornea. Although meibomian glands are lost with aging process, in DED patient rapid loss or dysfunction of meibomian glands could be a precursor to dry eye. Li et al explored the use of a SimCLR unsupervised neural network to categorize meibography images into subtypes, focusing on meibomian gland dysfunction on 65, 789 images.[68] SimCLR neural network achieved clustering patients with dry eye into six image-based subtypes. Patients in different subtypes harboured significantly different non-invasive tear break-up time (NIKTBUT), significantly correlated with TMH which are the classical tests performed for detecting DED (Table 12. Index 2).[68]

Tear Meniscus Height (TMH), the vertical height of the tear film at the lower eyelid margin indicates the tear production and it's stability. A reduced TMH often indicates insufficient tear volume, is an indicator of DED. Wang et al proposed a modified UNet-like model to automate the estimation of tear meniscus height (TMH) for dry eye screening.[69] The model, trained on 3,500 images and validated against ground truth data, achieved a Dice Similarity Coefficient of 0.99 for corneal segmentation and 0.92 for tear meniscus detection. The UNet-like model showed a sensitivity of 100% and a specificity of 91.3% (Table 12. Index 3).[69]

Tear film breakup time (TFBUT) is a critical parameter for diagnosing DED, as it directly reflects tear film stability, a key indicator of the disease. Shimizu et al developed a CNN-based model to estimate TFBUT from ocular surface videos recorded with a portable slit-lamp device.[70] Validated on 2,830 samples through a hold-out method, the model achieved an accuracy of 78.9%, demonstrating its potential to assist clinicians in diagnosing DED more effectively (Table 12. Index 4).[70]

Dry eye disease are inflammatory in nature and often presents with corneal and conjunctival epithelial pathologies. Corneal fluorescein staining (CFS) help revel epithelial pathologies that are not viable otherwise. The subjective quantification of the epithelial defects are often prone error and inter examiner variation. A method to quantify the defect might help in visualising the effect of treatment modalities in DED. Kim et al developed and validated a deep

Table 12 AI Tools for Diagnosis of Cornea and Dry Eye

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation data	Validation Method	Evaluation Parameters
1	Feng et al[67]	SVM (B)	Classification of corneal fluorescein staining in patients with DED.	307	77	Ten-fold Cross Validation	A: 82.67%
2	Li et al[68]	SimCLR neural network (B)	Categorize meibography images into subtypes.	65,789	16,447	Validated against gold standard	Dice coefficient: 0.8–1.0
3	Wang et al[69]	Modified UNet-like Model (B)	Automated estimation of TMH for dry eye screening	3500	1050	Hold-Out validation	A: 96%; CS: (IoU: 0.98); TMH: (IoU: 0.88, Se: 100, Sp: 91.3)
4	Shimizu et al[70]	CNN (B)	Diagnosis of dry eye disease (DED)	12,011	2,830	Hold-out Validation	A: 78.9%,Se:77.8, Sp:85.7
5	Kim et al[71]	U-Net (corneal segmentation) + VGG16 (PEE classification) + Density Map (NEI Score Estimation) (B)	Automated grading of dry eye disease severity	1,400	94	Internal and external validation	Corneal segmentation: (A: 89%, Se:82.0, Sp:96.0, AUC: 0.97, DCS: 0.962)

Abbreviations: CS, Cornea Segmentation; TMH, Tear Meniscus Height; DCS, Dice Similarity Coefficient.

learning-based fully automated grading system for assessing the severity of dry eye disease using corneal fluorescein staining images, adhering to the National Eye Institute (NEI) grading scale, which evaluates corneal fluorescein staining by scoring five corneal zones from 0 to 3, with a total severity score ranging from 0 to 15.[71] The system employs a three-step process: corneal segmentation with a U-Net architecture, classification of punctate epithelial erosions (PEE) using a VGG16-based model, and NEI score estimation through a density map of PEE regions. Utilizing an internal dataset of 1,400 images from Hospital 1 (Seoul National University Hospital) and an external dataset of 94 images from (Seoul National University Bundang Hospital), the system achieved a Dice coefficient of 0.962 for corneal segmentation and strong Spearman correlations of 0.868 and 0.863 with expert evaluations in internal and external validations, respectively (Table 12. Index 5).[71] Additionally, it demonstrated an 88% agreement rate in predicting DED improvement or deterioration. Despite its accuracy and strong alignment with expert assessments, the study acknowledged limitations such as data scarcity from a single hospital, potential inaccuracies in canthus localization due to environmental factors, and the need for broader multi-center validation. Overall, the automated system offers a clinically applicable, consistent, and objective tool for DED severity grading, promising to enhance diagnostic reliability and reduce observer variability in clinical settings.

The application of artificial intelligence (AI) in diagnosing dry eye disease (DED) is still restricted, largely because of the absence of standardized image formats and consistent analysis models. To overcome this, future research should focus on developing standardized imaging protocols and AI models that generalize across diverse clinical settings.

Management

Effective management in optometry consists of optimizing treatment plans, enhancing patient outcomes, and ensuring personalized care. AI tools are increasingly being integrated into the management phase of eye care, where they play a pivotal role in refining treatment strategies, facilitating efficiency in contact lenses and spectacle prescription, low vision rehabilitation, and streamlining referral pathways.

Contact Lenses & Spectacle Prescription

Management of ocular conditions are one the most important aspects of optometry work flow. Management strategy determines the prognosis of the disease. Our review indicates that the majority of AI-focused studies concentrate on optimizing Ortho-K contact lens fitting and assessment. This focus is understandable, given that myopia is the most common and the leading cause of visual impairment in comparison to other refractive errors. Orthokeratology, also known as Ortho-K, is a non-invasive approach to correcting vision that uses specially designed rigid gas-permeable (RGP) contact lenses. Studies have shown Ortho-K lenses are capable of stopping the progress of Myopia.[72] In Table 13, we have complied studies that help optimise Ortho-K lens for myopia and astigmatism, design lens fitting models, and identify myopia regression.

Yen and Ye developed a hybrid neural-genetic algorithm aimed at optimizing the design of contact lenses.[73] The study utilized a simulated dataset and a hybrid approach that integrated the CODE V optical design software with genetic algorithms to refine lens design parameters, specifically curvature and thickness, leading to enhanced visual clarity and comfort. The results showed significant improvements in spherical aberration (SA), transverse chromatic aberration (TCO), and modulation transfer function (MTF) values up to 46%, 43%, and 17%, respectively compared to traditional optimization methods (Table 13. Index 1).[73] This method also demonstrated higher image quality and better focus, as evidenced by improvements in the MTF values at various spatial frequencies. These advancements suggest that the proposed GA-NN model offers a more flexible and effective approach to contact lens design, with the potential for broader applications in myopia management and other vision correction strategies in the future.[73] While the study was based on simulated data, the algorithm showed up to a 46% improvement compared to existing methods, underscoring its potential in refining contact lens prescriptions for more precise vision correction.

Zhang et al conducted a study that further explored the application of artificial intelligence in orthokeratology, focusing on developing a model to improve the precision and efficiency of lens fitting.[74] The study employed logistic regression, linear regression, and decision tree analysis to create a fitting model based on the relationship between basic optometric examination data and effective orthokeratology lens prescriptions. Specifically, the variables Kf-FK and Ks-SK were analyzed, where Kf (Flat Keratometry) represents the flatter curvature of the cornea, and FK refers to the fitted or final lens parameter derived from this measurement. Similarly, Ks (Steep Keratometry) denotes the steeper curvature of the cornea, with SK being the corresponding fitted parameter. The model was validated on a test set of 294 samples, achieving accuracy rates of 80.0% to 87.0%, depending on the specific model used—whether it was the FK (Flat K-derived), SK (Steep K-derived), or the LR (Logistic Regression) model (Table 13. Index 2).[74] This study underscores how AI can significantly assist in customizing orthokeratology lens fittings, thereby enhancing both patient comfort and visual outcomes.

Tang et al took this a step further by using fully convolutional networks (FCN) and convolutional neural networks (CNN) to identify the boundaries and centre of the reshaped corneal area after orthokeratology treatment.[1] With a high intersection over union (IoU) of 0.90 for boundary detection, the model's accuracy in identifying treatment zones demonstrates AI's capacity to improve post-treatment monitoring and adjustments in orthokeratology (Table 13. Index 3).[75]

Similarly, a study exploring the prediction of ortho-k lens decentration leveraged an AI-based neural network to predict decentration direction with over 70% accuracy for both right (70.2%) and left eyes (71.8%).[76] The root mean square (RMS) errors for predicting decentration magnitude were 0.31 mm and 0.25 mm for right and left eyes, respectively (Table 12. Index 4). Zernike polynomial fitting quantified the induced higher-order aberrations (HOAs) and astigmatism, showing a moderate correlation (R = 0.38) between lens decentration and post-ortho-k astigmatism. Furthermore, tangential refractive power analysis revealed that decentrations >1 mm induced a mean astigmatism of +2.7 D in 14.5% of cases, underscoring the critical need for precise lens fitting to minimize adverse effects (Table 13, Index 4).[76]

Koo et al developed a machine-learning-based tool to optimize orthokeratology (ortho-K) lens fitting, aiming to reduce the traditional trial-and-error approach and enhance myopia control in children and adolescents.[77] Utilizing a dataset of 547 eyes from 297 Korean patients aged 7–20 years, the study employed CatBoost and Extra Trees

Table 13 AI Tools for Management Related to Contact Lenses and Spectacle Prescriptions

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation data	Validation Method	Evaluation Parameters
1	Yen and Ye[73]	HNA (B)	Optimize the design of contact lenses for myopic and astigmatic eyes	Simulated	Simulated	Cross-validation and fitness function evaluation	SA improved by 50.03%; TCO improved by 45.78%; MTF improved by 24.7%, over baseline designs.
2	Zhang et al[74]	LR[a] (W), LR[b] (W), and DT(B)	Develop an ortho-keratology lens fitting model	1173	294	Hold-Out Validation (train:80% and validation 20%)	FK model: (A: 81.0%); SK model: (A: 80.0%); LR: (A: 87.0%)
3	Tang et al[75]	FCN (B) and CNN (B)	Identify the boundary and centre of the reshaped corneal area (treatment zone) after ortho-keratology	5695	633	Hold-Out Validation (train:90% and validation 10%)	TB: (IoU: 0.90 ± 0.06 pixels); TZ: (IoU: 6.32 ± 0.66 pixels)
4	Lin et al[76]	AI-based Neural Network (B)	Predict magnitude and direction of ortho-k lens decentration	174	75	Leave-30%-out validation	Right Eye: (A: 70.2%); Left Eye: A: 71.8%)
5	Koo et al[77]	CatBoost (B), Extra Trees (B), RM (B)	Optimize ortho-K lens fitting, predicting toric lens options, diameter, base curve, and RZD	437	110	Fivefold cross-validation + internal validation	Toric Lens: (A: 92.7%, AUC: 0.970); OAD: (A: 86.4%, AUC: 0.92)
6	Zhang et al[78]	DL with Segformer architecture with self-attention (B)	Treatment Zone (TZ) and Peripheral Steepened Zone (PSZ) segmentation	1,211	135	Hold-Out validation	Overall: (A: 99.03%, mIoU = 97.19%); TZ segmentation: (IoU = 98.08%); PSZ segmentation: (IoU = 94.54%)

Abbreviations: HNA, Hybrid neural-genetic algorithm; SA, Spherical Aberration; TCO, Tangential Coma; MTF, Modulation Transfer Function; FCN, Fully Convolutional Network; LR[a], Logistic Regression; LR[b], Linear Regression; FK, Flat K-derived; SK, Steep K-derived; TB, Treatment Boundary; TZ, Treatment Zone; RM, Regression Model; mIoU, mean Intersection over Union.

algorithms for binary classification tasks—predicting toric lens options and overall diameters—and regression models for determining base curve, return zone depth, landing zone angle, and lens sagittal depth. The tool achieved high accuracies of 92.7% for toric lens selection and 86.4% for overall diameter, with mean absolute errors of 0.052 mm for base curve and 2.727 µm for return zone depth (Table 13, Index 5).[77] Validation through fivefold cross-validation and testing on a separate dataset demonstrated the machine-learning model's superior performance compared to traditional Initial Lens Selector (ILS) methods, particularly in predicting base curve and return zone depth. Despite limitations such as a homogeneous Korean-only dataset, lack of external validation, dependence on comprehensive clinical measurements, and challenges in model interpretability, the developed web-based application represents a significant advancement in ortho-K lens fitting. This tool offers the potential to improve patient outcomes and reduce reliance on practitioner expertise, thereby enhancing the efficiency and effectiveness of myopia management in clinical settings.

Zhang et al developed an automated deep learning system using the Segformer architecture with self-attention to accurately determine the Treatment Zone (TZ) and Peripheral Steepened Zone (PSZ) from corneal topography maps post-orthokeratology (OK) treatment in adolescents.[78] The model was trained and tested on a dataset of 1,346 images from 734 eyes of 369 patients, achieving impressive performance metrics including a mean Intersection over Union (mIoU) of 97.19%, mean Pixel Accuracy (mPA) of 98.98%, and overall accuracy of 99.03%. Specifically, TZ segmentation reached an IoU of 98.08%, recall of 99.33%, and precision of 98.74%, while PSZ segmentation achieved an IoU of 94.54%, recall of 98.48%, and precision of 95.95% (Table 13. Index 6).[78] Despite its high accuracy and efficiency, processing over 1,200 images per minute on a GPU, the AI model faces limitations such as reliance on two-dimensional data, device-specific training with the Medmont E300 topographer, and challenges in handling interference factors like tear film instability. Nonetheless, the system offers significant benefits by enhancing measurement consistency, reducing manual effort, and providing objective assessments, thereby improving clinical and research workflows in myopia management.

The integration of AI in contact lens wear primarily seem to focus on independence, personalization, and prognosis for low vision and visually impaired individuals.

Low Vision

One of the key aspects in low vision management is to improve the quality of life of the individual. As low vision is not only about vision loss but also about the person as a whole, every individual requires a personalised management plan. AI offers personalized solutions to improve the quality of life for individuals with severe visual impairments.

Table 14, compiles articles highlighting the significant role of AI in enhancing the independence and quality of life for individuals with low vision.

Kacorri et al developed a transfer learning-based model designed to empower blind individuals by enabling them to train a mobile application to recognize personal objects.[79] This model, utilized deep learning techniques, was trained on a dataset consisting of 450 samples and validated with 75 samples using a hold-out method combined with repeated random sampling. The resulting model achieved an impressive accuracy range of 96.9% to 99.6%, highlighting its effectiveness in assisting visually impaired users.[79] By allowing users to independently train the application to recognize their personal belongings, this approach significantly enhances the autonomy and independence of individuals with visual impairments (Table 14. Index 1).[79]

Ahmetovic et al introduced ReCog, a deep learning-based tool designed to help blind users recognize personal objects with a camera, achieving an accuracy of 94.0% when guided and 83.6% without guidance (Table 14. Index 2).[80] This innovation highlights the importance of AI in facilitating daily activities for low vision patients, making it a valuable tool in their overall management.

Dai et al developed a deep neural network (DNN) model to assist in device fitting for low vision patients by analyzing visual function, rehabilitation needs, and quality of life scores.[81] With an accuracy of 81.0%, the model helps tailor assistive devices to individual needs, improving the effectiveness of low vision rehabilitation (Table 14. Index 3).[81]

Wen et al explored the application of teachable AI in providing personalized accessibility solutions for the blind.[82] Using a small dataset of four short videos (200 frames), the model demonstrated accurate object localization up to 4 meters with an inference time of 100–200 milliseconds (Table 13. Index 4).[82] The AI was validated via an iterative on-device testing loop where user teaches the system. This approach underscores the potential of AI in creating adaptable and user-friendly solutions that cater to the specific needs of low vision individuals.

A primary objective in the management of low vision is to prevent further deterioration of functional vision in affected individuals. Many individuals with low vision retain some degree of functional vision, enabling them to use low vision devices effectively. However, low vision is often associated with confounding factors that can exacerbate vision loss over time. These factors must be carefully monitored to manage and mitigate the progression of vision loss, which may lead to complete visual impairment in some cases. Gui et al (2022) developed and validated deep learning models to predict the visual prognosis of low vision patients by integrating both structured and free-text data from electronic health records (EHR).[83] Utilizing a cohort of 5,547 patients with documented low vision over a ten-year period, the study incorporated structured inputs such as demographics, medical codes, and clinical measurements alongside ophthalmology clinical notes. The researchers employed the Clinical Language Annotation, Modelling, and Processing (CLAMP) tool for named entity recognition (NER) to extract relevant medical concepts from the free-text notes and compared different text representations, including domain-specific word embeddings and one-hot encoded CUIs (Concept Unique Identifiers). Among the models tested, those utilizing domain-specific word embeddings achieved the highest performance, with an AUROC of 0.82, outperforming models based on NER-extracted entities. This highlights the effectiveness of specialized text representations in capturing nuanced clinical information within ophthalmology (Table 14. Index 5).[83] The study demonstrated that

Table 14 AI Tools for Management of Low Vision

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation Data	Validation Method	Evaluation Parameters
1	Kacorri et al[79]	TL (B)	Enable blind people to train a mobile application to recognize personal objects.	4120	661	Hold-Out with Repeated Random Sampling	A: 50.7–99.6%
2	Ahmetovic et al[80]	DL (ReCog) (B)	Enable blind users to recognize their personal belongings.	2,142	150	Hold-Out Validation	Camera aiming: With guidance: (A: 94.0%); Without guidance: (A: 83.6%)
3	Dai et al[81]	DNN (B)	Assist in device fitting for low vision patients	529	50	Hold-Out with addiction 50 samples for performance testing	A: 81.0–85.0%
4	Wen et al[82]	Teachable AI (B)	Provide personalized accessibility solutions for the blind.	800	480	Iterative on-device testing loop where user teaches the system	Not Specified (Accurate object localization up to 4 meters with inference time: 100 −200 ms)
5	Gui et al[83]	CNN with D-SWE (B), NER-based CUI Representations (B)	Prediction of visual prognosis in low vision patients using structured and free-text EHR data	3,883	1,664	Hold-Out Validation (70:30 split)	D-SWE: (AUC: 0.78); Combination Model (Structured + D-SWE): (AUC = 0.82)

Abbreviations: TL, Transfer Learning; DNN, Deep Neural Network; D-SWE, Domain-Specific World Embedding.

combining structured data with rich free-text inputs enhances the accuracy of predicting whether patients would maintain low vision after one year. Despite limitations such as single-site data and challenges in NER accuracy, the study underscore the potential of advanced machine learning techniques to improve clinical decision support systems, facilitating targeted referrals to low vision services and ultimately enhancing patient outcomes through timely and appropriate interventions.

Referral Pathway Assistant

AI's role in managing eye care extends to optimizing referral pathways, ensuring that patients receive timely and appropriate care. Han et al developed an AI-based decision support system (DSS) based on an algorithm developed by DeepMind to assist in making referral decisions for retinal diseases.[84] The AI DSS was trained on 500 OCT images and validated against a reference standard (Table 15. Index 1).[84] The accuracy of the AI DSS model was assessed by comparing estimates of sensitivity and specificity of the DeepMind algorithm for referral decisions. Specifically, the primary analysis combined urgent and standard referral to the Hospital Eye Service, with statistical results indicating sensitivity of 85% and specificity of 92% with a 95% confidence interval.[51] These outcomes highlight its potential to support appropriate and timely clinical decision-making in optometry.

Table 15 AI Tools for Management Using Referral Pathway Assistant

Index	Ref	Model and Explainability	Function	No. Training Samples	Validation data	Validation Method	Evaluation Parameters
1	Han et al[84]	AI DSS (B)	Provide diagnoses and make referral decisions for retinal diseases.	500	288	Cross Validation against Reference Standard	A: 95%, Se: 85.0, S p: 92.0

Abbreviation: AI DSS, AI-based decision support system.

Conclusion

AI research in optometry has explored a wide range of 45 distinct models aimed at enhancing the screening, prediction, diagnosis, and management of conditions such as refractive errors, strabismus, amblyopia, contact lens use, spectacle prescription, low vision, corneal issues, dry eye, and referral pathways. These models span from traditional approaches to cutting-edge AI frameworks, reflecting the growing influence of AI in various aspects of optometry.

However, the generalizability and clinical reliability of these AI models are often compromised, particularly when trained on smaller datasets. Notably, some models demonstrated significantly better performance, while the majority did not, emphasizing the influence of factors such as sample size, data quality and distribution, demographic diversity, and testing and validation approaches. A comprehensive analysis of these variations, along with recommendations for future improvements, is presented below.

Limitations and Future Directions

Limited Sample Sizes

One of the major challenge in AI development for optometry is the limited size of datasets, often ranging from 40 to 5,000 samples, which are insufficient for training deep learning models. Small datasets restrict the ability to capture real-world variability, hindering generalization to broader populations and reducing clinical applicability. Models trained on such data risk overfitting, learning specific patterns instead of generalizable trends, resulting in poor performance on unseen data. Despite high reported metrics like accuracy, sensitivity, and specificity, these values may not reflect real-world outcomes due to the lack of diverse and robust validation datasets, limiting their practical reliability. To address this, collaborative data-sharing initiatives should be established to create larger and more diverse datasets. Techniques such as data augmentation and synthetic data generation can also be utilized to expand dataset size and variability, while transfer learning from large pre-trained models can help compensate for the limited availability of optometry-specific data.

Data Quality and Distribution

The variability in data might be influenced by uneven data quality or imbalanced datasets, which could have favored or hindered certain models. Addressing this limitation requires standardize data preprocessing pipelines, using balanced datasets, and incorporating methods to handle imbalances (eg, oversampling or weighted loss functions) can ensure fair and consistent model performance across different datasets.

Lack of Demographic Diversity

Most datasets used in the reviewed studies lack representation across diverse demographic groups. Factors such as age, gender, ethnicity, and geographical location are often underrepresented, introducing bias into AI predictions. For instance, a model trained predominantly on data from a specific ethnic group or region may perform poorly when applied to other populations. Addressing this limitation is critical to ensuring equity and fairness in AI applications. This can be achieved by curating datasets that include balanced representation across demographic groups and collaborating with international and regional organizations to collect data from underrepresented populations. Additionally, fairness and bias mitigation algorithms should be integrated into the model training process to address demographic imbalances and promote equitable performance.

Limited Real-World Testing for Clinical Integration

Most reviewed models are evaluated in controlled, experimental environments rather than real-world clinical settings. As a result, their robustness and practicality in routine optometric practice remain largely untested. Factors such as workflow integration and compatibility with existing diagnostic equipment are overlooked. To bridge this gap, pilot studies should be conducted in clinical environments to assess the real-world applicability and reliability of these models. Models should be designed with compatibility in mind, ensuring seamless integration with existing diagnostic workflows and

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equipment. Developing user-friendly interfaces and tools for clinicians and healthcare staff will further support practical adoption and usage in everyday clinical settings.

Improper Validation Methods

Even though a few studies reported accuracy around 90% with smaller samples, their validation methods were questionable, making them unreliable for broader application. Models trained and validated on the same dataset are particularly prone to bias, further limiting their generalizability. To overcome this limitation, rigorous validation protocols, such as cross-validation and external validation using independent datasets, must be adopted. Developing standardized benchmarks and validation frameworks for optometric AI models can also improve reliability and comparability. Furthermore, transparent reporting of validation methods and metrics will enhance the credibility and reproducibility of the research, ensuring the robustness of the models for real-world applications.

This review highlights the current limitations of AI models in optometry and outlines future directions to address these challenges, aiming to enhance model performance and provide optometrists with a comprehensive understanding of the field's current state. By recognizing the importance of robust training and validation methodologies and considering additional parameters, future AI models can be designed to be technically sound, practically applicable, and ethically responsible for integration into clinical practice.

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