Identification of ocular refraction using a novel intelligent retinoscopy system

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Research Article

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Abstract

**Background:** The evaluation of refraction is indispensable in ophthalmic clinics, generally requiring a refractor or retinoscopy under cycloplegia. Retinal fundus photographs (RFPs) supply a wealth of information related to the human eye and might provide a new approach that is more convenient and objective. Here, we aimed to develop and validate a fusion model-based intelligent retinoscopy system (FMIRS) to identify ocular refraction via RFPs and compare with the cycloplegic refraction. In this population-based comparative study, we retrospectively collected 11,973 RFPs from May 1, 2020 to November 20, 2021. The FMIRS was constructed, and the performance of the regression models of sphere and cylinder was evaluated. The accuracy, sensitivity, specificity, area under the receiver operating characteristic curve, and F1-score were used to evaluate the classification model of the cylinder axis.

**Results:** Overall, 11,973 images were included. For sphere and cylinder, the mean absolute error values between the FMIRS and cycloplegic refraction were 0.50 D and 0.31 D, representing an increase of 29.41% and 26.67%, respectively, when compared with those of the single models. The correlation coefficients (r) were 0.949 and 0.807, respectively. For axis analysis, the accuracy, specificity, sensitivity, and area under the curve value of the classification model were 0.89, 0.941, 0.882, and 0.814, respectively, and the F1-score was 0.88.

**Conclusions:** The FMIRS successfully identified ocular refraction accurately in sphere, cylinder, and axis, and it showed good agreement with the cycloplegic refraction. The RFPs can not only provide comprehensive fundus information but also the refraction state of the eye, emphasising their potential clinical value.

Background

Refractive errors are the most common ocular disorders and are the second leading cause of blindness [1–3]. Recently, the distribution of refractive errors worldwide has shifted towards myopia, or nearsightedness. Myopia has become an epidemic-like public health issue due to its soaring incidence and prevalence, and potentially long-term associations with sight-threatening ocular complications [4]. Hence, precise measurement and assessment of refraction are essential for evaluating the degree of ametropia and providing appropriate eye care. Clinical subjective refraction under cycloplegia is a routine technique for determining refractive errors. However, this procedure is laborious, time-consuming, and can sometimes result in blurred vision, photophobia, and the perception of glare due to pupil dilation [5–6]. Additionally, it is inconvenient and can be challenging for disabled or paediatric patients, especially in resource-limited settings. Even with the advent of autorefractors, the results of refraction measurement remain unsatisfactory because of the accommodation [7]. In addition to overestimating the prevalence and severity of myopia, these systems can affect preventive and corrective strategies for myopia. Unfortunately, data concerning refraction and its association with retinal fundus photographs (RFPs) are lacking. Therefore, a more effective method should be developed to improve detection, documentation, and prediction of refraction.

Fundus photography can objectively reflect retinal morphology and is commonly used in clinical practice. Changes in myopia cause distortion of the retinal image and deterioration of visual quality. The typical features of retinal morphology in myopia are characterised by tessellation and changes in the parapapillary or macular region and trajectory of the arteries. These changes are more pronounced in patients with high and pathological myopia [8–12]. In addition to these visible structures, fundus image intensities represent the amount of reflected light, which provides information on the complete state of the eye. Whether this information informs on ocular refraction and explains image distortions caused by astigmatism remains unclear.

Artificial intelligence (AI) has been extensively applied in the classification and prediction of medical data [13–15]. This technology has also achieved near-expert performance in helping clinical decision-making [16]. The broader
capacity of AI is applied to extract regions of interest (ROI) that doctors typically cannot recognise from images alone, thereby providing greater clinical insights and findings [17]. Numerous studies have highlighted the value of RFPs using AI, such as in screening for diabetic retinopathy and detecting cardiovascular disease, and a few studies have shown that deep learning systems could predict spherical equivalents using fundus photographs [18–20]. However, given the influence of population and algorithms, the results of these systems cannot completely represent the accurate ocular refraction. More importantly, these studies did not determine the cylinder axis.

Therefore, here, we developed a novel fusion model-based intelligent retinoscopy system (FMIRS) to effectively identify ocular refraction from RFPs and compared it to the cycloplegic refraction in sphere, cylinder, and axis.

**Results**

**Baseline characteristics**

Overall, 11,973 images were collected, 7,873 of which were processed and retained. A total of 7,086 images were eventually randomly selected to construct the regression model (RM) and classification model (CM) for sphere and cylinder, respectively, whereas the remaining 787 images were used for testing. Among the total images, 2,028 were used for the CM of the cylinder axis as the uneven axial distribution in the crowd. Patients’ age ranged from 6 to 40 years, with a mean (standard deviation, SD) of 18.5 (7.3) years. The mean sphere was −3.82 D (2.05 D) (range: -0.25 to -8.00 D) and the mean cylinder was −0.82 D (0.61 D) (range: 0 to -2.75 D). We divided the data to ensure that images acquired from the same patient were not split across the training and validation sets (Table 1).
Table 1
Summary of the training, validation, and test sets

<table>
<thead>
<tr>
<th></th>
<th>Training set</th>
<th>Validation set</th>
<th>Test set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (y), mean (SD)</td>
<td>18.35 (6.50)</td>
<td>18.72 (7.34)</td>
<td>18.94 (7.22)</td>
</tr>
<tr>
<td>Sex, (M / F)</td>
<td>3089 / 2422</td>
<td>702 / 873</td>
<td>346 / 441</td>
</tr>
<tr>
<td>Intra-ocular pressure (mmHg)</td>
<td>16.1 (2.01)</td>
<td>15.9 (2.16)</td>
<td>16.4 (1.78)</td>
</tr>
<tr>
<td>Uncorrected distance visual acuity (LogMAR)</td>
<td>0.68 (0.25)</td>
<td>0.69 (0.21)</td>
<td>0.69 (0.22)</td>
</tr>
<tr>
<td>Centre corneal thickness</td>
<td>551.57 (30.93)</td>
<td>555.17 (22.18)</td>
<td>547.28 (22.61)</td>
</tr>
<tr>
<td>K1</td>
<td>42.41 (1.25)</td>
<td>42.35 (1.33)</td>
<td>42.41 (1.31)</td>
</tr>
<tr>
<td>K2</td>
<td>43.75 (1.41)</td>
<td>43.99 (1.36)</td>
<td>43.96 (1.43)</td>
</tr>
<tr>
<td>RM (No. of images)</td>
<td>5511</td>
<td>1575</td>
<td>787</td>
</tr>
<tr>
<td>CM (No. of images)</td>
<td>5511</td>
<td>1575</td>
<td>787</td>
</tr>
<tr>
<td>A-CM a (No. of images)</td>
<td>1420</td>
<td>406</td>
<td>202</td>
</tr>
<tr>
<td>Sphere, mean (SD)</td>
<td>–3.77 (2.04)</td>
<td>–3.95 (2.05)</td>
<td>–3.95 (2.09)</td>
</tr>
<tr>
<td>Cylinder, mean (SD)</td>
<td>–0.82 (0.61)</td>
<td>–0.81 (0.60)</td>
<td>–0.83 (0.63)</td>
</tr>
<tr>
<td>Axis (W/A/O)</td>
<td>2920/1543/1048</td>
<td>882/504/189</td>
<td>519/204/64</td>
</tr>
<tr>
<td>SE, mean (SD)</td>
<td>–4.18 (2.11)</td>
<td>–4.36 (2.12)</td>
<td>–4.17 (2.12)</td>
</tr>
<tr>
<td>High myopia</td>
<td>36.9%</td>
<td>39.6%</td>
<td>36.2%</td>
</tr>
<tr>
<td>Moderate myopia</td>
<td>28.7%</td>
<td>29.1%</td>
<td>28.7%</td>
</tr>
<tr>
<td>Mild myopia</td>
<td>34.4%</td>
<td>31.3%</td>
<td>35.1%</td>
</tr>
</tbody>
</table>

Abbreviations: K, keratometry; RM, regression model; CM, classification model; A, Axis; W, with the rule; A, against the rule; O, oblique; SE, spherical equivalent.

a Only classification model

Performance of the FMIRS in test set

According to the results of the confusion matrix, we compared the performance of FMIRS with and without age as the eigenvector. The performance of each model (RM and CM) and the FMIRS for the test set is listed in Table 2. For sphere and cylinder, the mean absolute error (MAE) of the RM were 0.66 D and 0.38 D, respectively. The AUC values of the CM were 0.863 (95% confidence interval (CI): 0.839–0.887) and 0.834 (95% CI: 0.808–0.860), respectively, with AUC values of 0.8–0.9 indicating excellent performance [21]. The accuracy, specificity, sensitivity, and F1-score are shown in Table 2. For the FMIRS, the MAEs of sphere and cylinder were 0.50 D and 0.31 D, representing 29.41% and 26.67% increases, respectively, with respect to those for the RM. The overall distributions of the FMIRS and actual values were almost in a good agreement with those shown in the scatter diagram in Fig. 1A. The Pearson's correlation coefficient (r) values were 0.949 (95% CI: 0.942–0.956) and 0.807 (95% CI: 0.781–0.830), respectively. Figure 1B shows the Bland–Altman plot comparing the FMIRS and actual values in the test set. For the classification of the cylinder axis, the AUC value was 0.814 (95% CI: 0.708–0.902).
Table 2
Performance of single models and the FMIRS

<table>
<thead>
<tr>
<th>Model visualisation</th>
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<tr>
<td>To better visualise how the FMIRS was able to detect the cylinder axis from the RFPs directly, the attention maps were superimposed on the convolutional visualisation layer generated to understand the contributions of the ROI (Fig. 2). The retinal vascular regions were highlighted in these maps, and as a fundamental feature appeared in all images. Additionally, the macular areas, as another ROI, existed only in the with the rule (WTR) group and the oblique group. These observations were found in nearly all images.</td>
</tr>
</tbody>
</table>

Discussion
In this study, we developed and applied a novel FMIRS to identify the ocular refraction and compare it to the cycloplegic refraction. To our knowledge, this was the first intelligent retinoscopy system simultaneously analysing both sphere and cylinder (mean difference: 0.5 D and 0.31 D, respectively) and cylinder axis (AUC value: 0.814). The results derived from this system showed a strong correlation with clinical cycloplegic refraction ($r = 0.949$ and $r = 0.807$, $P < 0.0001$). Importantly, the study proved that the FMIRS was promising when considering all metrics (including sphere, cylinder, and axis). We further evaluated the performance of the different subgroups of refraction and found that the FMIRS could identify different refractions through common clinical retinal images with a consistent performance. It was proven that the FMIRS has the potential to have a beneficial effect on refractive assessment owing to its ability to represent the state of the human eye objectively and comprehensively.
As cycloplegic refraction is inconvenient and subject to the experience of ophthalmologists or optometrists, large-scale screening has been limited [22]. Non-cycloplegic refractive testing has been employed more commonly in emerging studies to identify refractive errors within larger populations. Simultaneously, AI-based methods to predict refractive errors via ocular images have been promising new hotspots of research [23]. In particular, a common consensus of these methods allowed algorithms to learn predictive features directly from the images from a large dataset of labelled examples without explicitly specifying rules or features [24]. However, the output of these algorithms only included the spherical equivalent (spherical equivalent (SE) = sphere + 1/2 cylinder) and could not reflect the complete status [20, 25]. Several studies have identified and segmented the visible structures of the retina based on AI algorithms, including the optical disc, fovea, and tessellations [26–27]. In fact, shifting myopia degrees could lead to these structural changes, making it possible to apply deep learning technologies for automatic myopia identification and detection, as algorithms could easily detect structural changes from fundus images. The acquisition of eye photographs and model training could improve performance. Moreover, images contain valuable, inconspicuous information, such as the light that reflects from the retina, lens, and cornea. The comprehensive information available from the data might be leveraged by the new FMIRS. Notably, the current FMIRS was more objective and practical and reached better predictive performance than cycloplegic refraction, making it appropriate for clinical practice.

Furthermore, we extracted the ROIs during model training and obtained the sphere and cylinder based on data from the entire retina, embracing the optical disc tilt, atrophy, and fovea morphology. Vascular regions were especially highlighted as a previously unnoticed feature. Further analysis of the cylinder axis using attention maps revealed informative features and locations. Interestingly, consistent focus on the vessels in the attention maps could indicate the axial results, and this has not been reported in previous studies. Different categories of astigmatism were also identified in different regions on the maps. WTR astigmatism was usually focused on areas parallel to the retinal blood vessels, whereas against the rule (ATR) astigmatism was focused on areas perpendicular to the vessels. Almost all areas of the optic disc could be observed across the three categories, although the macular region could not be observed in cases of ATR astigmatism. Oblique astigmatism did not seem to follow a specific distribution in the attention map and was mainly focused on the macular area.

Astigmatism is mainly from the differential amplification of major corneal meridians, but astigmatism assessment based on cornea alone is inaccurate [28]. When light passes through different meridians, the difference in refractive power could induce blurred images, causing retinal image distortion along the axis [6, 29]. The attention maps in the study highlighted this possibility and indicated a correlation between the ROI and anatomy. A previous study reported that astigmatism could induce changes in the thickness of the retinal nerve fibre and optic nerve head parameters during optical coherence tomography [30]. Chameen et al. [10] found that the distributions of the disc tilt axis and corneal curvature were similar, and astigmatism exhibited a strong relationship with retinal anatomy and suggested the same embryological origin. The findings of the current studies lay a foundation for understanding how the model identified this information. Although they did not establish causation, these maps might explain the image distortion caused by astigmatism and could help generate unbiased hypotheses for further study of the cylinder axis [31].

Measuring refraction without accommodation has been the standard for detecting myopia [32]. To achieve this, cycloplegic agents must be administered, especially in paediatric patients with a wide range of accommodations. The prevalence and severity of myopia are overestimated when cycloplegic agents are withheld [22]. Despite differences in the use of cycloplegic agents, measurement methods, age ranges of participants, and refractive status among studies, the reported mean difference between noncycloplegic and cycloplegic refractive errors ranged from 0.62 D to 1.23 D, with inter-method differences significantly decreasing with age [33]. Compared with cycloplegic refraction, the ocular refraction analysed using our intelligent retinoscopy performed with clinically acceptable accuracy and largely
corrected the overestimation of myopic shift. More particularly, it was helpful for evaluating different degrees of astigmatism.

Our system achieved a medical application of AI; the results demonstrated that personalised modelling with a CNN and CNN-based transfer learning was an improved estimation approach that could be used across diverse patient subgroups. Age was used as a contributing feature to improve performance. The system was developed using the clinical gold standard as the target to separately identify refractive errors in sphere, cylinder, and axis, and the feature extractors using the XGBoost algorithm reduced model variance, increased its robustness, and prevented overfitting of the class-unbalanced population data. We introduced a voting mechanism for validation, which allowed us to combine the single models while increasing accuracy and reducing bias. Indeed, RFPs were taken in patients at different time points; hence, the lighting and background of the images were not uniform, indicating the richness and diversity of our datasets. As fundus photography is used worldwide, and portable and affordable cameras are becoming more common and popular, this system is expected to have greater advantages for large-scale surveys. In short [34], the present approach enables integrated observation of retinal conditions and simultaneous assessment of refractive errors.

This study had several limitations. First, the imbalance of high myopia and astigmatism in the dataset might have affected the overall performance, although we included the relative outliers and minority classes with larger weights in the training set to address this problem. Second, data were collected from the same type of fundus camera, and the homogeneity of images was much higher than in other studies and situations. The absence of images from other sources limits the generalisability of the system. Finally, we excluded patients diagnosed with other ocular diseases, and changes in the fundus were only due to refractive errors. Future studies should utilise a larger multi-centre dataset and additional clinical results to determine the clinical applicability.

Conclusions

In this study, we developed an FMIRS for the identification of ocular refraction. The results were largely consistent with cycloplegic refraction measurements. This study indicated that the FMIRS was capable of assessing ocular refraction reliably and directly, avoiding time-consuming cycloplegic process. Importantly, the attention maps generated from this system might provide new perspectives to explain the image distortion caused by myopic astigmatism and help determine imaging biomarkers for diagnosing refractive errors. These findings also highlight the potential values of AI-based intelligent retinoscopy to provide detailed information on both retinal changes and refraction states simultaneously. In the future, combining FMIRS with smartphones might further enable patients to self-monitor refraction changes and might have potentially significant implications for eye care worldwide, especially in areas with limited healthcare resources.

Methods

Ethics statement

This study was registered in the Chinese Clinical Trial Register (ChiCTR2100049885), approved by the Ethics Committee of Tianjin Eye Hospital, and conducted in accordance with the tenets of the Declaration of Helsinki. The ethical committee waived the requirement for informed consent owing to the retrospective study design and the use of anonymised RFPs. This study followed the Standards for Reporting of Diagnostic Accuracy Study-AI (STARD-AI) reporting guidelines [35].

Data collection
The dataset was retrospectively collected from medical records at Tianjin Eye Hospital of Nankai University from May 1, 2020, to November 20, 2021, and analysed in December 2021. Relevant demographic information included sex and age; ocular parameters included uncorrected visual acuity, intraocular pressure (Topcon Inc., Tokyo, Japan), corneal morphology (Oculus Inc., Wetzlar, Germany), and fundus photography (Canon Inc., Tokyo, Japan). Patients with any other ocular diseases were excluded, such as corneal diseases, cataract, glaucoma, retinal disease, and a history of intraocular surgery. The values and parameters of both eyes were used in the main statistical analyses. Clinical subjective refraction was measured after cycloplegia, with sphere ranging from 0.75 D to −10.00 D and cylinder ranging from 0 D to −6.00 D. According to the SE refraction, the subgroups were identified as mild myopia (-3.0 D ≤ SE ≤ -0.50 D), moderate myopia (-5.00 D < SE < -3.00 D), and high myopia (SE ≤ -5.00 D) [36]. All measurements were performed by three optometrists with more than 10 years of experience, and there were no significant differences in the consistency of assessments. Overall, 11,973 images taken in patients at different time points were collected without pupil dilation. All images were acquired with a 45° field-of-view centred on the fovea.

The images were filtered according to the following criteria. (1) Images with complete fundus information were retained, including anatomical structures, such as optic disc, macula, and vessels. (2) Images with extremely low resolution, significant artifacts, or blurring were discarded. (3) Size and resolution were normalised for all images with the same magnification ratio and form. Furthermore, each image was labelled with the corresponding cycloplegic refraction, and the refractive status of each image was determined using the sphere, cylinder, and axis. The cleaned images were retained and divided into the training, validation, and test sets at a ratio of 7:2:1. The process of data collection is shown in Appendix 1.

**Data pre-processing and augmentation**

To retain as much practical information as possible in all images, the Hough transform was used to locate the optimal image boundary, determine the centre and radius of the standard circle, and construct the largest inscribed circle and square. Contrast-limited adaptive histogram equalisation was used to extract the red and green channels from an image to highlight the vascular structure and enhance contrast. We removed the proportion of invalid pixels to maintain the fundus as the largest inscribed circle within the area (Fig. 3A, b), followed by the largest inscribed square (Fig. 3A, f). Finally, the image was converted to a resolution of 512 × 512 pixels.

Data augmentation was performed during pre-processing: (1) random rotation was performed between −30° and +30° based on the original angle; (2) the sharpness was randomly adjusted to 0.5×, 1×, or 2× the original image; (3) the contrast was automatically set with a probability of p = 0.5; (4) the histogram of the image was randomly equalised with a probability of p = 0.5 (Fig. 3A, b, c, d, e). Data augmentation methods are presented in Appendix 2.

**Construction of the intelligent retinoscopy system**

Before constructing the system, the recorded parameters were filtered to determine which could be used as the eigenvectors (Fig. 3B). We further applied discrete variables scattered in the space with units of 0.25 D as labels, and sphere and cylinder as the output to ensure the output was clinically appropriate. Two different algorithms were adopted to construct the RM and CM. The specially designed voting mechanism was applied in the bagging stage to enhance the accuracy and overall generalisability of the models.

Considering the severe imbalance in the distribution of the axis caused by the population, we divided the data into the following three categories based on the type of astigmatism: WTR, ATR, and oblique (Fig. 3C).

**Regression model**
The training data were utilised to construct the RMs for sphere and cylinder. The mean and standard deviation (SD) of the red, green, and blue channels of the images were calculated, and normalised based on the results. We then input the normalised matrix into the pre-trained neural network. As age was easy to obtain and had an obvious correlation with sphere, we attempted to normalise age into an independent eigenvector as the input of the extreme gradient boosting (XGBoost) algorithm (Fig. 3C, c) to train and adjust the parameters. The MAE was selected as the loss function of XGBoost during the phase. The image normalisation method remained unchanged during the training and testing phases. ResNet was used as the backbone network, revising the output dimension of the final fully connected layer to one. Without loading pre-training parameters, we used the MAE as the loss function and trained from scratch.

**Classification model**

The sphere and cylinder were regarded as discrete variables, and 0.25 D was used as the minimum distance of the variable interval when constructing the CM. The data conforming to the population distribution were selected to alleviate extreme imbalances in categories and avoid the influence of outliers on the construction of the CM. ResNet (Fig. 3C, a) and DenseNet (Fig. 3C, b) were applied to classify the sphere and cylinder, respectively, wherein the fully connected layer units were modified to the corresponding category numbers. These models used pre-trained model weights and were fine-tuned during training. Focal loss was used as a loss function to train relative outliers and minority classes with larger weights to alleviate the category imbalance. For cylinder axis, three categories (WTR, ATR, and oblique) were divided based on the clinical data, and categorical differences were reduced by down-sampling.

**Fusion model**

A specially designed voting mechanism was applied to build the fusion model during the bagging stage.

\[
\left(\frac{\sum GT_{reg}}{n_{reg}} \cdot w_{reg} + \frac{\sum GT_{cls}}{n_{cls}} \cdot w_{cls}\right) + \frac{\sum GT_{all}}{n_{all}}
\]

In the above equation, MR denotes the model result value, GT the ground-truth value, \(n\) the number of samples, and \(w\) the weight of a specific model. Subscripts represent regression (reg), classification (cls), and all collected datasets (all). The fusion model was obtained by voting the weighted distance between the models and their respective actual centres. Finally, the new FMIRS was constructed using these algorithms.

**Comparison and evaluation of the FMIRS versus cycloplegic refraction**

The performance of the RM was calculated using the MAE between the ocular refraction and cycloplegic refraction. The MAE measured the forecast accuracy by averaging the absolute values of the residuals; it is expressed in the same units as the original response variable. It provided the average size of the error. We also calculated other metrics (accuracy, sensitivity, specificity, the area under the curve [AUC] value with its 95% confidence interval [CI], and F1-score) to assess the performance of the CM.

**Statistical analysis**

All analyses were performed using MedCalc, version 19.6.3 (MedCalc Software, Ostend, Belgium; http://www.medcalc.org). Continuous demographic variables are expressed as mean ± SD, and normality was assessed using the Kolmogorov–Smirnov test. The Pearson's correlation coefficient (\(r\)) was used to show the strength
of correlations. Bland–Altman plots were used to analyse the agreement between the FMIRS and actual values in different groups. The agreement was quantified by measuring whether 95% of the data points were within 2 SDs of the mean difference. Zero difference between the FMIRS and actual values indicated an ideal agreement [37].

**Abbreviations**

AI, Artificial intelligence; ATR, against the rule; CI, confidence interval; cls, classification; CM, classification model; FMIRS, fusion model-based intelligent retinoscopy system; MAE, mean absolute error; r, Pearson's correlation coefficient; reg, regression; RFP, retinal fundus photograph; RM, regression model; ROI, regions of interest; SD, standard deviation; SE, spherical equivalent; STARD-AI, Standards for Reporting of Diagnostic Accuracy Study-AI; WTR, with the rule

**Declarations**

**Ethics approval and consent to participate**

The study was approved by the Ethics Committee of Tianjin Eye Hospital and conducted in accordance with the tenets of the Declaration of Helsinki. The ethical committee waived the requirement for informed consent owing to the retrospective study design and the use of anonymised retinal fundus photographs. This study followed the Standards for Reporting of Diagnostic Accuracy Study-AI (STARD-AI) reporting guidelines.

**Consent for publication**

Not applicable.

**Availability of data and materials**

Data are available from the corresponding author on reasonable request.

**Competing interests**

The authors declare that they have no competing interests.

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**Authors' contributions**

HHZ and SDS served as co-first authors and contributed equally to this work. YW, MNS, and SJW served as co-senior authors and contributed equally to this work. The corresponding authors had full access to all data in the study and took responsibility for the integrity and accuracy of the data.

Concept and design: HHZ, SDS, XH, MNS, SJW, and YW.
Acquisition, analysis, or interpretation of data: HHZ, SDS, XYY, XC, YBW, MDZ, JXS, YLJ, and LHL.

Drafting of the manuscript: HHZ, SDS, and YW.

Critical revision of the manuscript for important intellectual content: JNM, QF, VJ, MNS, SJW, and YW.

Statistical analysis: HHZ and SDS.

Obtained funding: YW.

Administrative, technical, or material support: XYY, YLJ, LHL, XH, SJW, MNS, and YW.

Supervision: SJW, MNS, and YW.

All authors approved the final article.

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References

Figure 1

Relationship of the FMIRS and actual values

A (upper left and bottom left): The overall distribution of the FMIRS and actual values; the Y-axis represents the FMIRS values and X-axis represents the actual values. Upper is sphere; Bottom is cylinder. B (middle and right pictures): The Bland–Altman plot of the FMIRS and actual values in the test set; the Y-axis represents the difference between the values, and the X-axis represents the average of the two values. Pictures (a) and (b) are the performance of FMIRS in the sphere and cylinder, respectively; (c) is mild myopia; (d) is moderate myopia; and (e) represents high myopia.

FMIRS, fusion model-based intelligent retinoscopy system.

Figure 2

Attention maps of the eyes with three categories of astigmatism detected using FMIRS

(a) original image and visualisation of the right eye; (b) original image and visualisation of the left eye

FMIRS, fusion model-based intelligent retinoscopy system.

Figure 3

Diagram of the system construction

A (upper left picture): Image pre-processing and augmentation; (a) original RFPs; (b) the largest inscribed circle and rotation; (c) rotation and sharpness; (d) contrast-limited adaptive histogram equalisation was used to improve colour and spatial contrast between the structures and the background retina for RFPs; (e) histogram equalisation processing; (f) the largest inscribed square. B (upper right picture): The confusion matrix of the associated elements. The colours in the diagram represent correlation. C (bottom picture): Architecture of the FMIRS proposed in this study. (a, b) Networks for two different regression models and (c) the classification model.

RFP, retinal fundus photograph; FMIRS, fusion model-based intelligent retinoscopy system.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendix1.pdf