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ORIGINAL RESEARCH

AI-Assisted Screening for Diabetic Retinopathy and Fundus Abnormalities in a Large-Scale Physical Examination Population

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Purpose: Due to the high incidence rate of eye diseases, various artificial intelligence (AI) screening systems for retinal eye disorders have been developed at present. This study aimed to evaluate the diagnostic performance and clinical value of an AI-assisted system for large-scale screening of diabetic retinopathy (DR) and other fundus abnormalities in a real-world physical examination population.

Methods: This retrospective study analyzed 54,353 fundus examination records collected from the local hospital in 2020. An AI-assisted system was used to screen for DR and other retinal abnormalities. Manual interpretation was conducted to validate AI predictions, and data were stratified by comorbidities and systemic risk factors.

Results: Approximately 25% of individuals tested positive for fundus lesions. The AI-assisted system demonstrated high diagnostic performance, with a negative predictive value ≥96% and a positive predictive value ≥90%. Common abnormalities detected included retinal vascular sclerosis, drusen, maculopathy, optic cup enlargement, and hemorrhage. Higher positive detection rates were observed in individuals with a history of diabetes, hypertension, high myopia, and other systemic conditions, with detection rates increasing with disease duration.

Conclusion: AI-assisted screening offers an effective, scalable approach for early DR detection and can also identify systemic diseases with retinal manifestations. Integration of AI with big data platforms enables timely intervention, especially in underserved areas. Building a multi-institutional DR data platform may revolutionize retinal disease management and improve patient outcomes. This study supports the clinical application of AI in enhancing diagnostic efficiency and targeting high-risk populations for early intervention.

Keywords: artificial intelligence, diabetic retinopathy, deep learning, fundus screening, early detection

Introduction

Diabetic retinopathy (DR), a microvascular complication of diabetes, is characterized by microaneurysms, hemorrhages, exudation, and neovascularization.[1] As of 2017, over 114 million adults in China had diabetes, with nearly one-third developing DR in its early stages.[2] Epidemiological data estimate 17 to 47 million DR cases in China.[3] With the global rise in diabetes, DR has become a leading cause of vision loss among working-age adults.[4]

Fundus examination, a non-invasive method for visualizing retinal vessels and the optic nerve, is vital for DR detection.[5] Yet, over half of diabetic patients in China lack regular fundus screenings or standardized ophthalmic care, leading to delayed diagnoses and increased healthcare burden. In contrast, Europe and the US emphasize early DR screening. Studies show early detection and intervention significantly reduce blindness.[6] Remote screening via fundus photography enables early lesion identification and grading.[7] Programs like OPHTEL and TOSCA in Europe demonstrate the feasibility and acceptance of such systems.[8]

China's remote DR screening is in early stages. The BCDRT system launched in 2008 showed diagnostic consistency with ophthalmologists.[9] Despite growing awareness, challenges such as uneven medical resource distribution and a shortage of specialists hinder large-scale screening. AI-assisted diagnosis and cloud-based systems offer promising solutions for scalable deployment.[10]

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AI has advanced across medical imaging fields, particularly through deep learning techniques that simulate neural networks.[11] In ophthalmology, AI has been applied to automate retinal image analysis.[12] In ophthalmology, automated screening of retinal images has long been a key focus for AI development. The artificial intelligence diagnostic system for DR, IDx-DR, developed by IDx, has achieved remarkable results in DR diagnosis.[13] AI models using convolutional neural networks (CNNs) can also detect DME, AMD, and predict systemic health risks from fundus images.[14]

This study aims to develop an AI-assisted diagnostic model for DR using fundus imaging, enhancing early detection and linking ocular findings with systemic diseases. This approach may improve screening efficiency and access, particularly in underserved settings.

Materials and Methods

Study Population

This study retrospectively analyzed 54,353 cases of ophthalmic physical examination data collected from Huishi Ophthalmology between January 1 and June 30, 2020. Of these, 54,253 cases were obtained from the updated digital record system and 100 from the legacy system. The demographic data are shown in Table 1. The data were derived from 77 health examination centers affiliated with Huishi Ophthalmology, which are distributed across 19 provinces in China (Table 2). All data underwent rigorous statistical screening, and appropriate subsets were selected for validation and model development. The image data collected by the two systems are not much different, but the number of people inspecting in the old system is too small. In order to avoid errors in data statistics, the old system data is not included in subsequent analysis. The study protocol was approved by the Ethics Committee of the Affiliated Panyu Central Hospital, ensuring compliance with ethical standards for research involving human data.

Data Acquisition

Comprehensive data were collected across several dimensions to support the development and validation of the diagnostic model. Demographic and clinical information included variables such as age, gender, body weight, physical examination date, unique examination ID, and the initial diagnostic impressions recorded during screening. Medical history data were also compiled, focusing on conditions known to influence ocular health, such as hypertension, diabetes mellitus, glaucoma, high myopia, and other pre-existing retinal or fundus-related diseases.

To account for variability in imaging and technical parameters, detailed metadata were recorded for each image. These included the camera model used, pupil dilation status at the time of imaging, the condition of the optical media and

Table 1 Demographic Data

	Total (N=54253)	Proportion
Age (year)		
<30	6398	11.79%
30-40	13,541	24.96%
40-50	11,350	20.92%
50-60	14,224	26.22%
≥60	8740	16.11%
Gender		
Male	22154	40.83
Female	32099	59.17
Underlying disease		
Diabetes	2223	4.09%
Hypertension	5710	10.52%
Glaucoma	1633	3.01%
High myopia	89	0.16%
Other eye diseases	2547	4.69%
Other fundus diseases	678	1.25%

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Table 2 Statistics on Physical Examinations in Each Province [n(%)]

Province	Number of Physical Examinations	Number of Positive Cases	POSITIVE RATE	Significant Positive Proportion
Tianjin City	17732	4405	24.84%	86
Shanxi	17306	4417	25.52%	84
Shandong	7391	2223	30.08%	64
Guangdong	6276	1164	18.55%	17
Anhui	1456	492	33.79%	6
Henan	893	427	47.82%	15
Zhejiang	793	203	25.60%	2
Yunnan	718	183	25.49%	3
Guizhou	381	87	22.83%	4
Sichuan	366	87	23.77%	0
Heilongjiang	311	91	29.26%	2
Gansu	169	30	17.75%	1
Hainan	117	38	32.48%	1
Jilin	109	35	32.11%	1
Liaoning	100	38	38.00%	1
Jiangsu	85	5	5.88%	0
Hubei	23	7	30.43%	0
Chongqing	22	5	22.73%	0
Jiangxi	5	1	20.00%	0
Total	54253	13,938	25.69%	287

lens, as well as image-specific parameters such as shooting angle, distance, focus quality, and lens positioning. Diagnostic personnel data were also documented, covering the diagnostician's name, professional level, number of readings conducted, rate of sampling inspections, and key performance indicators such as disease prediction rates (positive and negative), referral rates, diagnostic sensitivity, specificity, and overall accuracy. Based on the initial reading outcomes, all fundus images were categorized into either a negative or positive image database to support downstream model training and evaluation.

Development of the Multimodal Deep Learning-Based AI Diagnostic Model

The construction of the diagnostic model was based on a multimodal deep learning architecture that integrated clinical, image-based, and diagnostic metadata. As shown in Figure 1, the development workflow involved five core steps: multimodal data collection, image annotation, feature extraction, model training and prediction, and final performance evaluation.

The annotation of fundus photographs was performed using a semi-automated system designed to support high-throughput (Figure 2), multi-disease labeling. This system incorporated artificial intelligence components to assist with quality control and lesion detection. Professional ophthalmologists underwent dedicated training on the annotation platform, including familiarization with the software interface and standard operating procedures. Using this system, high-quality fundus images were subjected to lesion segmentation and labeling. Lesions annotated included intraretinal hemorrhages, microaneurysms, retinal hard and soft exudates (cotton-wool spots), fibroproliferative membranes, neovascularization, venous beading, venous loops, and intraretinal microvascular abnormalities (IRMA), among others.

To ensure annotation reliability and consistency, a multi-tiered quality control protocol was implemented throughout the annotation process. Each image was independently annotated by two trained ophthalmologists in accordance with strict quality control guidelines. The annotations were then reviewed using a specialized software platform, with discrepancies resolved by manual adjudication. Additionally, random image samples and automated verification checks were used to assess annotator consistency and accuracy in real time. If disagreements arose between the two primary annotators, the case was escalated to a senior retinal specialist (deputy chief physician or above) for final adjudication.

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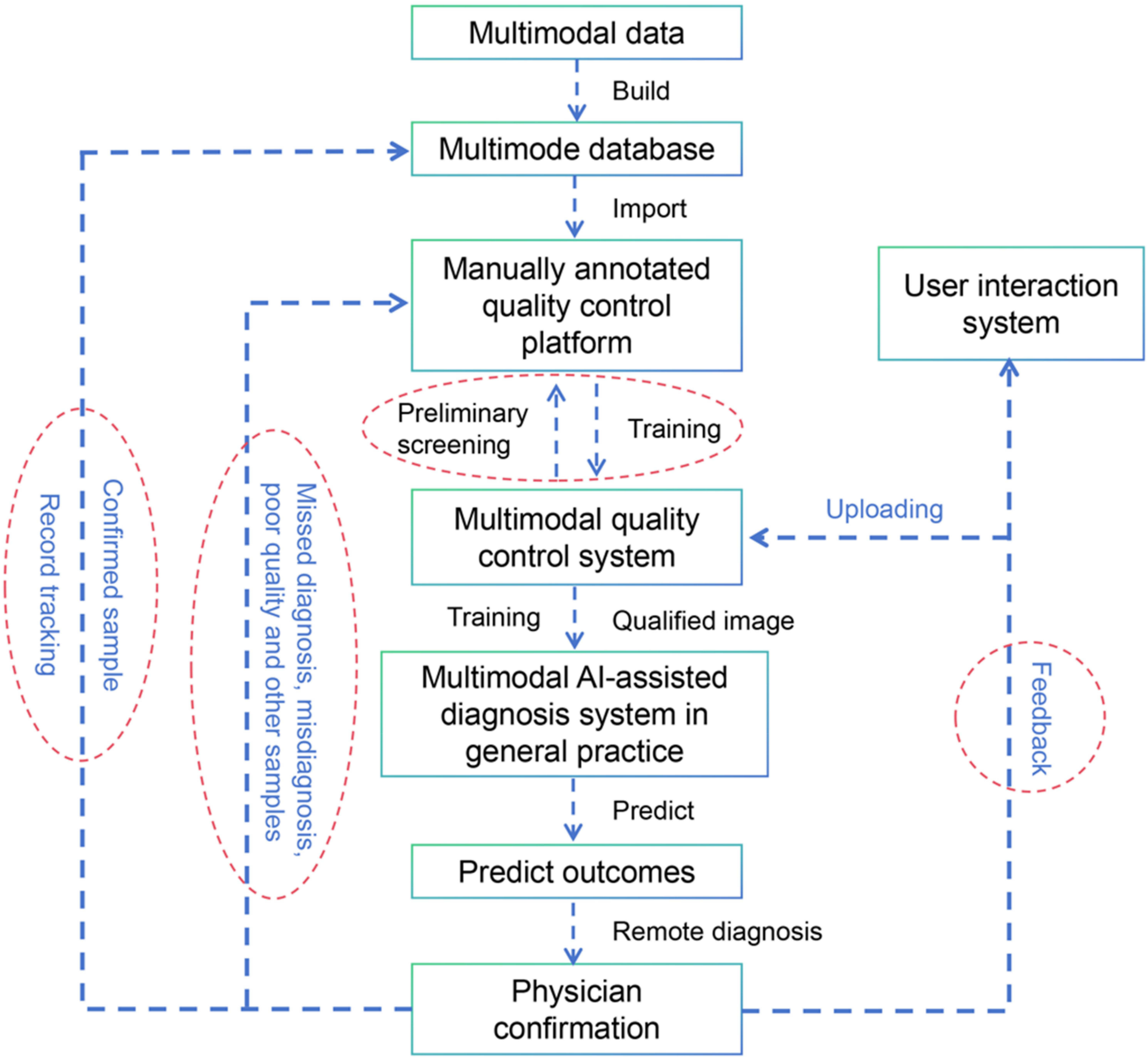

Figure 1 Workflow of a multimodal AI-assisted diagnostic system in general practice. The process begins with the collection and construction of multimodal data, which are imported into a multimodal database. These data are further processed through a manually annotated quality control platform, followed by preliminary screening and training steps. The qualified images are then integrated into a multimodal quality control system. After training, these images are used in a multimodal AI-assisted diagnostic system to predict clinical outcomes. Predicted results undergo physician confirmation and remote diagnosis. Simultaneously, a user interaction system facilitates data uploading and feedback, enabling system optimization through iterative model training, model design, and post-diagnosis data analysis. Dashed lines indicate iterative and feedback loops essential for model refinement and clinical validation.

Following annotation, a dataset was constructed specifically for diabetic retinopathy (DR), with each image graded according to the International Clinical Diabetic Retinopathy Disease Severity Scale. This five-tier classification system ranged from Grade 0 (no DR) to Grade 4 (severe DR). Once consensus was reached between the annotators, or a third-party adjudication was completed, the confirmed image labels were fed back into the AI system for model optimization. The consistency between the AI's diagnostic output and the physicians' assessments was continuously monitored and used to refine the model's learning process.

The training of the AI model leveraged the multimodal dataset consisting of image features, clinical variables, and diagnostic metadata (Figure 3). First, the image is preprocessed, the CNN model is used as a feature extractor to detect lesions in the two-dimensional image, and the features of different modalities are mapped to the same semantic space through the DenseNet neural network for integration. Finally, the SegFormer semantic segmentation network based on

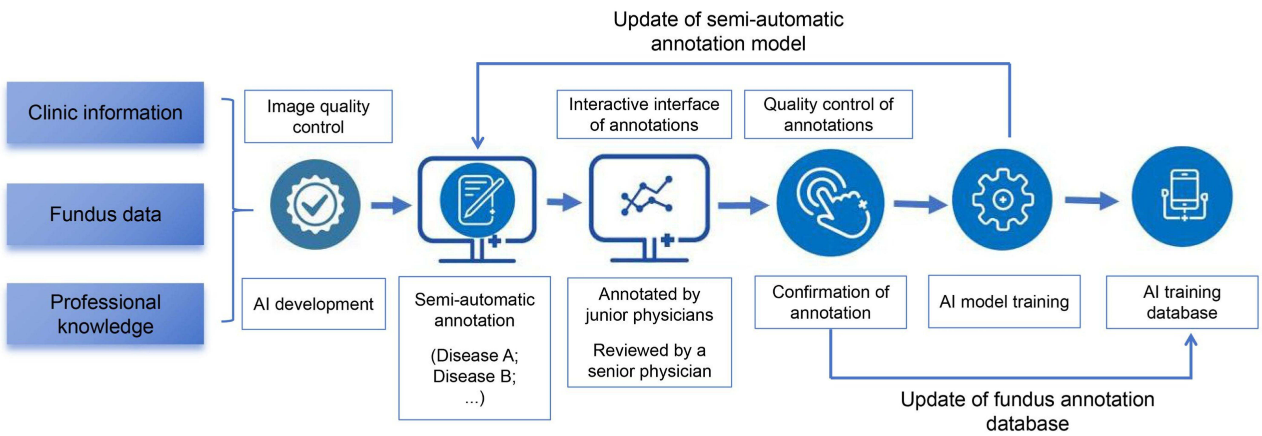

Figure 2 Workflow for the development and refinement of a semi-automatic annotation model for fundus data. Clinical information, fundus data, and professional knowledge are integrated to support AI development. The workflow begins with image quality control, followed by semi-automatic annotation of disease types (eg, Disease A, Disease B). Annotations are initially conducted by junior physicians and subsequently reviewed by senior physicians using an interactive interface. Quality control of annotations ensures reliability before confirmation. The validated annotations feed into AI model training, contributing to the AI training database. Both the fundus annotation database and the semi-automatic annotation model are continuously updated based on new inputs and quality-checked annotations.

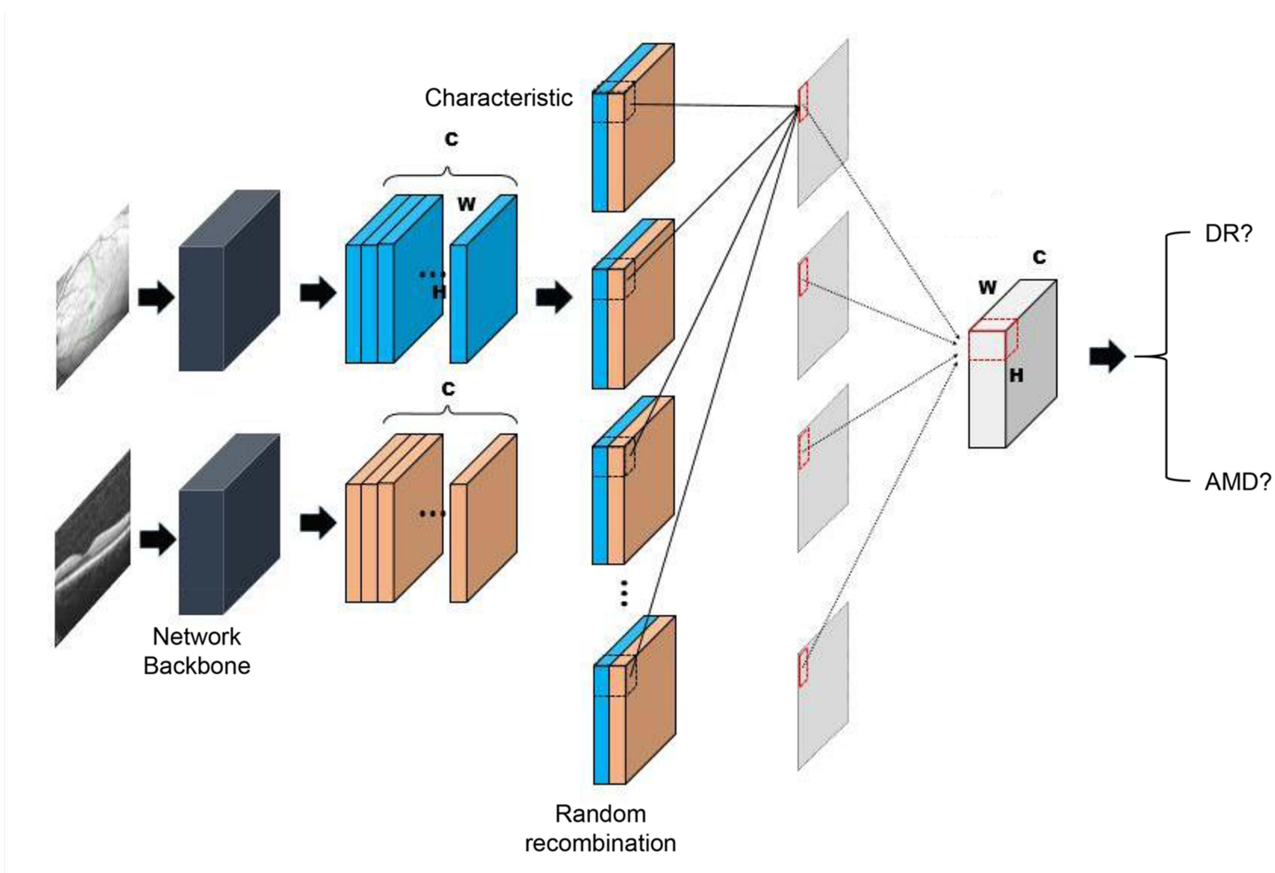

Figure 3 Schematic of a deep learning-based multi-disease classification framework for retinal images. Input retinal images are processed through a network backbone to extract deep feature representations. The extracted features are represented as characteristic maps, which undergo random recombination to enhance diversity and robustness. These recombined features are spatially aligned and integrated for classification. The final output layer predicts the presence of specific retinal diseases, including diabetic retinopathy (DR) and age-related macular degeneration (AMD), based on the learned features. The architecture emphasizes spatial feature selection and fusion to improve diagnostic accuracy across multiple retinal conditions.

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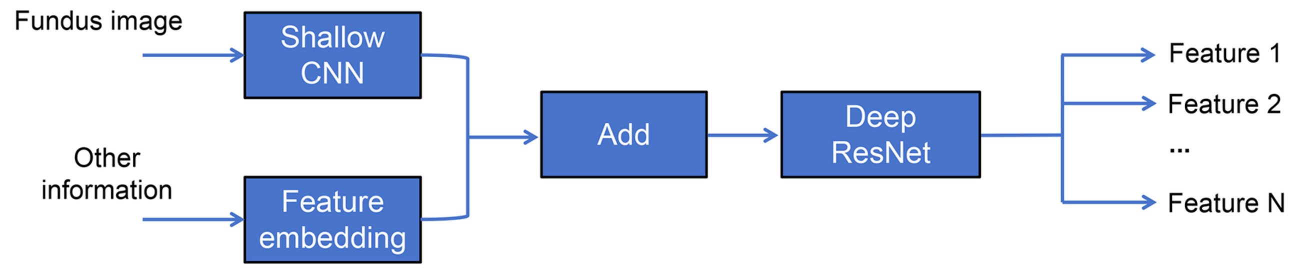

Figure 4 Multi-mode deep learning neural network based on AI. After preprocessing the image, shallow lesion detection is carried out on the image in a CNN neural network, feature vectors of different modalities are spliced, and then the features of different modalities are mapped to the same semantic space through deep CNN (DenseNet). Use the Transformer architecture to extract graphical features and combine them with text.

the Transformer architecture is used to extract the features (Figure 4). These vectors were then subjected to random combination and permutation to generate diverse training samples that improved the model's robustness. Multi-parameter deep learning training was conducted, allowing the system to make accurate predictions based on complex interactions between modalities. Set the training dataset and the test dataset to a ratio of 3:1, and perform image enhancement processing operations on the training dataset data. During training, we use the AdamW optimizer to train the artificial intelligence model, with the weight attenuation set to 0.01, the learning rate adopts a polynomial attenuation strategy, and the network batch size set to 4. Perform 15000 iterations on the constructed dataset.

Model Evaluation

After the AI model was successfully constructed, four sets of patient data sets were obtained from the physical examination center for model testing. The images of the testing set were not preprocessed. The model quality was evaluated by detecting positive rate, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), receiver operating characteristic (ROC) curve-area under the curve AUC, area under the PR curve (AP) and other indicators. The constructed AI model was then used to analyze the ophthalmic physical examination data of 54253 cases. The diagnostic results of AI-assisted doctors were compared against the gold standard manual diagnoses performed by board-certified ophthalmologists to evaluate the diagnostic efficiency of AI-assisted clinicians. Key evaluation metrics included diagnostic accuracy, sensitivity, and specificity. The prevalence of fundus lesions in the examined population was calculated, and the characteristics of detected lesions were analyzed.

Subgroup analyses were conducted to explore variations in diagnostic performance and lesion prevalence across different demographic and clinical profiles, including stratification by age, and presence of comorbidities such as diabetes, hypertension, and other ocular diseases. These analyses were used to construct a refined DR database with enhanced granularity.

Statistical Analysis

All statistical analyses were performed using standardized software tools. Classification accuracy of the AI model was calculated using the Scikit-learn package (version 0.19.0), while MedCalc software (version 20.0.22) was used for computing AUC, sensitivity, specificity, and other diagnostic performance indices. All categorical variables were expressed as frequencies and percentages.

Results

Establishment of the AI Database

A total of 54,353 individuals participated in the physical examination at Huishi Ophthalmology. Among them, the new system tested a total of 54,253 individuals, identified 13,938 cases (25.69%) with positive fundus lesions between January and June (Table 3). Due to the COVID-19 pandemic in February, there was only one set of physical examination data. The small sample size did not affect the statistical results. The monthly positive rate of the new system remained relatively stable at approximately 25.00%, with variations not exceeding 2.83%. This consistency indicates stable performance in the system's testing capabilities.

Table 3 Statistics of Physical Examination Results [n(%)]

Month	Number of Physical Examinations	Positive Rate	Significant Positive Proportion
January	9805	2523 (25.73%)	29 (0.30%)
February	1	0 (0.00%)	0 (0.00%)
March	1034	264 (25.53%)	4 (0.39%)
April	5766	1514 (26.26%)	23 (0.40%)
May	14357	3424 (23.85%)	68 (0.47%)
June	23290	6213 (26.68%)	163 (0.70%)
Total	54253	13,938 (25.69%)	287 (0.53%)

Diagnostic Efficiency of AI Models

Before the experiment, the prediction results of the AI model on the testing set data are shown in Table 4. The positive rates of the data sets are between 10% and 20%. The prediction sensitivity, specificity and NPV of the AI model are all reach 90%, and the diagnostic sensitivity for major positive cases can reach 100%. The test results of the testing set show that the AI model performs well and has good recognition and diagnosis capabilities for fundus images.

The AI-assisted diagnosis system was used to aid in the identification and screening of diabetic retinopathy (DR). A total of 108,099 fundus images were annotated from the 54,253 physical examination cases, excluding those images that did not meet quality standards. Sixteen professional doctors participated in diagnosing these images. Of the total samples, 107,262 (99.2%) were consistent between manual interpretation by the ophthalmologists and the AI model's judgment. The diagnostic level of AI-assisted system is stable, with a negative predictive rate ≥ 96%. With an average positive detection rate of 25.69%, the referral rate can be controlled below 30%. With the help of the AI-assisted system, the positive predictive rate and accuracy rate by doctors are basically ≥ 90% (see Table 5). At the same time, since the diagnostic samples are mainly positive pictures, the diagnostic specificity is not high.

Analysis of Positive Sign Proportions

The proportion of positive signs was calculated based on the final image interpretation results, as shown in Figure 5. Among the 23 categories of positive signs, the top five were: retinal arteriosclerosis (18.74%), retinal drusen (18.11%),

Table 4 Evaluation of the Predictive Performance of AI Models in the Testing Set

Testing Set	Positive Rate	Sensibility	Specificity	PPV	NPV	ROC-AUC	AP
1	13.58%	90.11%	94.02%	70.29%	98.37%	0.978%	0.913%
2	18.96%	92.33%	90.16%	68.70%	98.05%	0.972%	0.914%
3	20.62%	95.89%	91.22%	73.93%	98.84%	0.985%	0.950%
4	20.00%	94.15%	94.47%	80.96%	98.47%	0.981%	0.927%

Table 5 Analysis of the Efficiency of AI-Assisted Diagnosis

Doctors	Test Amount	Sampling Inspection Quantity	Positive Sign		
			Sensibility	Accuracy	Specificity
A1	10474	308	92.25%	90.58%	46.15%
A2	7204	116	90.20%	91.38%	81.82%
A3	5338	464	95.04%	92.89%	45.45%
A4	6344	100	94.78%	93.00%	90.91%
A5	5286	66	89.36%	90.91%	0.00%
A6	3749	297	93.08%	92.59%	40.00%
A7	13069	467	92.16%	92.08%	50.00%
A8	18326	489	93.85%	92.84%	68.00%

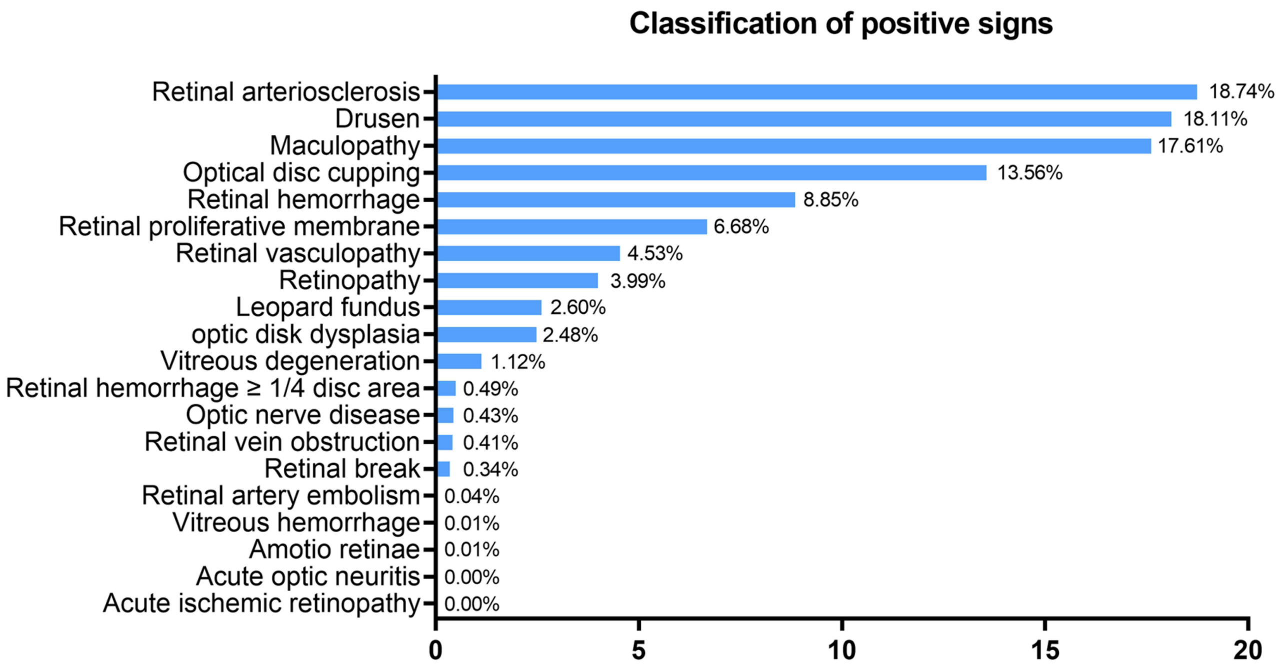

Figure 5 Distribution of positive signs. Bar chart showing the classification and prevalence of positive retinal signs observed in a study population. The most common findings were Retinal Arteriosclerosis (18.74%), Drusen (18.11%), and Maculopathy (17.61%), The x-axis represents the percentage prevalence, and the y-axis lists the specific retinal abnormalities. Percentages are displayed adjacent to each category for clarity.

maculopathy (17.61%), optic disc cupping (13.56%), and retinal hemorrhage enlargement (8.85%), which together accounted for 76.87% of all positive findings. Further subdivision of the retinal and vascular abnormalities revealed that the incidence of terms such as increased inner-retinal reflectivity/copper-wire arteries (16.50%), drusen ≥ 250 µm (16.45%), and a cup/disc ratio of the optic disc area ≥ 0.6 (12.86%) were notably higher (Table 6). These significant features, including enhanced retinal artery reflection, drusen, and maculopathy, were closely associated with DR.

Table 6 Classified Positive Signs

Diseased Area	Positive Signs	Number	Positive Proportion
Peripheral retinal and vascular abnormalities	Inner-retinal reflectivity/copper-wire arteries	4594	16.50%
	Drusen: ≥250um	4580	16.45%
	Bleeding: Present	2107	7.57%
	Atrophic change/scar	616	2.21%
	Arteriovenous chiasm nicking (≥1/2)	591	2.12%
	Cotton-wool spots	458	1.64%
	Proliferative membranes	1639	5.89%
	Pigmentation change: ≥ 1/4DA	356	1.28%
	Hard exudates	308	1.11%
Optic disc area and perioptic disk area	Cup to disk ratio ≥ 0.6	3582	12.86%
	Retinal nerve fiber layer defect	381	1.37%
	Medullated fibers	322	1.16%
	Consistent with ISNT	293	1.05%
Macular region (central fovea 2DD)	Pigmentation change: >250 um	2785	10.00%
	Drusen > 65um: Pigmentation change	1396	5.01%
	Leopard fundus: Grade 3	671	2.41%
Other abnormalities of fundus	Vitreous degeneration	286	1.03%

Note: Only entries with a positive ratio greater than 1.00% are listed.

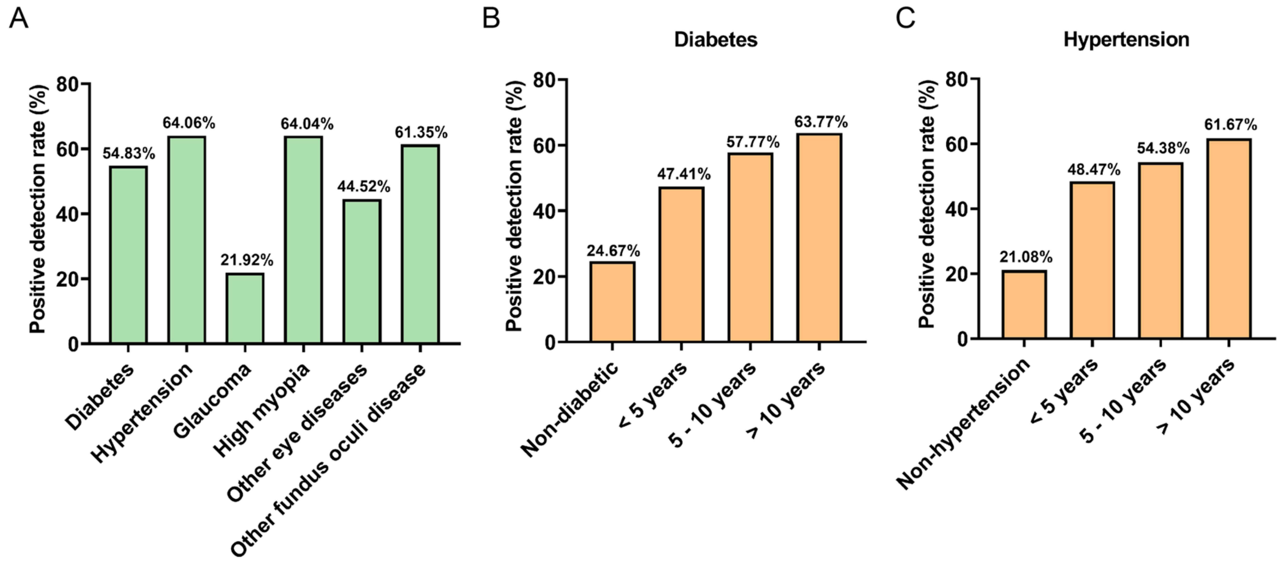

Figure 6 Analysis of DR Positive detection rate among medical examiners with different medical histories. (**A**) Distribution of positive detection rates in other diseases; (**B**) Distribution of positive detection rate in diabetic population; (**C**) Distribution of positive detection rate in hypertensive population.

Relationship Between Fundus Lesion Detection Rates and Medical History

Among the physical examination population, 2223 individuals had a history of diabetes, with a positive detection rate of fundus lesions of 54.83%, and the relative risk (RR) was 2.24. Among the 5710 individuals with a history of hypertension, the positive detection rate was 54.06% (RR=2.42). Furthermore, the positive detection rate for individuals with a history of glaucoma was 21.92% (RR=0.85), for those with high myopia it was 64.04% (RR=2.50), and for those with other eye diseases, the rate was 44.52%. Individuals with a history of other fundus diseases had a positive detection rate of 61.35% (Figure 6A). In comparison to the overall positive detection rate of 25.69%, individuals with underlying medical conditions such as diabetes, hypertension, and high myopia were significantly more likely to develop DR. Further analysis of the subgroups of individuals with diabetes and hypertension revealed that the positive detection rate of DR increased with the duration of the respective conditions (Figures 6B and C). This suggests that screening for fundus diseases should be tailored to individuals with these underlying medical conditions, prioritizing early diagnosis of DR in these populations.

Discussion

Diabetic retinopathy (DR) and other retinal diseases, including diabetic macular edema (DME), glaucomatous retinopathy, optic neuropathy, and age-related macular degeneration (AMD), are major causes of vision impairment worldwide. Early detection and timely intervention are crucial for slowing disease progression and improving patient outcomes.[15,16] Integrating Artificial Intelligence (AI) into ophthalmology, particularly for retinal diseases, offers a promising solution to enhance the efficiency and accessibility of DR screening.[17]

AI's deep learning capabilities enable it to process large datasets, recognize patterns, and continuously improve its diagnostic performance. By automating the detection of fundus diseases, AI enhances screening efficiency and reduces diagnostic errors, such as misdiagnosis and missed diagnoses. This is especially valuable for systemic conditions like hypertension and diabetes, which can manifest through retinal changes, offering insights into patients' broader health status.[18]

In this study, we analyzed 54,353 physical examination records from Huishi Ophthalmology, focusing on AI-assisted DR screening. Excluding data from the older system, we found that approximately 25% of the population tested positive for fundus lesions. This suggests that retinal diseases are common and warrant enhanced screening efforts. The use of AI in DR diagnosis is crucial for improving detection rates and preventing disease progression.

Our study's diagnostic efficiency aligns with previous AI models in the field. Systems such as Google AI, IDx-DR, and RetmarkerDR have shown similar capabilities in DR detection. For instance, IDx-DR, which was FDA-approved in

2018, demonstrated 100% sensitivity and 97.8% specificity in clinical trials involving 1616 patients.[19,20] In our analysis, after manual labeling and AI screening, the AI-assisted system achieved a high accuracy rate, with manual interpretation showing a negative predictive rate of ≥96% and a positive predictive rate of ≥90%. This level of performance highlights the reliability of AI models in assisting clinicians with DR detection and diagnosis.[21] On the basis of AI interpretation, using manual interpretation again can again improve the positive diagnosis rate of pictures, indicating that the AI-assisted + manual interpretation model has a good application prospect. In current clinical treatment, some institutions use deep learning-based AI diagnosis systems to conduct preliminary evaluation of patients 'eye test results, and then review and final diagnosis by senior ophthalmologists.[22,23] The AI system has shown good sensitivity and specificity for most retinal diseases. Therefore, the AI-assisted screening system has important clinical significance in promoting grassroots DR screening and improving the efficiency of manual diagnosis.

Further analysis of the positive signs in fundus images revealed common retinal abnormalities, including retinal vascular sclerosis, retinal drusen, maculopathy, optic cup enlargement, and retinal hemorrhage. These signs are indicative of various retinal diseases and suggest the importance of incorporating these key features into AI databases to improve diagnostic accuracy.[24] Notably, individuals with histories of hypertension, diabetes, high myopia, and other ocular diseases exhibited higher rates of DR, with the positive detection rate increasing as the duration of these conditions extended.[25] Multiple studies have also shown that factors such as diabetes, disease duration, age, hypertension, hyperlipidemia, and male gender are all high-risk factors for DR.[26,27] These findings underscore the need to focus on at-risk populations for DR screening, as early detection can prevent further complications.[28]

The integration of AI technology in DR screening has the potential to create a more efficient and scalable system for monitoring patients' retinal health.[29] By combining AI with big data platforms, healthcare institutions can provide a more comprehensive approach to disease management.[30] AI-driven platforms can transmit critical data to specialized ophthalmologists, facilitating early intervention and ensuring timely treatment.[31] This approach could be particularly beneficial in rural or underserved areas, where access to specialized care is limited.

This study highlights the value of AI-assisted annotation and prediction in retinal disease screening. By combining manual annotation with AI model training, we were able to enhance both annotation accuracy and predictive performance. The AI-assisted system can now detect a variety of systemic diseases, such as hypertension and diabetes, by analyzing fundus images.[32] This capability is crucial, as these diseases often manifest in the retina, offering an additional layer of early detection for other systemic health issues.

Ultimately, creating a DR big data platform that integrates patient data from multiple medical institutions could revolutionize the way DR and other retinal diseases are monitored. Such a platform would support clinicians, improve diagnostic efficiency, and enable early detection and treatment of DR, helping prevent severe vision impairment and related complications.[33] This study demonstrates that AI-based predictive models hold significant promise for the early diagnosis of DR and other retinal diseases, providing a crucial tool for improving patient outcomes.

Data Sharing Statement

The data that support the findings of this study are available upon request from the corresponding author.

Ethical Approval and Informed Consent Statements

All procedures performed in study involving human participants were in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethics Committee of the Affiliated Panyu Central Hospital of Guangzhou Medical University (PYRC-2025-104-01). All patients who could understand the information provided written informed consent by themselves, while legally authorized representatives of patients who were not capable of understanding the information provided the written informed consent on their behalf.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

1. Tan TE, Wong TY. Diabetic retinopathy: looking forward to 2030. *Front Endocrinol*. 2022;13:1077669. doi:10.3389/fendo.2022.1077669
2. Khan RMM, Chua ZJY, Tan JC, Yang Y, Liao Z, Zhao Y. From pre-diabetes to diabetes: diagnosis, treatments and translational research. *Medicina*. 2019;55(9):546. doi:10.3390/medicina55090546
3. Song P, Yu J, Chan KY, Theodoratou E, Rudan I. Prevalence, risk factors and burden of diabetic retinopathy in China: a systematic review and meta-analysis. *J Glob Health*. 2018;8(1):10803. doi:10.7189/jogh.08.010803
4. Lin KY, Hsih WH, Lin YB, Wen CY, Chang TJ. Update in the epidemiology, risk factors, screening, and treatment of diabetic retinopathy. *J Diabetes Investig*. 2021;12(8):1322–1325. doi:10.1111/jdi.13480
5. Venkatesh R, Reddy N, Jayadev C, Pulipaka RS, Yadav NK, Basavaraj TM. Proliferative diabetic retinopathy detection: comparison of clinical examination, optomap photographs and fluorescein angiography. *Nepal J Ophthalmol*. 2022;14(28):86–96. doi:10.3126/nepjoph.v14i2.39516
6. Scanlon PH. The English national screening programme for diabetic retinopathy 2003-2016. *Acta Diabetol*. 2017;54(6):515–525. doi:10.1007/s00592-017-0974-1
7. Grauslund J. Diabetic retinopathy screening in the emerging era of artificial intelligence. *Diabetologia*. 2022;65(9):1415–1423. doi:10.1007/s00125-022-05727-0
8. Wong CYT, O'Byrne C, Taribagil P, Liu T, Antaki F, Keane PA. Comparing code-free and bespoke deep learning approaches in ophthalmology. *Graefes Arch Clin Exp Ophthalmol*. 2024;262(9):2785–2798. doi:10.1007/s00417-024-06432-x
9. Ruta LM, Magliano DJ, Lemesurier R, Taylor HR, Zimmet PZ, Shaw JE. Prevalence of diabetic retinopathy in type 2 diabetes in developing and developed countries. *Diabet Med*. 2013;30(4):387–398. doi:10.1111/dme.12119
10. Li JO, Liu H, Ting DSJ, et al. Digital technology, tele-medicine and artificial intelligence in ophthalmology: a global perspective. *Prog Retin Eye Res*. 2021;82:100900. doi:10.1016/j.preteyeres.2020.100900
11. Sun X, Yin Y, Yang Q, Huo T. Artificial intelligence in cardiovascular diseases: diagnostic and therapeutic perspectives. *Eur J Med Res*. 2023;28(1):242. doi:10.1186/s40001-023-01065-y
12. Lin D, Xiong J, Liu C, et al. Application of comprehensive artificial intelligence retinal expert (CARE) system: a national real-world evidence study. *Lancet Digit Health*. 2021;3(8):e486–e495. doi:10.1016/S2589-7500(21)00086-8
13. Paul S, Tayar A, Morawiec-Kisiel E, et al. Einsatz von künstlicher Intelligenz im Screening auf diabetische Retinopathie an einer diabetologischen Schwerpunktklinik. *Die Ophthalmologie*. 2022;119(7):705–713. doi:10.1007/s00347-021-01556-5
14. Chen YM, Huang WT, Ho WH, Tsai JT. Classification of age-related macular degeneration using convolutional-neural-network-based transfer learning. *BMC Bioinf*. 2021;22(Suppl 5):99. doi:10.1186/s12859-021-04001-1
15. Moshfeghi AA, Lanitis T, Kropat G, et al. Social cost of blindness due to AMD and diabetic retinopathy in the United States in 2020. *Ophthalmic Surg Lasers Imaging Retina*. 2020;51(4):S6–S14. doi:10.3928/23258160-20200401-01
16. Sharif NA. Glaucomatous optic neuropathy treatment options: the promise of novel therapeutics, techniques and tools to help preserve vision. *Neural Regen Res*. 2018;13(7):1145–1150. doi:10.4103/1673-5374.235017
17. Zafar S, Mahjoub H, Mehta N, Domalpally A, Channa R. Artificial intelligence algorithms in diabetic retinopathy screening. *Curr Diab Rep*. 2022;22(6):267–274. doi:10.1007/s11892-022-01467-y
18. Sheng B, Chen X, Li T, et al. An overview of artificial intelligence in diabetic retinopathy and other ocular diseases. *Front Public Health*. 2022;10:971943. doi:10.3389/fpubh.2022.971943
19. van der Heijden AA, Abramoff MD, Verbraak F, van Hecke MV, Liem A, Nijpels G. Validation of automated screening for referable diabetic retinopathy with the IDx-DR device in the Hoorn diabetes care system. *Acta Ophthalmol*. 2018;96(1):63–68. doi:10.1111/aos.13613
20. Verbraak FD, Abramoff MD, Bausch GCF, et al. Diagnostic accuracy of a device for the automated detection of diabetic retinopathy in a primary care setting. *Diabetes Care*. 2019;42(4):651–656. doi:10.2337/dc18-0148
21. Alsadoun L, Ali H, Mushtaq MM, et al. Artificial intelligence (AI)-enhanced detection of diabetic retinopathy from fundus images: the current landscape and future directions. *Cureus*. 2024;16(8):e67844. doi:10.7759/cureus.67844
22. Wei Q, Chi L, Li M, Qiu Q, Liu Q. Practical applications of artificial intelligence diagnostic systems in fundus retinal disease screening. *Int J Gen Med*. 2025;18:1173–1180. doi:10.2147/IJGM.S507100
23. Keel S, Lee PY, Scheetz J, et al. Feasibility and patient acceptability of a novel artificial intelligence-based screening model for diabetic retinopathy at endocrinology outpatient services: a pilot study. *Sci Rep*. 2018;8(1):4330. doi:10.1038/s41598-018-22612-2
24. Parmar UPS, Surico PL, Singh RB, et al. Artificial intelligence (AI) for early diagnosis of retinal diseases. *Medicina*. 2024;60(4):527. doi:10.3390/medicina60040527
25. Pieńczykowska K, Bryl A, Mrugacz M. Link between metabolic syndrome, inflammation, and eye diseases. *Int J Mol Sci*. 2025;26(5):2174. doi:10.3390/ijms26052174

26. Yin L, Zhang D, Ren Q, Su X, Sun Z. Prevalence and risk factors of diabetic retinopathy in diabetic patients: a community based cross-sectional study. *Medicine*. 2020;99(9):e19236. doi:10.1097/MD.0000000000019236
27. Trott M, Driscoll R, Pardhan S. Associations between diabetic retinopathy and modifiable risk factors: an umbrella review of meta-analyses. *Diabet Med*. 2022;39(6):e14796. doi:10.1111/dme.14796
28. Zulu N, Piotie PN, Webb EM, Maphenduka WG, Cook S, Rheeder P. Screening for diabetic retinopathy at a health centre in South Africa: a cross-sectional study. *J Public Health Afr*. 2025;16(1):681. doi:10.4102/jphia.v16i1.681
29. Raman R, Dasgupta D, Ramasamy K, George R, Mohan V, Ting D. Using artificial intelligence for diabetic retinopathy screening: policy implications. *Indian J Ophthalmol*. 2021;69(11):2993–2998. doi:10.4103/ijo.IJO_1420_21
30. Majnaric LT, Babic F, O'Sullivan S, Holzinger A. AI and big data in healthcare: towards a more comprehensive research framework for multimorbidity. *J Clin Med*. 2021;10(4):766. doi:10.3390/jcm10040766
31. Olawade DB, Weerasinghe K, Mathugamage M, et al. Enhancing ophthalmic diagnosis and treatment with artificial intelligence. *Medicina*. 2025;61(3):433. doi:10.3390/medicina61030433
32. Ghenciu LA, Dima M, Stoicescu ER, Iacob R, Boru C, Hategan OA. Retinal imaging-based oculomics: artificial intelligence as a tool in the diagnosis of cardiovascular and metabolic diseases. *Biomedicines*. 2024;12(9):2150. doi:10.3390/biomedicines12092150
33. Xiong K, Wang W, Gong X, et al. Influence of high myopia on choriocapillaris perfusion and choroidal thickness in diabetic patients without diabetic retinopathy. *Retina*. 2022;42(6):1077–1084. doi:10.1097/IAE.0000000000003427

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