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ISSN 2959-409X

Using Artificial Intelligence to Detect Cardiovascular Disease through Retinal Imaging: A Review

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Abstract:
Cardiovascular diseases cause a large number of deaths and disabilities worldwide. To reduce the related losses and burdens, it is especially important to promote early non-invasive screening methods. In recent years, with the development of AI, retinal images can become a more important tool in cardiovascular risk assessment. This article reviews the application of artificial intelligence in the screening of cardiovascular diseases using retinal images and finds that AI can accurately predict cardiovascular disease risks from retinal images and can achieve better performance by integrating multimodal data and using large-scale databases. However, the heterogeneity of data, cross-population applicability and ethical issues still limit the discoveries in this field. In the future, larger-scale model training, multi-task learning and different-level data fusion can be used to improve the predictive ability and accuracy of the model. At the same time, this method has potential in remote medical care, personalized medical care, and public health fields.

Keywords: Artificial Intelligence, Retinal Imaging, Cardiovascular Disease, Risk Prediction

1. Introduction

Cardiovascular diseases (CVDs) are currently one of the main causes of death and disability worldwide, responsible for 30-40% of deaths annually and a huge burden on public health care systems[1]. Risk factors such as hypertension, high blood sugar and abnormal lipid levels - all with little apparent signs early on - makes these diseases difficult to be screened in large populations in a timely manner using traditional methods such as blood pressure measurement, lipid testing or electrocardiogram screening [2]. It is imperative that researchers find more effective detection methods as soon as possible [2].Quantitative parameters derived from retinal images - such as vessel diameter or branching patterns - appear to occur before cardiovascular events [3], suggesting that retinal images should become noninvasive tools suitable for large-scale screening programs [4].

Retinal microcirculation provides the “window” into overall systemic vascular health, just as the eyes would be used as the window for examining sys-

ISSN 2959-409X

temic arterial health. Characteristics such as narrowing of retinal arteries, dilatant veins, angle changes tortuosity microaneurysms bleeding points have all been linked with atherosclerosis heart failure stroke [1]. A meta-analysis of populations has also shown that for every 3mm change in retinal arterioles diameter there was an approximate 10mm Hg change in systolic blood pressure indicating this correlation [1].

Most recently, retinal images have been shown to be reliable predictors of cardiovascular metabolic abnormalities. Zhang et al. (2020) performed a cross-sectional study and demonstrated this finding in Henan Province of China using 1,222 fundus color photographs from 625 participants and their hematological parameters from six deep learning models with AUC values of 0.8880 for hyperglycemia; 0.7766 for hypertension came in at 0.7766; and while dyslipidemia came into place with 0.7003 [2]. Furthermore, this model can be used to predict hematological parameters like hematocrit and mean corpuscular hemoglobin concentration (MCHC) suggesting that retinal images have applications beyond just the eye diseases themselves [2]. Furthermore, research has shown the possibility of using this technology in large-scale screening in the rural areas to reduce compliance and the economic cost of traditional blood tests [2].

OCT/OCTA imaging technology, used in combination with traditional fundus photography, provides increased resolution and depth perception, allowing researchers to view capillary plexuses and choroidal structures in three dimensions [1]. Imaging parameters like diameter, branching angle and fractal dimension have been linked with coronary heart disease, peripheral arterial disease, and drug-induced cardiotoxicity; by using OCT/OCTA quantitative analysis combined with artificial intelligence, clinicians can detect risk early and implement targeted interventions quickly [1].

This review summarizes recent advances in using artificial intelligence for cardiovascular disease screening and risk prediction using retinal images, including methodological approaches, validation results, clinical value assessments, and challenges faced when using retinal images as diagnostic data.

2. Multimodal Imaging and Risk Stratification

Several screening systems using artificial intelligence for diabetic retinopathy screening have already been cleared by regulatory authorities for use in clinics [5]. Experience from research on retinal images can provide valuable lessons for research on cardiovascular disorders: Retinal vessel features are closely related to arteriosclerosis, hypertension, and heart diseases. Artificial intelligence training models can identify subtle changes that improve risk assessment [6].

Artificial Intelligence can not only be used for disease detection but also as a tool for risk stratification and prognosis evaluation. As part of clinical research, deep learning models can use information collected from fundus images and optical coherence tomography, as well as patient databases to produce a more comprehensive risk evaluation framework. This approach provides the foundation for precision medicine in systemic diseases, such as cardiovascular [7]. Artificial intelligence has also led to an upsurge in quantitative analysis that makes objective measurements such as caliber measurement and branching pattern determination possible, replacing subjective measurements made by humans [5].

3. Advantages over Traditional Cardiovascular Risk Assessment

Artificial Intelligence based on retinal images has provided new opportunities for cardiovascular disease screening. Traditional assessments were based on blood tests, imaging examinations, and clinical history studies; these methods had serious disadvantages that affected detection such as high costs and complicated operations that required high patient compliance [8]. With the current conditions, artificial intelligence has now become part of the process of evaluating cardiovascular risks [8].

Hu et al. (2023). showed that cardiovascular-related risk factors and outcomes can be predicted reliably from fundus images using deep learning models in accordance with the results of previous studies. The Research team conducted a systematic review and meta-analysis over 26 studies that reported 42 sorts of cardiovascular outcomes, i.e., 33 sorts of risk factors (such as BMI, blood sugar, blood lipids), 4 sorts of cardiac imaging markers, 2 sorts of cardiovascular risk scores, 2 sorts of cardiovascular events' incidence rates. The found that deep learning models leveraging retinal photos could acquire AUROC 0.96 for demographic classification and AUROC 0.77 for 45-year-old hypertensive risk model.80 for the prediction of diabetes, and AUROC varying between 0.68 and 0.81 for the prediction of future cardiovascular events, thus with potential [9].

Subsequent research expands its application. Lee et al. (2023) constructed a multimodal deep learning model including fundus pictures and standard clinical factors; they found that the AUC value was much greater than 0.72 when forecasting the 10-year risk of atherosclerotic cardiovascular disease (ASCVD) while showing enhanced predictive capabilities for severe events such as myocardial infarction and stroke - significantly enhancing precision and reliability when conducting risk assessments[10].

4. Clinical Implementation and Validation Studies

The experimental project conducted by Hu et al. (2025). at main Australian medical centers, the 361 participants aged 45-70 years all enrolled in. Researchers used an AI algorithm (rpCVD) and automated fundus images to determine the risk. The imaging success rate was 93.9 percent and the correlation of rpCVD and WHO conventional risk scores (PCC=0.526) were moderate. AUC of rpCVD for predicting future cardiovascular events over the next decade was 0.672, like WHO risk score 0.693; implying AI may obtain similar predictive effectiveness using retinal pictures alone. Interestingly, 92.5 of participants and 87.5 of primary care doctors liked using it; this indicates it can work effectively and be accepted clinical settings [11].

Rim et al. (2020) provided critical information at the application level. They used a large cohort from a national population and applied a deep learning model to analyze the fundus images of patients - detected subtle vascular abnormalities such as narrow artery diameters, increased tortuosity of veins, abnormal bifurcation angles, and validated its effectiveness for prediction of systemic diseases. Research showed that this model attained an AUC up to 0.96 in internal validation for gender prediction, and an AUC range from 0.80 to 0.91 using external multi-center data sets (Beijing Eye Study and Singapore SEED cohort), with sensitivities from 0.70 to 0.93. These results suggested this approach is accurate in predicting cardiovascular risks such as hypertension and atherosclerosis, across regions and populations [8]. Several research have shown that the accuracy of deep learning models has almost reached that of conventional risk prediction approaches. Wang et al. (2025) developed an AI prediction model using more than 280,000 fundus pictures. The AUC for predicting major cardiovascular events (myocardial infarction, stroke, and cardiovascular mortality) was 0.732 (95% CI: 0.715 - 0.749), which is like the Framingham risk score (AUC = 0.739). This shows that it is clinically equivalent.

5. Discussion

Despite promising progress in feasibility and accuracy, AI-based retinal imaging still faces critical challenges before its clinical and public health potential can be fully realized. The research revealed a substantial deterioration in model performance during cross-center external validation. In the training cohort, the AUC might surpass 0.73; however, in the external datasets, it ranged from 0.67 to 0.70, indicating its restricted generalization capacity [12].

The primary element influencing the model's stability is data heterogeneity. Haner et al. (2023) noted that the quality of retinal pictures is affected by the model's shooting device type, imaging resolution, and the operator's level of expertise. In their research and analysis of the literature, they found that the availability of photos in various studies might vary by as much as 15% to 30%. AI frequently makes mistakes because photographs are blurry or not well lighted. Moreover, variations in race, age, and gender influence the model's applicability. For instance, several models have an AUROC of 0.75 for the white population, which decreases to 0.68 for the East Asian population, indicating that cross-population validation remains a critical procedure [13].

Another major problem is that the model is hard to interpret. Veritti et al. (2023) noted that although visualization techniques like Grad-CAM may highlight the model's primary focal points, including the optic nerve head, major blood arteries, and macula, physicians sometimes struggle to clearly associate these "hot zones" with disease causes. For instance, research found that more than 40% of the model's decision regions did not match the known pathological alterations. This shows that the "black box" character of AI is still present. This lack of openness makes it harder for clinicians to use AI advice in clinical situations[14].

In addition, study design has several problems. Now, most AI models rely on retrospective data and do not include long-term follow-up. Wang et al. (2025) assert that although the short-term (<5 years) risk prediction AUC may surpass 0.70, there is inadequate evidence for long-term (≥10 years) predictions, rendering confirmation of their efficacy in long-term prognosis unattainable. Many studies, however, just use one label, like hypertension or diabetes, and do not consider other characteristics like clinical, genetic, and lifestyle factors[12].

Ethical and legal problems should not be ignored either. An et al. (2025) said that AI models commonly use big health datasets, yet more than 80% of the training data originates from rich nations. If applied directly to low-income areas, it might cause prediction bias and make health disparities even worse. Additionally, the research revealed that the sensitivity of some models decreased by over 20% in minority ethnic groups, indicating the presence of racial bias hazards [15]. At the same time, it is still unclear who is legally responsible for AI in clinical settings. If the AI's suggestions go against what the doctor thinks or if the wrong forecast leads to a wrong diagnosis,

ISSN 2959-409X

the question of who is responsible is still up in the air [14]. Huang et al. (2023) propose that causal reasoning and multi-scale visualization techniques be combined to increase doctors' trust and willingness to use artificial intelligence (AI) [16]. Such methods help them comprehend the correlations between predicted model outputs and clinical phenomena more readily, thereby increasing acceptance. Furthermore, future research must explore AI technologies with explainable models, as this would ensure models provide both prediction results but also reasonable pathological explanations.

AI could play an instrumental role in early screening and risk stratification for cardiovascular diseases. Retinal examination, due to its noninvasive, low-cost, and highly repeatable nature, enables rapid population-wide assessments without requiring expensive equipment [17]. Integrating such approaches with interpretable AI models could not only enhance early screening and risk stratification for cardiovascular diseases but also facilitate broader accessibility, including in grassroots medical settings.

Olawade et al. (2025) highlight how AI's potential can enhance remote medical services and regions with limited resources, particularly low- and middle-income countries with few medical resources[18]. Portable fundus imaging equipment combined with AI systems enables remote diagnosis and real-time risk evaluation, helping narrow health disparities caused by medical imbalance. Rane et al. (2023) state how AI-driven remote screening platforms combined with mobile medical platforms enable cross-regional health management with continuous follow-up of outcomes[19].

AI and retinal images combined can offer personalized medical care to individual patients[20]. AI can offer personalized risk prediction and treatment recommendations using multiple sources of data (clinical variables as well as genetic information). Chew et al. (2024) present an approach which not only assists doctors in formulating intervention strategies but can be dynamically adjusted during long-term follow-up to move away from group prediction towards individual customization. Their research asserts that using AI with retinal images for dynamic monitoring provides continuous risk assessment curves to patients to optimize timing of drug treatments or lifestyle interventions[21].

AI technology can significantly boost clinical workflow efficiency. While traditional cardiovascular risk evaluation processes tend to take too much time and require collaboration among multiple disciplines, AI systems can automate retinal feature extraction and structured report generation to decrease doctors' time on repetitive tasks [18]. Not only does this relieve staff shortages in healthcare; but more focus can now be resolute towards complex cases and personalized decision-making by physicians themselves.

Arnould et al. (2022) noted how artificial intelligence could revolutionize disease prevention and control models at a public health level[17]. If AI analysis were integrated into physical exams or routine eye screenings, medical systems may quickly identify individuals at high risk for cardiovascular events early. Not only may this decrease incidence rates, but it may also alleviate medical economic burden by decreasing hospitalization rates and long-term treatment costs; Rane et al. (2023) believe scaling this application up would expand cardiovascular disease prevention from individual clinical practice to population health management practices[19].

Addressing these limitations while leveraging the opportunities could accelerate the integration of AI-based retinal imaging into routine cardiovascular care and population health strategies.

6. Conclusion

Cardiovascular diseases are among the leading causes of death and disability worldwide, creating an urgent need for effective, noninvasive, scalable screening methods that provide more timely assessment. Retinal images, due to their capability of reflecting microcirculation changes, have increasingly become a valuable way of measuring cardiovascular risk assessment. Recently, AI technology has even further extended this potential of detection and prediction. Current research demonstrates that AI models can successfully predict various cardiovascular risk factors and events from retinal images due to multimodal data integration, large databases, interpretability methods. However, data heterogeneity, inadequate cross-population universality, and ethical/legal issues remain major obstacles in clinical translation. Future development directions must include large-scale pre-training, multitask learning and the incorporation of multilevel data sources into an individualized and precise risk evaluation system. Meanwhile, AI combined with retinal images is expected to play an essential part in remote medical services, personalized interventions, and public health promotion.

References

[1] Ghenciu, L. A., Dima, M., Stoicescu, E. R., Iacob, R., Boru, C., & Hațegan, O. A. (2024). Retinal Imaging-Based Oculomics: Artificial intelligence as a tool in the diagnosis of cardiovascular and metabolic diseases. Biomedicines, 12(9), 2150. https://doi.org/10.3390/biomedicines12092150

[2] Zhang, L., Yuan, M., An, Z., Zhao, X., Wu, H., Li, H., Wang, Y., Sun, B., Li, H., Ding, S., Zeng, X., Chao, L., Li, P., & Wu,

W. (2020). Prediction of hypertension, hyperglycemia and dyslipidemia from retinal fundus photographs via deep learning: A cross-sectional study of chronic diseases in central China. PLoS ONE, 15(5), e0233166. https://doi.org/10.1371/journal.pone.0233166

[3] Rudnicka, A. R., Welikala, R., Barman, S., Foster, P. J., Luben, R., Hayat, S., Khaw, K., Whincup, P., Strachan, D., & Owen, C. G. (2022). Artificial intelligence-enabled retinal vasculometry for prediction of circulatory mortality, myocardial infarction and stroke. British Journal of Ophthalmology, 106(12), 1722–1729. https://doi.org/10.1136/bjo-2022-321842

[4] Vujosevic, S., Aldington, S. J., Silva, P., Hernández, C., Scanlon, P., Peto, T., & Simó, R. (2020). Screening for diabetic retinopathy: new perspectives and challenges. The Lancet Diabetes & Endocrinology, 8(4), 337–347. https://doi.org/10.1016/s2213-8587(19)30411-5

[5] Tan, T., & Wong, T. Y. (2023). Diabetic retinopathy: Looking forward to 2030. Frontiers in Endocrinology, 13. https://doi.org/10.3389/fendo.2022.1077669

[6] Dong, L., He, W., Zhang, R., Ge, Z., Wang, Y. X., Zhou, J., Xu, J., Shao, L., Wang, Q., Yan, Y., Xie, Y., Fang, L., Wang, H., Wang, Y., Zhu, X., Wang, J., Zhang, C., Wang, H., Wang, Y., . . . Wei, W. B. (2022). Artificial intelligence for screening of multiple retinal and optic nerve diseases. JAMA Network Open, 5(5), e229960. https://doi.org/10.1001/jamanetworkopen.2022.9960

[7] Varela, M. D., Sen, S., De Guimaraes, T. a. C., Kabiri, N., Pontikos, N., Balaskas, K., & Michaelides, M. (2023). Artificial intelligence in retinal disease: clinical application, challenges, and future directions. Graefe S Archive for Clinical and Experimental Ophthalmology, 261(11), 3283–3297. https://doi.org/10.1007/s00417-023-06052-x

[8] Rim, T. H., Lee, G., Kim, Y., Tham, Y., Lee, C. J., Baik, S. J., Kim, Y. A., Yu, M., Deshmukh, M., Lee, B. K., Park, S., Kim, H. C., Sabayanagam, C., Ting, D. S. W., Wang, Y. X., Jonas, J. B., Kim, S. S., Wong, T. Y., & Cheng, C. (2020). Prediction of systemic biomarkers from retinal photographs: development and validation of deep-learning algorithms. The Lancet Digital Health, 2(10), e526–e536. https://doi.org/10.1016/s2589-7500(20)30216-8

[9] Hu, W., Yii, F. S. L., Chen, R., Zhang, X., Shang, X., Kiburg, K., Woods, E., Vingrys, A., Zhang, L., Zhu, Z., & He, M. (2023). A Systematic Review and Meta-Analysis of applying Deep learning in the prediction of the risk of cardiovascular diseases from Retinal Images. Translational Vision Science & Technology, 12(7), 14. https://doi.org/10.1167/tvst.12.7.14

[10] Lee, Y. C., Cha, J., Shim, I., Park, W., Kang, S. W., Lim, D. H., & Won, H. (2023). Multimodal deep learning of fundus abnormalities and traditional risk factors for cardiovascular risk prediction. Npj Digital Medicine, 6(1). https://doi.org/10.1038/s41746-023-00748-4

[11] Hu, W., Lin, Z., Clark, M., Henwood, J., Shang, X., Chen, R., Kiburg, K., Zhang, L., Ge, Z., Van Wijngaarden, P., Zhu, Z., & He, M. (2025). Real-world feasibility, accuracy and acceptability of automated retinal photography and AI-based cardiovascular disease risk assessment in Australian primary care settings: a pragmatic trial. Npj Digital Medicine, 8(1). https://doi.org/10.1038/s41746-025-01436-1

[12] Wang, J., Wang, Y. X., Zeng, D., Zhu, Z., Li, D., Liu, Y., Sheng, B., Grzybowski, A., & Wong, T. Y. (2025). Artificial intelligence-enhanced retinal imaging as a biomarker for systemic diseases. Theranostics, 15(8), 3223–3233. https://doi.org/10.7150/thno.100786

[13] Häner, N. U., Dysli, C., & Munk, M. R. (2023). Imaging in retinal vascular disease: A review. Clinical and Experimental Ophthalmology, 51(3), 217–228. https://doi.org/10.1111/ceo.14203

[14] Veritti, D., Rubinato, L., Sarao, V., De Nardin, A., Foresti, G. L., & Lanzetta, P. (2023). Behind the mask: a critical perspective on the ethical, moral, and legal implications of AI in ophthalmology. Graefe S Archive for Clinical and Experimental Ophthalmology, 262(3), 975–982. https://doi.org/10.1007/s00417-023-06245-4

[15] An, S., Teo, K., McConnell, M. V., Marshall, J., Galloway, C., & Squirrell, D. (2025). AI explainability in oculomics: how it works, its role in establishing trust, and what still needs to be addressed. Progress in Retinal and Eye Research, 101352. https://doi.org/10.1016/j.preteyeres.2025.101352

[16] Huang, Y., Cheung, C. Y., Li, D., Tham, Y. C., Sheng, B., Cheng, C. Y., Wang, Y. X., & Wong, T. Y. (2023). AI-integrated ocular imaging for predicting cardiovascular disease: advancements and future outlook. Eye, 38(3), 464–472. https://doi.org/10.1038/s41433-023-02724-4

[17] Arnould, L., Meriaudeau, F., Guenancia, C., Germanese, C., Delcourt, C., Kawasaki, R., Cheung, C. Y., Creuzot-Garcher, C., & Grzybowski, A. (2022). Using artificial intelligence to analyse the retinal vascular network: The future of cardiovascular risk Assessment based on Oculomics? A Narrative review. Ophthalmology and Therapy, 12(2), 657–674. https://doi.org/10.1007/s40123-022-00641-5

[18] Olawade, D. B., Weerasinghe, K., Mathugamage, M. D. D. E., Odetayo, A., Aderinto, N., Teke, J., & Boussios, S. (2025). Enhancing Ophthalmic Diagnosis and Treatment with Artificial Intelligence. Medicina, 61(3), 433. https://doi.org/10.3390/medicina61030433

[19] Rane, N., Choudhary, S., & Rane, J. (2023). Explainable Artificial Intelligence (XAI) in healthcare: Interpretable Models for Clinical Decision Support. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4637897

[20] Khokhar, P. B., Gravino, C., & Palomba, F. (2025). Advances in artificial intelligence for diabetes prediction: insights from a systematic literature review. Artificial Intelligence in Medicine, 103132. https://doi.org/10.1016/j.artmed.2025.103132

ISSN 2959-409X

[21] Chew, E. Y., Burns, S. A., Abraham, A. G., Bakhoum, M. F., Beckman, J. A., Chui, T. Y. P., Finger, R. P., Frangi, A. F., Gottesman, R. F., Grant, M. B., Hanssen, H., Lee, C. S., Meyer, M. L., Rizzoni, D., Rudnicka, A. R., Schuman, J. S., Seidelmann, S. B., Tang, W. H. W., Adhikari, B. B., . . . Oh, Y. S. (2024). Standardization and clinical applications of retinal imaging biomarkers for cardiovascular disease: a Roadmap from an NHLBI workshop. Nature Reviews Cardiology, 22(1), 47–63. https://doi.org/10.1038/s41569-024-01060-8