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Artificial Intelligence in Assessing Cardiovascular Disease

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Abstract:

Cardiovascular disease (CVD) assessment has long relied on traditional methods that are often subjective, time-consuming, and limited in predictive accuracy, creating a significant gap for more objective and scalable tools. To address this gap, artificial intelligence (AI) is profoundly transforming the assessment and management of CVD, enabling a shift from these conventional approaches to data-driven, precise, and predictive paradigms. This review comprehensively summarizes the latest advancements in AI applications across major CVD diagnostic modalities, including cardiac imaging (echocardiography and cardiac computed tomography), physiological signal processing (electrocardiogram and photoplethysmography from wearable devices), and multimodal risk prediction. AI algorithms demonstrate expert-level performance in automating the quantification of key metrics such as ejection fraction and coronary calcium, detecting subtle arrhythmias, and identifying early signs of cardiac dysfunction. Furthermore, by integrating multimodal data—such as electronic health records (EHRs) and retinal images—AI models excel in predicting individual risks of major adverse cardiovascular events, heart failure (HF) hospitalization, and mortality, outperforming conventional risk stratification tools. Despite these significant developments, challenges related to data quality, model interpretability, and clinical integration still exist. The future focus will be on three major directions: introducing large language models (LLMs) to build a more intelligent patient management system, developing adaptive analysis systems with continuous learning capabilities, and expanding the application of AI in auxiliary diagnosis and treatment. Through a human-machine collaboration model, to provide clinical solutions for CVD prevention and treatment that are both personalized and preventive.

Keywords: Artificial Intelligence; Cardiovascular Diseases; Deep Learning; Diagnosis; Risk Prediction

1. Introduction

CVD remain the leading cause of death and morbidity worldwide, imposing a heavy burden on the global healthcare system. Accurate and timely assessment of CVD is crucial for effective intervention and improving patient prognosis. However, traditional diagnostic methods often rely on subjective interpretation of imaging examinations, physiological signals, and clinical risk scores. This is time-consuming and unstable and has limited ability in predicting individual risks. This inherent subjectivity, combined with the increasing complexity of patient data, highlights the urgent need for more objective, efficient, and precise tools in clinical cardiology.

The rapid development of AI, especially deep learning (DL), has brought a new era to medical diagnosis. AI algorithms excel in identifying complex, nonlinear patterns in large-scale, high-dimensional data, a capability perfectly aligned with the multifaceted characteristics of cardiovascular medicine. By leveraging data from various sources, such as EHRs, medical imaging, and wearable devices, AI brings unprecedented potential for transformation in the CVD care process—from initial screening and diagnosis to risk stratification and long-term management.

This review aims to comprehensively summarize the status of AI in CVD assessment and its transformative impact. It explores the applications in key areas, including automatic analysis of cardiac imaging (echocardiography and computed tomography), interpretation of physiological signals (electrocardiogram and photoplethysmography), and integration of multimodal data for personalized risk prediction. Additionally, the article critically examines ongoing challenges related to clinical implementation, model interpretability, and data bias, while looking forward to the future directions that may further integrate AI into the precision cardiology system, providing support for clinicians and improving patient care.

2. Applications of AI in the Diagnosis and Evaluation of CVD

2.1 Imaging-Based Assessment

2.1.1 Echocardiography

Echocardiography is an important method for evaluating the heart. However, its interpretation used to rely heavily on the operator and was time-consuming. AI is changing this field by enabling fully automated and accurate analysis, surpassing human performance in certain tasks and revealing new diagnostic insights.

The most mature applications involve automated quantification. AI algorithms can measure left ventricular ejection fraction (LVEF) with expert-level accuracy, facilitating reliable serial monitoring even by non-specialists [1,2]. DL models also perform comprehensive cardiac chamber segmentation, allowing precise quantification of volumes, mass, and strain (Fig 1) [3]. In disease detection, AI identifies subtle patterns imperceptible to the human eye, such as regional wall motion abnormalities (AUC=0.99) [4] and valvular diseases like aortic stenosis through integration of 2D and Doppler features [5].

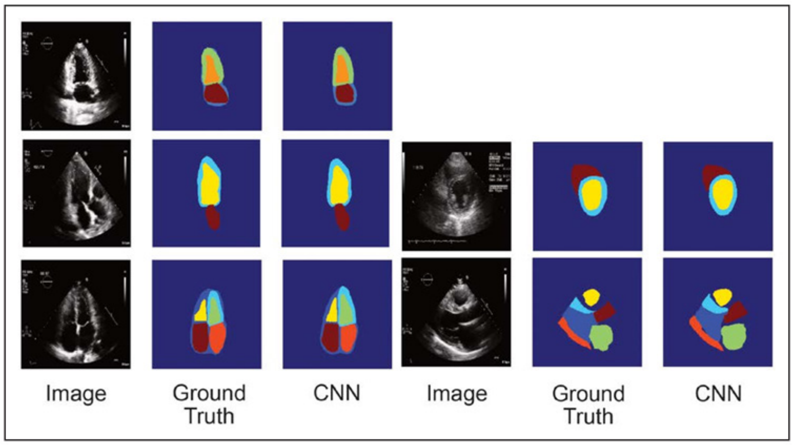

Fig. 1 Automated cardiac chamber segmentation using a convolutional neural network (CNN). Representative examples show the model's performance across five standard echocardiographic views by comparing the original image, expert manual tracing (ground truth), and automated AI segmentation. The high agreement between manual and automated outlines demonstrates the capability of AI to achieve expert-level quantification of cardiac structures, which is fundamental for calculating volumes, mass, and strain (A2c: apical 2-chamber; A3c: apical 3-chamber; A4c: apical 4-chamber; PLAX: parasternal long axis). Adapted from Zhang et al. [3].

AI has demonstrated unique advantages in distinguishing

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complex diseases that are difficult to diagnose with traditional echocardiography. For instance, it can differentiate constrictive pericarditis from restrictive cardiomyopathy with an AUC value of 0.96, providing a quantitative solution to a typical diagnostic challenge [6]. Similarly, AI can accurately identify cardiac amyloidosis and hypertrophic cardiomyopathy (C-statistic: 0.87-0.93), tasks that usually require specialized knowledge from professionals [3]. Notably, the diagnostic ability of AI is comparable to that of experienced clinicians, with a study showing its performance to be equivalent to that of experts (AUC = 0.99 vs. 0.98), and it outperforms resident physicians in detecting wall motion abnormalities (AUC = 0.90) [4].

In addition to diagnosis, AI has enhanced the ability to predict prognosis. By combining echocardiographic data with clinical information, AI models can predict outcomes such as all-cause mortality, with an accuracy rate (AUC = 0.82) significantly higher than traditional clinical risk scores (AUC ranging from 0.69 to 0.79) [7]. This capability transforms echocardiography from a purely diagnostic tool into a predictive engine for personalized medicine.

2.1.2 Cardiac computed tomography

Cardiac computed tomography (CT), particularly coronary CT angiography (CCTA), is a first-line non-invasive tool for coronary anatomical evaluation, though its traditional interpretation remains labor-intensive and subjective. AI integration is transforming CCTA from a purely anatomical tool into an automated, functional, and prognostic platform.

In quantitative analysis, AI achieves expert-level accuracy. DL models enable fully automated coronary artery calcium (CAC) scoring, with one multi-center model (n > 20,000) showing strong agreement with manual scoring and serving as an independent predictor of events (HR = 4.3) [8]. AI also accurately quantifies epicardial adipose tissue (EAT), where volume and attenuation correlate with cardiovascular risk, offloading repetitive tasks and providing objective measurements [9].

For disease diagnosis, AI enhances CCTA value by automatically detecting ≥25% stenosis with high sensitivity (93%) and specificity (95%), rivaling expert performance [10]. Beyond stenosis, AI enables precise plaque analysis—including vulnerable plaque identification—and bridges anatomy with function by non-invasively computing fractional flow reserve (FFRct) from CCTA (AUC = 0.84 for predicting FFR ≤0.8), aiding revascularization decisions [11,12].

In risk stratification, AI excels by integrating CCTA-derived features (plaque composition, segment scores) with clinical data to predict individual long-term risk. Models from the CONFIRM registry predicted 5-year all-cause mortality (AUC = 0.77–0.79), significantly outperforming traditional risk scores, highlighting AI's ability to extract imperceptible prognostic cues for personalized early warning [13,14].

2.2 Breakthroughs of AI in CVD Physiological Signal Processing

2.2.1 Electrocardiogram

Traditional electrocardiogram (ECG) interpretation relies heavily on clinician expertise, often lacking sensitivity for paroxysmal arrhythmias and early cardiac dysfunction. AI, particularly DL, now enables automated, in-depth ECG analysis, significantly advancing cardiovascular risk assessment and early diagnosis.

In arrhythmia detection, AI excels in early identification of atrial fibrillation (AF). Using CNNs, models can analyze sinus rhythm ECG to detect subtle features of atrial electrophysiological remodeling [15]. A model trained on 650,000 ECGs predicted AF risk from 10-second sinus rhythm segments (AUC=0.87), improving to AUC=0.90 with repeated tracings [16]. AI also outperforms general cardiologists in multi-class arrhythmia diagnosis, accurately categorizing 12 rhythm types [17].

A breakthrough lies in cardiac function assessment, where AI predicts LVEF from routine ECGs. One CNN model, trained on paired ECG-echocardiography data, identified patients with LVEF ≤35% with an AUC of 0.93 and accuracy around 86% [18]. Notably, AI-positive patients with initially normal echocardiography had a fourfold higher risk (HR=4.1) of progressing to overt dysfunction, indicating an ability to detect electrophysiological abnormalities during compensatory phases and providing a critical window for early intervention [18].

2.2.2 Wearable Devices

Advances in AI have transformed consumer wearable devices into effective tools for cardiovascular monitoring, enabling medical-grade arrhythmia screening through photoplethysmography (PPG) and DL. This shift facilitates continuous, real-world AF detection outside clinical settings.

Despite susceptibility to motion artifacts, DL models (e.g., CNN, LSTM) achieve high AF classification accuracy, with reported sensitivity of 94.80% and specificity of 96.96%. Models operating on dynamic wearable data (AUROC: 0.977) perform comparably to those using in-hospital resting data (AUROC: 0.983), demonstrating strong robustness [19].

The Apple Heart Study, a large-scale virtual trial with over 410,000 participants, confirmed real-world feasibility. The algorithm showed high specificity, with irregular pulse notification rates of 0.52% overall and 3.2% in high-risk older adults. Among those completing follow-up, the positive predictive value reached 84%, with 89% of AF episodes lasting over one hour, and 57% of notified participants sought clinical consultation, forming an effective monitoring-intervention loop [20].

However, challenges remain, including low user compliance—only 20.8% completed confirmatory testing in the Apple study—as well as signal artifacts, limited generalizability, and insufficient sensitivity data [19]. As wearables diversify into rings and patches, enabling seamless monitoring, AI-driven screening promises a shift toward dynamic, personalized, and preventive cardiovascular care.

2.3 AI-Driven Multimodal Risk Prediction and Precision Management

AI is reshaping the cardiovascular risk assessment paradigm by integrating multimodal data—such as EHRs and medical imaging—to enable dynamic, individualized prediction of hard clinical endpoints like HF hospitalization and mortality.

In risk prediction, AI-driven analysis of EHR leverages both structured data and clinical text to capture complex, nonlinear relationships for prognosticating outcomes. For instance, one study employing logistic regression and gradient boosting methods integrated 179 clinical variables, successfully identifying high-risk individuals for HF six months before clinical diagnosis, highlighting AI's potential for long-term risk early warning and stratified management [21].

A significant advancement is the incorporation of non-traditional data sources such as retinal images, which serve as a non-invasive window into systemic microvascular health. AI-based analysis of retinal images (rpCVD) performs comparably to the WHO risk model in predicting 10-year cardiovascular events (AUC: 0.672 vs. 0.693) [22]. Furthermore, in patients with coronary artery disease, retinal AI models can efficiently screen for mild cognitive impairment (MCI), achieving AUCs of 0.832 and 0.776 in internal and external validation sets respectively (using MMSE <27 as threshold), thereby revealing clinically significant heart-brain comorbidity risks (see Fig. 2 for the AI development workflow) [23].

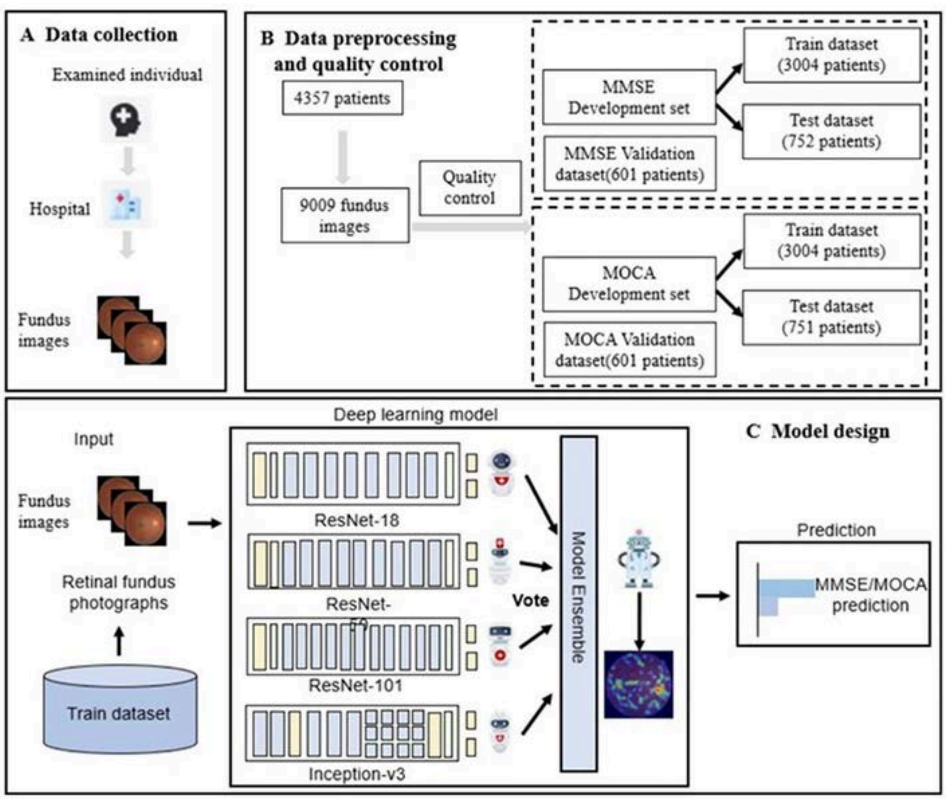

Fig. 2 Workflow for developing and validating a DL model to screen for MCI using retinal images [23].

This AI model, which achieved high predictive accuracy (AUC: 0.832-0.776) in validation sets, was developed through a structured process: (A) recruitment of participants and fundus image acquisition; (B) comprehensive data preprocessing and division into training, validation, and test sets; (C) design and training of an ensemble DL

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model (based on ResNet and Inception architectures) to output predictions for standard cognitive assessment scores (MMSE/MoCA).

Beyond prediction, AI is redefining risk factor assessment through DL. Algorithms can automatically extract hundreds of subtle vascular features from color fundus photographs (CFPs) to construct predictive models. Poplin et al. [24] developed a model using only retinal images to predict 5-year major adverse cardiovascular event (MACE) risk (AUROC = 0.73), a performance comparable to conventional risk calculators. More innovatively, AI-derived biomarkers such as "retinal age gap" (the difference between retinal age and chronological age) have been shown to significantly predict stroke risk (HR = 2.37), offering a novel digital biomarker of vascular aging [25].

These tools show high clinical feasibility, with retinal imaging being rapid (<2 minutes), successful (93.9%), and well-accepted by patients and clinicians [22]. However, challenges remain regarding cost, trust, and data integration. Future work should focus on optimizing algorithms for high-risk groups, multicenter validation, and deeper EHR integration.

3. Discussion

3.1 Limitations

Despite its potential, the clinical application of AI in CVD management faces three major challenges.

First, data quality and bias issues significantly limit model performance. AI models rely on EHRs and medical images, which often come from single sources with inconsistent annotations. Variability in data collection protocols, equipment, and patient demographics across institutions leads to substantial heterogeneity, causing performance degradation when models are applied to new settings. Limited data for rare diseases or specific demographic groups can introduce systematic biases and worsen healthcare disparities [26]. Additionally, strict privacy regulations hinder data sharing and large-scale, high-quality dataset curation [27].

Second, the lack of interpretability and trust in AI models impedes clinical adoption. The "black-box" nature of many DL systems makes it difficult for clinicians to understand AI-driven decisions, eroding confidence—especially when errors occur [28]. Poor model calibration may also lead to mismatches between predicted probabilities and actual outcomes, affecting clinical reliability [29]. Although techniques like saliency maps and feature importance analysis are being developed to improve transparency, they remain early-stage and lack standardization.

Third, there are numerous obstacles in the clinical integration process. Embedding AI tools into existing workflows requires redesigning the nursing process, extensive system integration, and comprehensive training for all staff [30]. Currently, there is still a lack of sufficient practical evidence to prove that AI tools can improve patient treatment outcomes or reduce medical costs. The regulatory framework for medical devices based on AI (especially self-learning algorithms) is still evolving, and the standards for assessing their safety and effectiveness are not yet clear. Moreover, due to the lack of clear accountability criteria for medical errors related to AI, this further hinders its application [5].

Therefore, for AI to be widely used in cardiology, it is necessary to overcome obstacles in data quality, model interpretability, and clinical integration. Solving these challenges requires interdisciplinary collaboration to promote technological progress, establish standards, and improve regulatory policies.

3.2 Future Directions

Despite some challenges, the prospects of AI in cardiology remain broad, with several key directions emerging.

LLMs have great potential in patient management and medical research. By processing natural language, LLMs can automate patient communication, generate clinical records, and extract insights from research data. When combined with multimodal health data (including medical images, EHRs, and genomics data), LLMs will become intelligent integrated tools, significantly enhancing clinical decision support and resource utilization efficiency [5, 31].

Patient-centered AI systems that utilize continuous learning will be able to conduct dynamic and personalized risk assessment and intervention. Using real-time data from wearable devices (such as ECGs, photoplethysmogram) these models will continuously adapt to individual patients and the changing clinical environment, shifting care from response to prevention and promoting early intervention [30].

AI will not replace clinicians but will enhance doctors' capabilities in precision medicine. By revealing subtle patterns beyond human perception and automating tedious analytical tasks, AI can support complex decisions such as risk classification, treatment optimization, and prognosis assessment. This collaboration enables treatment plans to be more information-based and more personalized [5, 30].

4. Conclusion

The application of AI in the field of cardiovascular medicine represents a significant shift from traditional subjective assessment to a data-based, precise, and predictive care model. In this review, the transformative impact of AI on various aspects of CVD assessment has been elaborated. In cardiac imaging, AI algorithms can now quantify ejection fraction, cardiac chamber volume, and coronary artery calcification with expert-level accuracy, while also identifying subtle features of diseases such as cardiac amyloidosis and constrictive pericarditis. In physiological signal analysis, DL models extract previously inaccessible key information from ECGs and pulse wave signals, enabling the early detection of AF and even predicting asymptomatic left ventricular dysfunction—demonstrating the ability to identify risks long before clinical symptoms appear.

The most convincing aspect is the ability of AI to integrate and interpret multimodal data. By integrating data from EHRs, retinal images, and wearable devices, AI provides an overall view of an individual's cardiovascular health. It is no longer limited to a single diagnostic task but offers comprehensive risk stratification analysis, capable of predicting serious clinical endpoints such as hospitalization for HF and death, with a prediction effect that exceeds traditional risk models. Innovative technologies such as "retinal age gap" and AI-based vascular indicators are redefining traditional risk factors, providing non-invasive and scalable biomarkers for large-scale population screening and personalized prevention.

However, transforming AI from the research stage to routine clinical practice is still an ongoing process. A series of major challenges must be overcome, including concerns about data quality and inherent biases, the "black box" nature of complex algorithms, and the practical issues of embedding AI tools into existing clinical workflows. The interpretability of models, compliance, and the need for real-world validation are key obstacles that require interdisciplinary collaboration to solve.

Looking ahead, the future of AI in cardiology is bright and points toward more intelligent, adaptive, and human-centered healthcare systems. The emergence of LLMs offers new potential for managing patient data and assisting clinical decision-making. Continuous learning AI systems can evolve with new data, maintaining relevance and accuracy over time. Most importantly, AI will serve as a powerful collaborator to clinicians—enhancing their capabilities, automating routine tasks, and supporting more informed and personalized patient management. It is not a replacement for human expertise but a catalyst for a new era of precision cardiology, where technology and clinical wisdom combine to improve outcomes, enhance efficiency, and transform the patient experience.

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