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Artificial Intelligence in Cardiovascular Diagnostics: Integration of Laboratory Biomarkers, Medical Imaging, and Molecular Data

Neha Arif
Department of Radiography and Imaging Technology, Faculty of Allied Health Sciences, Government College University Faisalabad, Faisalabad, Pakistan.
nehaarif325@gmail.com

Hafsa Shafiq
Department of Medicine & Surgery, Aviceena Medical and Dental College, Lahore, Pakistan.
hifsashafiq4661@gmail.com

Moiza Noor*
Department of Medical Laboratory Technology, Faculty of Medical Sciences, Government College University Faisalabad, Faisalabad, Pakistan.
Corresponding Author: moizanoor704@gmail.com
ORCID: 0009-0007-0566-2176

Taha Shahbaz
Department of Medicine and Surgery, University College of Medicine and Dentistry, Lahore, Pakistan.
tahashahbaz256@gmail.com

Aswad Khan
Department of Biotechnology, International Islamic University Islamabad, Islamabad, Pakistan.

Hafsa Noor
Department of Medicine and Surgery, Muhammad Medical College, Mirpurkhas, Pakistan.
memonsaima73@gmail.com

Khalil Ahmed
Department of Medical Laboratory Technology, Faculty of Allied Health Sciences, The University of Lahore, Lahore, Pakistan.
khalilasif72@gmail.com

Eman Farrukh
Department of Medical Laboratory Technology, Faculty of Medical Sciences, Government College University Faisalabad, Faisalabad, Pakistan.
emanfarrukh20@gmail.com

Muhammad Abdullah Butt*
Department of Food Science, Faculty of Life Sciences, Government College University Faisalabad, Faisalabad, Pakistan.
Corresponding Author: muhammadabdullahbuttfst@gmail.com

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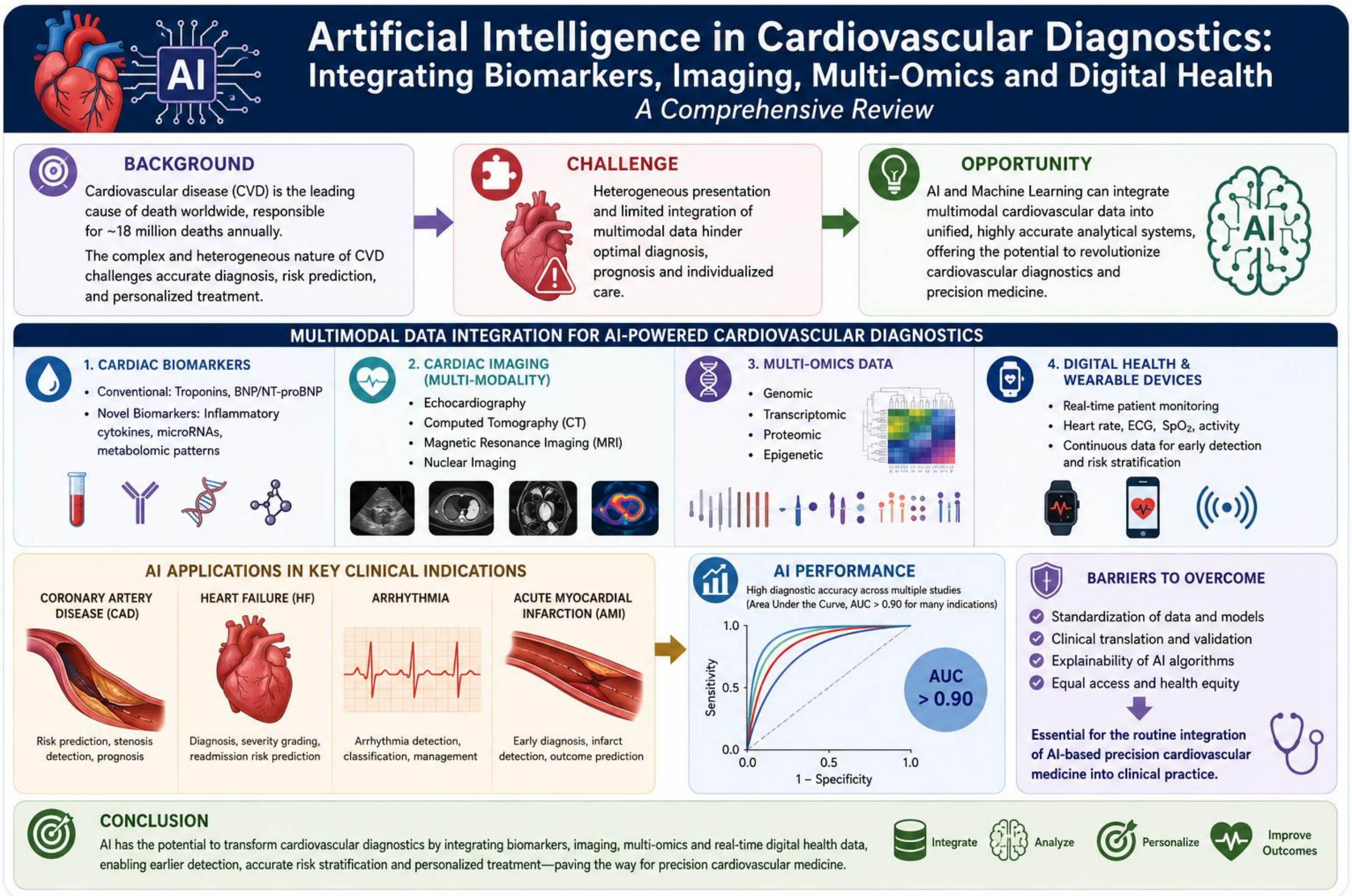
Corresponding E-mails & Authors*:
Moiza Noor*
moizanoor704@gmail.com
Muhammad Abdullah Butt*
muhammadabdullahbuttfst@gmail.com

Abstract

The largest burden of disease and mortality worldwide is due to cardiovascular disease (CVD), accounting for an estimated 18 million deaths each year. Nevertheless, the complex and heterogeneous presentation of the disease still poses an enormous challenge in terms of optimal diagnosis, prognostication of risk, and individual treatment paradigms. Given the potential of artificial intelligence and machine learning (ML) to integrate the multimodal information available in the cardiovascular realm, such as laboratory parameters, imaging, and genomic and molecular information, into a unified, highly accurate analytical system, it has the potential to revolutionize cardiovascular diagnosis. This review outlines and summarizes current approaches to the use of AI for cardiovascular diagnostics using cardiac biomarkers (conventional and newer types of cardiac biomarkers such as cardiac troponins, natriuretic peptides, inflammatory cytokines, microRNAs, and metabolomic patterns); cardiac imaging (multi-modality imaging, such as echocardiography, computed tomography, magnetic resonance imaging, and nuclear imaging); and multi-omics data analysis (genomic, transcriptomic, proteomic, and epigenetic markers). Target clinical indications for the use of coronary artery disease (CAD), heart failure (HF), arrhythmia detection and management, and acute myocardial infarction (AMI) are discussed. In addition, a role for real-time patient monitoring with wearable digital health technologies and devices is also reviewed. The high diagnostic accuracy (area under the curve routinely > 0.90 for many indications) that these AI models have achieved to date must be overcome to overcome barriers to standardization, clinical translation and validation, explainability of the

algorithms, and equal access before effective AI-based precision cardiovascular medicine can be routinely integrated into clinical practice.



INTRODUCTION

Cardiovascular disease (CVD) is the leading cause of death in developed and developing countries worldwide. According to the latest statistics, 17.5 million people die due to CVD each year globally, responsible for 31% of all deaths. CVD includes many non-communicable and burdensome conditions such as hypertension, atherosclerosis, cardiomyopathy, and heart failure (HF). Due to the presence of both genetic and environmental factors, the disease cannot be fully explained by a single cause (Hemmati et al., 2023). CVD is the leading cause of morbidity and mortality, affecting over 523 million people globally. In fact, the World Health Organization (WHO) estimated nearly 18 million global deaths due to CVD in 2019. On the North

American continent, CVD accounted for 36.4 million years of life lost and 4.5 million years lived with disability between 2000 and 2019. In the United States, CVD had an economic burden of over 32 billion dollars in 2016. In view of its high prevalence and cost, there is still an urgent need to discover the pathophysiology of CVD, and there is much to understand about its therapeutics and management. Although there is a diverse array of heart disease etiologies, the involvement of aberrant inflammatory processes seems to be a common link between different types of CVDs (Zhang & Dhalla, 2024). The global epidemic of metabolic diseases, as well as the upstream social determinants of health, share common pathobiological pathways in accelerating CVD, causing social and economic implications worldwide. Moreover, the complex and diverse nature of CVDs, influenced by culture, genetics, socioeconomics, and other region-specific determinants, presents challenges in adopting a one-size-fits-all approach when addressing the global CVD burden (Chong et al., 2025).

The global prevalence of CVD is still high. Further, it is important to recognize and to emphasize that CVD is largely still a preventable disease. Modifiable risk factors have been shown to account for >90% of the risk for developing CVD. This makes prioritizing preventative measures that reduce CVD risk factors necessary to lessen the burden of CVD. Key to the reduction of CVD risk factors is increasing healthy lifestyle (HL) behaviors. HL behaviors can influence several CVD risk factors, including smoking, diabetes, and obesity, as well as the less commonly measured risk factor, cardiorespiratory fitness (CRF). However, many HL behaviors have worsened over the years. For example, performing regular physical activity (PA) is important for decreasing CVD risk, yet since at least the 1950s, there has been a gradual decline in daily levels of PA due to technology, society, and community changes. These decreases in PA are associated with worsening CVD risk factor profiles such as increased obesity levels and decreased CRF levels (Kaminsky et al., 2021).

Conventional clinical assessment and imaging have been supplanted by an integrated precision-based approach that brings together laboratory biomarkers, multimodal imaging, molecular profiling, and artificial intelligence (AI) to facilitate CV diagnosis (Netala et al., 2025). Electrocardiography (ECG), echocardiography, coronary angiography (CAG), computed tomography (CT), positron emission tomography (PET), single-photon emission computed tomography (SPECT), and cardiac magnetic resonance imaging (MRI) are still the mainstay of the traditional diagnostic approaches for cardiac structure, perfusion, ischemia, and functional abnormalities (Kim et al., 2022). Circulating biomarkers, in addition to imaging, are vital in the early detection and management of CVDs. Biomarkers like CK-MB, myoglobin, heart-type fatty acid binding protein (H-FABP), and cardiac myosin-binding protein-C give further information about myocardial injury, in addition to cardiac troponins, which continue to be the gold standard for the diagnosis of myocardial infarction (Netala et al., 2025). Biomarkers such as B-type natriuretic peptide (BNP), N-terminal pro-BNP (NT-proBNP), mid-regional pro-adrenomedullin (MR-proADM), and copeptin are extensively utilized for diagnosis and prognosis, as well as to monitor the severity of HF. Other markers of cardiovascular risk and atherosclerotic disease evaluation include inflammatory and oxidative stress markers like C-reactive protein (CRP), high-sensitivity C-reactive protein (hs-CRP), interleukin-6 (IL-6), tumor necrosis factor-alpha (TNF-α), galectin-3, growth differentiation factor-15 (GDF-15), ST2, and myeloperoxidase (MPO) (Noor et al., 2025). Recent advances highlight the use of a combination of a biomarker profile with molecular imaging to enhance the accuracy of diagnosis and disease characterization. Targeted PET and SPECT imaging with tracers can add imaging to the data from serum markers to visualize inflammation, fibrosis, thrombosis, and metabolic changes. In addition, novel molecular markers are becoming available for early and subclinical disease diagnosis, such as microRNAs, long non-coding RNAs (lncRNAs), cell-free DNA (cfDNA), and metabolomic signatures like trimethylamine N-oxide (TMAO) and branched-chain amino acids (Tingen et al., 2023). Adoption of the multi-omics approach coupled with AI and machine learning algorithms has also facilitated the discovery of new cardiovascular phenotypes, biomarker signatures, and tailored treatment approaches (Batta et al., 2024). Simultaneously, digital biomarkers derived from wearable devices and EHRs, such as heart rate variability and continuous ECG monitoring, are increasingly used to predict risks in real time and for remote patient monitoring (Nazir et al., 2025). However, some key issues, such as the lack of standardization, clinical validation, and cost-effectiveness and accessibility, still pose major obstacles to large-scale implementation.

AI is a rapidly evolving transdisciplinary field that integrates computer science, statistics, psychology, neuroscience, material science, mechanical engineering, and computer hardware design to develop algorithms that aim to simulate human intuition, decision-making, and objects. The overarching aims of AI in cardiovascular medicine are threefold: to optimize patient care, improve efficiency, and improve clinical outcomes. In cardiology, there has been a growth in the potential sources of new patient data, as well as advances in investigations and therapies, which position the field well to uniquely benefit from AI (Haq et al., 2022).

This review will provide a comprehensive overview of how AI-driven approaches are transforming the detection, classification, and prognostic assessment of CVDs. It will highlight the clinical significance of combining biochemical, imaging, and molecular data to enhance the diagnostic accuracy, support, and precision of medicine.

Artificial Intelligence in Cardiovascular Medicine:

AI is the technology that enables machines, in particular computer systems, to mimic human cognitive function. It integrates tasks like learning, reasoning, problem solving, perception, and understanding language, allowing computers to derive insights from data, make informed decisions, and solve complex problems. A convolutional neural network (CNN) represents a specialized architecture tailored for analyzing visual imagery within the broader category of deep neural networks (DNNs). They utilize convolutional layers that apply filtering operations to efficiently capture spatial patterns in the data. Deep learning (DL), a specialized area within machine learning

(ML), utilizes multi-layered neural networks to learn from vast datasets with little need for manual feature engineering. This approach is highly effective for complex tasks, including image and speech recognition, as it allows the networks to autonomously discern and analyze various data elements (Lüscher et al., 2024). Machine learning (ML) refers to a set of techniques that enable AI, and these techniques vary in their objectives, applications, and architectures. ML is an iterative process that involves approximating complex mathematical relationships between inputs and outputs by learning from a large data set to predict values from new, unseen data. Supervised learning (SL) refers to algorithms learning rules between a set of inputs and outputs using a labeled training dataset (referred to as mapping) to predict outcomes for new inputs. Supervised ML algorithms are especially useful when the research question involves classification or regression-based analysis. A well-labeled training data set can be reused if the pre-specified features do not need to be changed. However, the drawbacks of SL include the often time-consuming and costly process of accurately labeling a large data set. Compared to traditional ML algorithms, deep learning requires minimal data preparation or feature engineering. Unsupervised learning (USL) is a different form of learning that uses unlabeled data to discover underlying relationships and is often referred to as knowledge discovery (Haq et al., 2022). The origins of AI can be traced to Alan Turing, who explored the mathematical possibility of AI and described how to build and test intelligent machines in the early 1950s. However, computers lacked the functional capabilities to implement this theoretical knowledge at the time. As computing power improved and information could be stored, processed, and extracted, ML algorithm development flourished in the 1970s and 1980s. Early work focused on AI applications in computer gaming, but its role in clinical decision-making only began taking shape in the 1990s (van Assen et al., 2022). In cardiology, the first applications of AI were the development of self-learning neural networks applied to electrocardiography (ECG). One of the earliest works, in 1990, trained a self-learning neural network using 60 ECGs to localize the atrioventricular accessory pathway in patients with Wolff-Parkinson-White syndrome by using the polarity of the delta waves as an input. In a testing cohort of 25 ECGs, the algorithm correctly localized the atrioventricular pathway in 23 patients. As AI techniques developed and computing power continued to improve, applications of AI in cardiology expanded to other fields, including cardiac imaging, electrophysiology, HF, and interventional procedures. In 1999, a study applied artificial neural networks to echocardiography to segment images into either blood or tissue regions. The study trained the ML algorithm using 279 images and compared the algorithm to manual segmentation by two independent investigators and found good agreement (R = 0.93). More recently, the development of big-data analytical techniques has further opened the field of cardiology. Big-data analytical techniques have focused on integrating and synthesizing various multimodal imaging data points, including various omics data, imaging, ECG, and unstructured free text (Haq et al., 2022).

Laboratory Biomarkers in AI-Based Cardiovascular Diagnostics:

Biomarkers are critical tools for probing, assessing, and managing cardiovascular risk. In 2001, the National Institute of Health Consortium defined a biomarker as a "characteristic that is objectively measured and evaluated as an indicator of normal biological processes, pathogenic processes, or pharmacologic responses to a therapeutic intervention." Given the deadly consequences of undiagnosed CVD—including heart attack and sudden cardiac arrest—the American Heart Association, in 2009, unprecedentedly established criteria for assessing the usefulness and accuracy of cardiovascular biomarkers (Kim et al., 2023).

Traditional biomarkers:

Traditional biomarkers have long been central to the diagnosis, risk stratification, and management of CVDs, which remain the leading cause of morbidity and mortality worldwide. Key traditional biomarkers such as cardiac troponins (cTns), natriuretic peptides (NP and NT-proNP), C-reactive protein (CRP), creatine kinase-MB (CK-MB), and lipid profiles are routinely used in clinical practice for detecting myocardial injury, HF, and atherosclerotic risk (Nasser et al., 2024). Two circulating biomarkers, high-sensitivity CRP and the cTns, appear in the blood when cardiac myocytes undergo necrosis. Testing for high-sensitivity C-reactive protein and cTn plays a crucial role in the diagnosis, risk stratification, and care of patients with CVD. Early diagnosis of CVD can be achieved in the first 2 hours of patient admission through the evaluation of dynamic changes in the concentration of cTns. Although cTns are the gold-standard biomarkers for acute CVD caused by cardiomyocyte necrosis, false-positive results can be problematic because increased cTn levels are observed in nonischemic myocardial injury (e.g., myocarditis and cardiotoxicity) and in other conditions with multifactorial injury (e.g., congestive HF [CHF] and pulmonary embolism) (Kim et al., 2023; Chaulin, 2022). NPs are essential in the diagnosis and prognosis of HF. Chronic inflammation is a sign of CVDs, and inflammatory markers such as CRP and interleukin-6 (IL-6) can be used to determine chronic inflammation (Netala et al., 2025). While traditional biomarkers have their proven value, they suffer from certain drawbacks in terms of sensitivity, specificity, and early disease detection, leading to continued research on identifying new biomarkers and combinations of multiple biomarkers to achieve greater predictive accuracy. These biomarkers are being increasingly combined with cutting-edge technologies to enable increasingly personalized cardiovascular care (Bokhari et al., 2025).

Advanced and Emerging Biomarkers:

Many genetic variants discovered by genome-wide association studies (GWAS) have been identified as being associated with risk for CVD, based on their effects on lipid levels, blood pressure, inflammatory pathways, and cardiac function. A genetic test for certain gene mutations or polygenic test scores can help determine if someone has a higher lifetime risk of CAD, high blood pressure, arrhythmia, cardiomyopathy, or HF (Vargghese 2024). The use of genetic information in clinical practice has been slow to take off, however, because of the complexity of the gene-environment interactions. Soluble proteins of the immune system are secreted by leukocytes and other cells in the body. IL is a family of cytokines that are used for communication among cells of the body, including leukocytes. They are involved in the pathogenesis of many important diseases, such as autoimmune inflammatory diseases and CVDs (Nazir et al., 2025). Inflammatory cytokines like IL-6, tumor necrosis factor alpha (TNFα), members of the interleukin-1 family (IL-1α/β/18/33), IL-8, IL-10/12, growth differentiation factor-15 (GDF-15), myeloperoxidase (MPO), galectin-3 (Gal-3), soluble suppression of tumorigenicity 2 (sST2), pentraxin 3 (PTX3), high-sensitivity C-reactive protein (hsCRP), and others are strongly associated with atherosclerosis progression and adverse cardiovascular outcomes (Haybar et al., 2023; Taghdiri, 2024). These cytokines are associated with the current inflammatory state of the vessels and could provide additional prognostic information beyond traditional risk factors. Metabolomic profiling can be used to identify small molecule metabolites related to CVD risk, including trimethylamine N-oxide (TMAO), oxylipins, amino acid derivatives, lipid metabolites (such as lipoprotein-associated phospholipase A2), and cystatin-C, which provides a broad picture of the metabolic dysregulation in the disease process (Thupakula et al., 2022). Changes in metabolites can identify early pathophysiological changes in the absence of clinical symptoms. Using proteomics/lipidomics for integration further supports precision risk assessment. MicroRNAs (miRNAs) are short, non-coding RNA molecules that have a post-transcriptional gene regulation function. They are resistant to body fluids and are specific to tissues/diseases. Several miRNA signatures are dysregulated in CAD, myocardial infarction (MI), HF, arrhythmias, pulmonary hypertension, and atherosclerosis. The panels of several miRNAs might be superior diagnostic and/or prognostic markers. But challenges remain regarding the standardization of measurement techniques and the reproducibility of studies (Weng et al., 2022).

AI integration

Laboratory parameters like cholesterol ratios, blood pressure, and cystatin C, and other non-traditional parameters, such as calcium, have been consistently superior when used in AI models (You et al., 2023). The automated ML frameworks (AutoPrognosis) with hundreds of variables derived from the large biobank datasets gave higher AUC-ROC values compared to traditional models, while the hybrid ensemble learning (e.g., combining multiple ML algorithms with explainable AI) gave higher AUC-ROC values (Cho et al., 2021). Predicting acute cardiovascular events has been well shown to be effective with AI-based algorithms. In cases where DL was applied to ECG images, the technology could be used to make accurate predictions for people's risk of HF across multinational populations, and ML models for the prediction of mortality risk following an acute MI outperformed logistic regression when using EHR data. Clinical features combined with imaging or ECG-based biomarkers led to better early detection of MI or HF events using ensemble methods (Dhingra et al., 2025).

Biomarker Type	Examples	Clinical Use	Limitations	References
Traditional	Troponin, CK-MB, BNP, CRP	MI diagnosis, HF monitoring	Limited specificity	(Kim et al., 2023; Chaulin, 2022)
Genetic	SNPs, Polygenic Risk Scores	Risk prediction	Gene-environment interactions	(Vargghese 2024)
Inflammatory	IL-6, TNF-α, GDF-15	Inflammation assessment	Variable expression	(Haybar et al 2023; Taghdiri, 2024)
Metabolomic	TMAO, Oxylipins	Early disease detection	Standardization needed	(Thupakula et al 2022)

Epigenetic	DNA methylation markers	Risk stratification	Limited clinical use	(Yousefi et al., 2022
microRNAs	miR-21, miR-133a	Prognosis and diagnosis	Measurement challenges	(Weng et al., 2022)

Medical Imaging and AI:

AI has contributed in many ways to the improvement of cardiovascular imaging (CDVI) in various modalities. CNN pipelines can be used in echocardiography to classify views, segment chambers, and detect disease with high accuracy (around 96% for view identification) and measure ejection fraction (EF) and myocardial strain with high reliability, equal to or higher than manual interpretation (Moradi et al., 2024). AI-powered echo further aids in the detection of various diseases like HF, coronary artery disease (CAD), ischemic heart disease, valvular disorders, and pulmonary hypertension, which are at the level of an expert. In cardiac computed tomography (CCT) and computed tomography angiography (CTA), AI has automated the coronary artery calcium scoring process with remarkable accuracy in comparison to manual assessments and has been able to quantify coronary plaques and detect coronary stenosis with an accuracy of more than 96% (Myśliwiec et al., 2026). In addition, by analyzing CCT images, radiomics can enhance the characterization of tissue and plaque phenotyping, which will also assist in more accurate cardiovascular risk stratification. The Dice similarity score for FCN, especially U-Net-based architecture in cardiac magnetic resonance imaging (CMR), is in the range of 0.88 to 0.95 for the segmentation of ventricles and atria, with EF and volume measurement results in the range of inter-observer variations (Edpuganti et al., 2025). AI can also be used to classify CAD, predict major adverse cardiovascular events (MACE), identify cardiac remodeling, and characterize myocardial scar and edema, and radiomics can help distinguish acute from chronic myocardial infarction and predict microvascular obstruction in the CMR. Moreover, AI-driven DL algorithms facilitate myocardial perfusion evaluation and disease prognosis in nuclear imaging and SPECT, increasing the scope of AI in full cardiac diagnostics (Haupt et al., 2025; Marey et al., 2025).

In addition to modality-specific applications, AI has transformed the field of CDVI, enabling automated image analysis, diagnosing diseases, assessing function, and more. Image segmentation via DL algorithms allows highly reproducible delineation of cardiac structures in a fast and reproducible manner and minimizes observer variability, which is crucial for a large number of quantitative analyses (Jiménez-Jara et al., 2025). AI systems can precisely diagnose the disease, describe the disease's atherosclerotic plaque, and calculate the burden of CA calcium, thereby gaining more accuracy in diagnosis, risk stratification, etc. Advanced radiomics approaches have the potential to further improve cardiovascular assessment by quantifying subtle imaging features that are linked to plaque vulnerability, tissue composition, and adverse clinical outcomes (Jiang et al., 2020). Furthermore, AI-driven functional analysis automatically determines important cardiac parameters such as ventricular volumes, ejection fraction, and myocardial strain, aiding in effective patient monitoring and the assessment of treatment efficacy. These functions not only enhance the efficiency of workflow and help achieve the uniformity of diagnosis but also facilitate more individualized and data-driven cardiovascular treatment.

Imaging Modality	**AI Application**	**Clinical Benefit**	References
Echocardiography	View classification, EF calculation	Faster diagnosis	(Moradi et al., 2024)
CT/CTA	Calcium scoring, plaque analysis	CAD detection	(Myśliwiec et al., 2026)

Cardiac MRI	Chamber segmentation, scar detection	Accurate prognosis	(Papetti et al., 2023)
PET/SPECT	Perfusion analysis	Ischemia detection	(Haupt et al., 2025; Marey et al., 2025)
ECG Imaging	Arrhythmia classification	Early diagnosis	(Pokharel et al., 2024)

Molecular and Genomic Data in Cardiovascular AI:

The integration of AI and multi-omics technologies in CVD research is a rapidly developing process that brings together genomic, transcriptomic, proteomic, and epigenetic data to help understand disease mechanisms and enhance the prediction of disease risk (DeGroat et al., 2024). Single-nucleotide polymorphisms (SNPs) and gene expression profiles from RNA sequencing have been used in genomic studies to identify variants and transcriptomic signatures associated with CVDs, as well as molecular pathways that play a major role in the development of HF, atrial fibrillation (AF), hypertrophic cardiomyopathy (HCM), and atherosclerotic cardiovascular disease (ASCVD) (Mitsis et al., 2025). Proteomic analysis is also used to aid in cardiovascular risk assessment: Identification of protein biomarkers and development of proteomic risk scores, which have the potential of providing further prognostic information beyond current clinical risk models for CAD, AF, HF, and cardiovascular mortality (Nordestgaard et al., 2025). Epigenetic studies have shown that epigenetic changes in DNA methylation of genes in the lipid metabolism and inflammatory pathway are closely linked to atherosclerosis progression and long-term coronary risk. In addition, multi-omics studies of cardiac fibrosis have uncovered intricate relationships among genetic, epigenetic, transcriptomic, proteomic, and metabolic pathways and identified novel disease pathways and cell-type–specific targets for therapy that could facilitate the advancement of precision cardiovascular care (Singh et al., 2024).

Precision cardiovascular medicine has seen a growing role for AI and ML, including the ability to identify genetic risk factors, integrate multi-omics, and personalize therapeutic strategies. Small numbers of highly predictive features have been identified by AI analysis of single-nucleotide polymorphism (SNP) and transcriptomic datasets that can classify CVD with an accuracy of close to 96–100% and have identified biomarkers such as RPL36AP37 and HBA1 (DeGroat et al., 2024). Large-scale, genome-wide association studies (GWAS) have also led to the development of polygenic risk scores (PRS) that further improve risk prediction for ASCVD and other CVDs. CardiOmicScore is a deep learning method that combines proteomic and metabolomic data to better predict disease than traditional clinical models and to uncover molecular targets for the disease (Wang et al., 2023). Likewise, network medicine was applied to integrate transcriptomic data with protein–protein interaction networks to identify disease mechanisms unique to patients with a hypertrophic cardiomyopathy (HCM) diagnosis, such as fibrosis pathways, to support molecular disease subtyping and therefore improvement of the understanding of disease heterogeneity. The advancements highlight the significance of AI in the analysis of high-dimensional multi-omics data and its ability to uncover intricate biological connections involved in CVDs (Johansson et al., 2023; Luo et al., 2026).

AI's capabilities in multi-omics data integration are also fueling the advancement of personalized cardiovascular medicine, which can be used to predict individual CD risks, patient prognosis, and optimal treatment. A combination of genomic, transcriptomic, proteomic, metabolomic, and interactome data from deep phenotyping approaches can lead to the identification of novel phenotypes of the disease, new therapeutic targets, and rational polypharmacy approaches for diseases like ASCVD, HF, AF, and HCM (Ogunjobi et al., 2026). The use of genetic testing in pharmacogenomics has been shown to increase the efficacy of medications, reduce adverse effects, and improve the cost-effectiveness of drugs in certain populations of patients, with several examples existing, such as CYP2C19–clopidogrel, CYP2C9/VKORC1–warfarin, and

SLCO1B1–simvastatin (Usova et al., 2021). A wide range of genetic variants have been identified to affect response to antiplatelet agents, anticoagulants, statins, beta-blockers, and HF therapies, but their clinical uptake is still limited due to gaps in knowledge and practical issues (Magavern et al., 2022). The potential for future pharmacogenomic-integrated, AI-driven frameworks, leveraging imaging and other 'omics' data, to deliver greater insights into drug-response biology and offer truly personalized treatment approaches—especially for those who must take multiple medications for CVDs—is exciting (Lin et al., 2025).

Clinical Applications:

AI is being used across all aspects of the CVD care pathway, including early diagnosis, risk stratification, prognosis, and long-term monitoring. In the diagnosis of CAD, the ML and DL algorithms, using information from the CCTA, calcium scoring, cardiac magnetic resonance imaging (CMR), clinical records, and laboratory parameters, can accurately identify CAD and determine the risk of the patient, thereby saving the need for invasive diagnostic procedures (Ogunpola et al., 2024). AI models based on CMR have been shown to have excellent diagnostic accuracy in both the identification of CAD patients and the prediction of major adverse cardiovascular events (MACE), arrhythmias, and post-infarction cardiac remodeling (Ghaffari Jolfayi et al., 2025). In various CVD indications such as CAD, HF, stroke, and arrhythmia, the accuracy of these advanced ML algorithms is high, with the area under the curve (AUC) values typically being in the range of 0.88–0.93 across the different indications (Baghdadi et al., 2023). AI has also demonstrated great potential in the fields of HF prognosis and arrhythmia detection. Deep CNNs can be used to detect LV dysfunction and HF even when the ECGs are not clinically abnormal, thereby enabling timely detection and treatment (Mostafa et al., 2025). Furthermore, there are several models based on CNN that have been used to classify different CVDs using ECG and phonocardiogram (PCG) data, which have been successfully used. Wearable-device-based AI systems have a great diagnostic performance for AF, with a pooled diagnostic performance that reaches 95% sensitivity and 97% specificity, whereas for some other types of ML, such as DL, results are generally better than traditional ML (Neri et al., 2023).

AI is also revolutionizing the management of acute myocardial infarction (AMI) and helping to provide continuous cardiovascular monitoring via wearable and digital health technologies (Gupta et al., 2025). In ECG analysis, DL algorithms can quickly differentiate MI from other CVDs such as CAD and CHF, with high diagnostic accuracy, including up to 98.5% in some studies (Rana et al., 2025). In addition to diagnosis, AI-powered monitoring systems have become more and more effective in forecasting cardiovascular events, hospital emergency room readmission, and surgical interventions (Wu & Guo 2025). Wearable sensors that can capture electrocardiographic, photoplethysmographic (PPG), and mechanocardiographic signals enable real-time patient monitoring in the outside environment (Castaneda et al., 2018). The new digital cardiovascular twins rely on integrated data from wearable devices, laboratory tests, imaging, and genetic testing, plus complex deep learning, graph-based, and transformer models to detect ischemia, arrhythmias, and other cardiovascular abnormalities weeks in advance of symptoms, allowing for proactive and personalized care (Galli et al., 2022). While the use of wearable technology for predicting myocardial infarction and cardiac arrest is not as well established as for the detection of atrial fibrillation, the present results suggest the increasing feasibility of using AI-enabled continuous monitoring to enhance cardiovascular outcomes and post-operative patient management (Kaisti et al., 2019).

Figure: Clinical Application of AI in CVDs:

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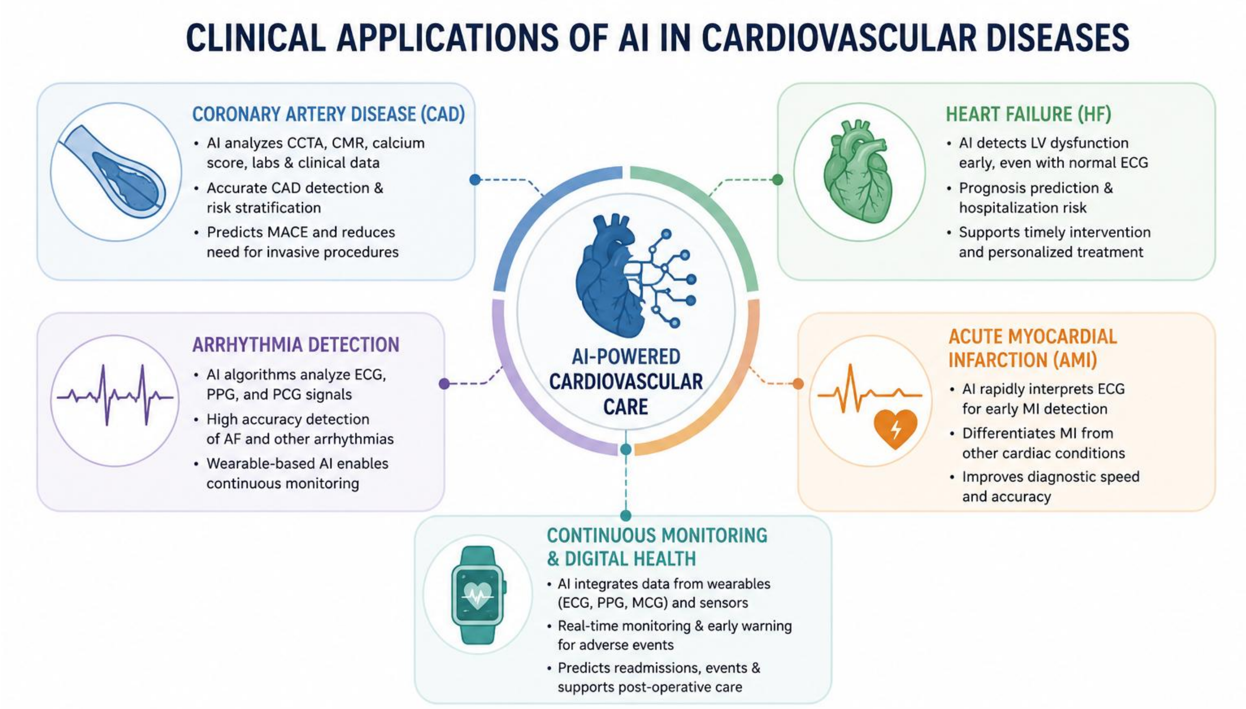

AI combines clinical, imaging, and physiological information to aid diagnosis, risk stratification, and management of CVD. AI tools enhance the identification of cardiovascular conditions such as CAD, HF, arrhythmias, and AMI and allow for long-term patient monitoring for tailored cardiovascular care.

Future Prospective:

Going forward, the goal of AI in the field of CVD diagnostics will be to develop patient-centric, transparent, and clinically relevant diagnostic tools that can integrate multiple sources of patient data. The constant work to develop explainable AI models will earn the trust of clinicians by explaining the decision-making process for diagnosis. Completely virtual cardiac patient models, created from patient imaging, laboratory data, genomic information, and data from wearable devices, may enable us to simulate the course of the disease and personalize therapeutic approaches in a simulated, individualized way. Federated learning will aid in creating accurate AI models without compromising patient privacy. Combined use of multi-omics platforms and AI will be transformative in precision cardiovascular medicine, allowing for the discovery of new disease biomarkers and pathways and the ability to predict the individual response to therapies. The future of cardiovascular drug therapy lies in personalization, which can be achieved by pharmacogenomics-informed AI systems. Close observation of the patient will be possible due to the use of wearable technology and remotely monitored physiological signals. Creating effective and affordable AI tools that can be used in low-resource areas is key to reducing global cardiovascular health disparities. Increasing amounts of validation studies and improving regulatory mechanisms will eventually make AI a standard diagnostic and clinical tool in cardiovascular practice.

Conclusion:

The combined utilizations of lab biomarkers, multi-modal CDVI, and molecular and genomics information in diagnoses and risk assessment and management of CVDs represent a paradigm shift. AI tools from supervised and unsupervised ML, DL, and the integration of multi-omics data have been proven to possess a greater diagnostic and prognostic capability over classical clinical models across a diverse spectrum of CVD conditions like CAD, HF, arrhythmia, and acute MI. Multi-omics data of biochemical, imaging, and molecular information to construct the comprehensive AI framework could lead to novel CVD phenotypes and enable the detection of earlier preclinical diseases and the identification of future risks. Cardiovascular monitoring through AI and wearable devices simultaneously is providing effective CVD care and monitoring outside the hospital and assuring risk assessment and personalized disease management.

Despite the vast promise, a lot of challenges remain to be addressed. The clinical utility of AI for CVD can only be achieved through a coordinated approach to deal with challenges of data heterogeneity and lack of standardization, insufficient prospective validation, the "black-box" nature of algorithms, and inequitable accessibility. Finding a responsible path to the broad clinical use of AI in cardiovascular disease relies upon a concerted effort through collaborative efforts of cardiologists, data scientists, molecular biologists, bioethicists, and regulators, and substantial investment into a multitude of comprehensive and representative training sets. As many of these barriers continue to fall away, AI will become the standard in cardiovascular personalized medicine, altering early diagnosis, optimizing the treatment strategy, and ultimately reducing the overwhelming global burden of CVDs.

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