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The Application of Artificial Intelligence in the Field of Cardiovascular Diseases Focuses on Both Diagnostic and Therapeutic Aspects

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Abstract

In the field of medicine, advanced computer algorithms use artificial intelligence (AI) to retrieve information from large databases. AI has the potential to accelerate the identification and management of cardiovascular diseases (CVDs), including conditions such as heart failure, atrial fibrillation, valvular heart disease, hypertrophic cardiomyopathy, congenital heart disease, and several others. From a clinical perspective, AI improves CVD diagnosis, increases the usefulness of auxiliary tools, aids in stratifying and identifying different types of diseases, and enables accurate outcome prediction. We anticipate that state-of-the-art AI algorithms, designed to extract minute connections from extensive healthcare data, will address more challenging tasks compared to earlier methods. The goal of this review is to emphasize the current uses of AI in CVDs, thereby equipping doctors with little knowledge of computer science to gain a deeper understanding and effectively use AI algorithms in clinical practice.

Key words: *Advanced computer algorithms, Artificial intelligence, Cardiovascular diseases*

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Introduction

Artificial intelligence (AI) simulates human cognitive processes in machines, notably computers. There are three processes: learning, reasoning, and self-correction. AI draws on cardiology, psychology, linguistics, philosophy, neurology, and more. AI enables systems to learn from their experiences without requiring programming. The system incorporates decision trees, neural networks, and clustering methods. These systems advise and solve issues using rules and knowledge systems. This machine learning method involves an agent learning to make choices via environmental interaction. The agent gets incentives or punishments to achieve the desired results (1, 2).

Clinicians can use AI-processed echocardiograms (ECGs) to diagnose heart failure (HF), atrial fibrillation (AF), anemia, hypertrophic cardiomyopathy (HCMP), and pulmonary hypertension (PH). Validated and proven algorithms may minimize doctors' cognitive strain by providing pre-diagnosis, rectifying mistakes, and avoiding misdiagnosis (3-10). AI uses machine learning to uncover minute correlations in data, thereby removing the necessity for human encoding. Subtle findings may transform human illness prediction, diagnosis, prognosis, and recovery (11). Unsupervised learning classifies samples using data analysis for a large number of samples without category information, such as clustering and association rule-learning algorithms (12). Reinforcement learning combines supervised and unsupervised learning, enabling failures and trials to improve algorithm accuracy (13).

Deep learning (DL), artificial neural networks (ANN), and support vector machines (SVM) are the most often used algorithms in medicine (14). ANNs are better at ECG analysis (15), whereas SVMs improve illness stratification (16). Over-ftting, under-ftting, and misspecification prevented ANNs and SVMs from disposing of all situations equally (17). Cardiovascular medicine uses CNNs, RNNs, and DNNs for deep learning analysis of visual data (18). Despite their pros and cons, these algorithms diagnose, forecast, and stratify cardiovascular illnesses successfully. This review provides a concise overview of the uses of AI in cardiovascular diseases (CVDs) from the perspective of clinicians, aiming to improve their understanding and utilization of these technologies.

AI-aided CVD diagnosis

AI-aided CVD diagnosis is used to identify, diagnose, and treat CVDs. AI can improve CVD diagnosis and treatment accuracy, efficiency, and accessibility, revolutionizing healthcare. AI systems may use data on patient demographics, medical history, and biomarkers to predict CVD risk. The prediction algorithms may identify high-risk individuals who may benefit from early intervention and prevention. AI-powered computerized tomography (CT), magnetic resonance imaging (MRI), and echocardiography may help interpret cardiac pictures. Deep learning algorithms can identify minor irregularities, assess disease severity, and provide diagnostic insights from medical pictures for more accurate and rapid diagnosis. AI systems can analyze symptoms, lab tests, and medical history to help physicians diagnose and treat patients (19-24).

Decision-support technologies may provide evidence-based recommendations, identify mistakes, and propose patient-specific treatment strategies. Wearable gadgets and mobile health apps with AI can track heart rate (HR), blood pressure (BP), and activity outside of clinical settings. Remote monitoring technologies may identify CV irregularities early, enable real-time therapies, and promote patient participation in disease care. AI algorithms can analyze genomes, proteomics, and molecular pathways to find new drug targets, optimize therapeutic candidates, and speed up CV drug development. AI may help researchers create new CVD medicines faster. AI-based predictive modelling may use several patient data sources to provide personalised risk profiles and therapy recommendations. Precision medicine tactics improve patient outcomes and reduce side effects (25, 26).

Valvular heart disease (VHD)

AI-aided VHD diagnostics uses AI to identify, diagnose, and treat VHD. To discover and quantify heart valve shape and function issues, AI systems may assess echocardiograms, cardiac MRIs, and CT images. These algorithms are capable of quantifying valve characteristics, checking valve shape and motion, and diagnosing valve stenosis or regurgitation. By automating image processing, AI can help physicians analyze complicated cardiac pictures and make accurate diagnoses. AI models may use clinical data, imaging results, and other characteristics to segment VHD patients by risk of disease progression, complications, or bad outcomes. AI-driven risk stratification technologies help refine patient care and clinical decision-making by identifying high-risk patients who may benefit from early intervention or closer monitoring (27, 28).

AI-powered decision support systems, which use patient-specific data such as clinical history, symptoms, imaging findings, and laboratory tests, may provide evidence-based CVD therapy recommendations. Depending on patient features and illness severity, these decision-support tools may help doctors choose drug therapy, valve repair, or valve replacement. In real time, AI-enabled remote monitoring devices and mobile health apps may measure VHD signs, including heart rate, rhythm, and BP. Remote monitoring technologies may help delay VHD by monitoring patients' CV conditions and alerting doctors to major changes or worsening symptoms. AI algorithms can analyze massive databases of patient outcomes, treatment responses, and clinical characteristics to create customised VHD treatment regimens. AI-driven treatment planning considers age, comorbidities, illness severity, and patient preferences. Modern computer programmes that can look at large amounts of complicated medical data, help with early detection and risk stratification, back up doctors' decisions, and make treatment plans more specific for each patient could make CV care better (29, 30).

Atrial fibrillation (AF)

AI detects, diagnoses, and treats AF, a common heart arrhythmia. Palpitations, shortness of breath, and exhaustion are caused by irregular and fast heartbeats in the atria in AF. AI systems that use ECG records can reliably detect AF. Even with modest or intermittent arrhythmia, deep learning algorithms trained on huge ECG datasets may recognise AF patterns. AI-powered ECG interpretation tools may help doctors identify and treat AF during regular checkups. AI-enabled smartwatches and fitness trackers may identify AF outside of clinical settings by monitoring HR and rhythm. These devices detect AF episodes using algorithms to analyze HR variability (HRV) and rhythm anomalies. AF management and results may be improved by AI-driven wearable technology's remote monitoring and early diagnosis (31,32).

Demographics, medical history, and comorbidities may be used by AI models to predict AF and its consequences, such as stroke or HF. AI-driven risk prediction techniques may improve AF management and tailored therapy by identifying high-risk patients who may benefit from preventative treatments or closer monitoring. ECG results, symptoms, medication history, and comorbidities may be used by AI algorithms to improve AF therapy. Decision support systems may help doctors choose antiarrhythmics and anticoagulants and weigh the risks and advantages of rhythm vs. rate management. AI-driven therapy optimisation systems that incorporate patient preferences may enhance the results and quality of life of AF patients (33, 34).

AI systems may combine ECG, imaging, laboratory, and electronic health record data to enhance AF clinical decision-making. These systems may analyze and synthesise diverse data sources to deliver actionable insights, aid healthcare provider care coordination, and aid patient decision-making. Healthcare teams may customize and improve AF treatment using AI-driven clinical decision assistance (35).

Coronary artery disease (CAD)

We use AI to identify, diagnose, risk-evaluate, and treat CAD. Plaque narrows or blocks heart muscle blood channels, reducing blood flow and oxygen delivery. To forecast CAD risk, AI systems may examine vast datasets, including demographics, medical history, lifestyle variables, and biomarkers. By identifying high-risk people who may benefit from preventative treatments or lifestyle changes, AI-driven risk prediction models may prioritize resources and enhance outcomes. CTA and MRI, which use AI, can detect and characterize plaque buildup, coronary artery stenosis (narrowing), and cardiac function. Medical image analysis using deep learning algorithms may uncover minor anomalies, assess illness severity, and give diagnostic insights for a more accurate and fast diagnosis (36, 37).

AI algorithms can identify ischemia and other cardiac irregularities caused by CAD in ECG records. Artificial intelligence-driven ECG interpretation systems may assist doctors in identifying CAD patients and guiding diagnostic and therapeutic strategies by automatically evaluating ECG readings and indicating problematic outcomes for further assessment. AI systems can combine clinical data, imaging results, laboratory tests, and other factors to provide evidence-based CAD care recommendations. Based on patient features and disease severity, these decision-support systems may assist doctors in choosing drug therapy, percutaneous coronary intervention (PCI), or coronary artery bypass grafting (CABG). Remote monitoring devices and mobile health apps can check blood pressure, HR, and physical activity in real time outside of clinical settings using AI (38, 39).

Remote monitoring technologies may help avoid CAD problems by continually monitoring patients and notifying healthcare practitioners of major changes or worsening symptoms. AI algorithms may assess clinical history, genetic data, and therapy responses to create customized treatment recommendations. AI-driven treatment planning technologies improve therapeutic options and patient outcomes by incorporating age, comorbidities, illness severity, and patient preferences (35).

HF

We use AI to identify, forecast, risk-evaluate, and treat heart failure (HF). To forecast HF or bad outcomes like hospitalisation or death, AI systems may examine massive datasets of demographic data, medical history, laboratory results, imaging findings, and other factors.

Artificial intelligence-driven risk prediction models have the potential to improve patient care and outcomes by identifying high-risk people who may benefit from preventative measures or closer monitoring. AI-enabled wearable devices and mobile health apps can monitor HR, rhythm, breathing rate, and activity levels to identify HF decompensation and aggravation. Remote monitoring technologies may help avoid hospital readmissions by assessing symptom intensity and notifying patients and healthcare professionals when HF symptoms are deteriorating (3, 5).

HF patients may benefit from AI-powered echocardiography, cardiac MRI, and nuclear imaging to examine cardiac anatomy and function. To improve HF diagnosis and risk stratification, deep learning algorithms can analyze medical pictures to detect cardiac anomalies, measure ventricular size and function, evaluate valve function, and forecast outcomes. AI algorithms may analyze N-terminus pro-B-type natriuretic peptide (NT-proBNP), cardiac troponins, and inflammatory markers to diagnose disease severity, track therapy response, and predict clinical outcomes in HF patients. AI-driven prediction models may monitor disease development and guide treatment by merging biomarker readings with clinical and imaging data (20).

AI algorithms can enhance HF therapy by analyzing patient-specific data such as symptoms, test findings, medication history, and comorbidities. Depending on the patient's condition and how bad the illness is, clinical decision support technologies may help doctors choose which drugs, device-based interventions (like cardiac resynchronization therapy (CRT) or implanted cardioverter-defibrillators (ICD)), and lifestyle changes to make. AI algorithms can customize HF therapy strategies based on patient data. AI-driven care planning systems may improve patient outcomes and quality of life by addressing each HF patient's individual requirements and problems, taking into account age, comorbidities, disease severity, treatment choices, and socioeconomic position (40).

CM

We use AI to identify, classify, risk-evaluate, and treat CM, a diverse set of cardiac muscle illnesses. AI-powered imaging modalities, including echocardiography, cardiac MRI, and nuclear imaging, may help evaluate heart anatomy and function in CM patients. Deep learning algorithms can look at medical images and find patterns of myocardial dysfunction, measure ventricular size and function, check myocardial perfusion and viability, and guess how CM will turn out. This makes diagnosis and risk stratification better. Based on the results of DNA sequencing, AI systems can look for genetic variations that are connected to inherited CMs like hypertrophic, dilated, and arrhythmogenic CM. AI-driven prediction models may help genetic CM patients make tailored treatment choices, interpret genetic testing and counseling, and understand disease pathophysiology by combining genetic, clinical, and imaging data (23, 41). By looking at biomarker data like NT-proBNP, cardiac troponins, and inflammatory markers, AI algorithms may be able to figure out how bad a patient's CM is, how well their treatment is working, and what their clinical outcomes will be. Biomarker measures combined with clinical and imaging data may help AI-driven prediction models forecast disease progression and guide treatment. In ECG records, AI algorithms may identify CM symptoms such as ventricular enlargement, conduction problems, and arrhythmias. AI-driven ECG interpretation technologies may help doctors discover CM patients and improve diagnosis and therapy by automatically evaluating ECG readings and reporting bad outcomes. AI algorithms can enhance CM therapy choices by analyzing patient-specific data such as symptoms, test findings, medication history, and comorbidities. Based on patient characteristics and disease severity, these decision support systems may assist doctors in choosing pharmaceutical medications, device-based interventions, and lifestyle changes (42, 43).

Congenital heart disease (CHD)

CHD is the most common congenital disability, causing considerable postnatal mortality (44). Pregnancy restricts the detection of CHD due to a shortage of skilled sonographers or missing imaging frames (45). Clinicians cannot detect abnormal image frames, whereas trained AI-ECG models can (43). To distinguish normal hearts from CHD, Arnaout et al. (43) trained a neural network on over 100,000 echocardiographic and screening ultrasound images from 18 to 24 weeks. It distinguished normal from diseased hearts in the internal test set, with an AUC of 0.99 and a 100% negative predictive value. Even on lower-quality fetal images taken outside of hospitals, the DL-based screening ultrasonography model efficiently identifies CHD. AI models may help clinicians make decisions (5, 23, 42). AI technology is becoming more widespread, so AI-based models may screen for and improve early disease identification and treatment in settings with limited equipment (6, 23, 25).

AI-aided CVD stratifcation and typing

AI-aided CVD classification and typing accurately labels and rates cardiovascular conditions in individuals. Modern computer algorithms analyse medical history, clinical testing, imaging examinations, genetic data, and lifestyle variables. AI systems may use varied data sources to classify people by CVD risk. AI-driven risk stratification models may find high-risk patients who could benefit from preventative measures or closer monitoring by looking at their demographics, medical history, biomarkers, and other factors. This can help make the best use of resources and improve outcomes. AI can categorize CVD subgroups by aetiology, pathophysiology, and clinical symptoms (46, 47).

Using clinical data and imaging investigations, AI systems can distinguish HCMP and DCMP cardiomyopathy or CAD phenotypes. AI-driven typing algorithms enhance illness categorization and therapy techniques. Using longitudinal patient data, AI models may predict CVD development and outcomes. Using patient characteristics, treatment responses, and disease trajectories, these predictive models may predict disease progression, adverse events (e.g., myocardial infarction (MI), stroke), and death. By identifying high-risk patients, AI-driven predictive modeling may support tailored therapies and clinical decision-making. AI can predict cardiovascular disease therapy responses using patient-specific data (48-50).

AI-driven prediction models can estimate therapeutic efficacy, adverse effects, and treatment failure by looking at genetic variability, biomarker profiles, comorbidities, and treatment history. This lets clinicians make treatment plans that do the most good and the least harm. By incorporating patient-specific data, AI may create personalised CVD treatment programmes and risk reduction measures. Artificial intelligence-driven personalised medicine may maximize therapeutic choices, treatment adherence, and patient outcomes by incorporating genetic, clinical, and lifestyle aspects (51-53).

AI-aided CVD outcome prediction

AI helps predict the evolution and prognosis of CVDs in people. Modern computer algorithms analyze medical history, clinical testing, imaging examinations, genetic data, and lifestyle variables. AI can classify people at risk for CV events, including MI, strokes, and cardiac death. By assessing demographics, medical history, biomarkers, and other data, AI-driven risk stratification models may identify high-risk patients and lead customized therapies to minimize risk factors and enhance outcomes. AI models can anticipate CVD development. Data from large patient cohorts may help AI-driven disease progression models predict illness exacerbations, comorbidities, and functional decline (54-59).

Clinicians may use these predictive models to forecast disease trajectories, adapt therapy, and improve patient care to avoid poor consequences. AI algorithms may anticipate varied CVD therapy responses.

Prediction models that are run by AI look at genetic differences, biomarker profiles, comorbidities, and treatment history to figure out how well drugs work, what side effects they have, and whether a treatment failed. To enhance therapeutic benefit and avoid damage, these prediction models provide individualised therapy selection, dosage adjustment, and monitoring. In individual individuals, AI models may be able to predict MI, stroke, and HF aggravation. By combining clinical, imaging, and biomarker data, AI-driven event prediction models may be able to find people who are more likely to have bad outcomes and help them receive more targeted treatments. Early identification of high-risk patients allows for appropriate pharmaceutical, lifestyle, and procedural treatments to reduce adverse events and improve patient outcomes (60-63).

Limitations

Several challenges must be resolved before AI may be employed in supplementary diagnosis:

(1) Humans cannot comprehend AI network intermediate layers, requiring further research to improve user trust in AI tools (6, 23, 26).

(2) To confirm the reliability of these models on a larger scale and with more patients, more research is required (23, 26, 29).

(3) Further research is required to assess AI technology's cost-effectiveness in auxiliary diagnostics and clinical impact (5). The main topic points of recent studies are shown in Table 1.

Conclusion

Medical professionals use AI to extract data from large databases using sophisticated computer algorithms. AI may speed up the detection and treatment of CVDs, including HF, AF, VHD, HCMP, CHD, and others. Clinically, AI improves CVD diagnosis, auxiliary tool effectiveness, disease stratification and type, and outcome prediction. We predict that recent AI algorithms, designed to capture tiny correlations from large healthcare data, will tackle more challenging tasks than previous approaches. This study aims to highlight current AI applications in CVDs, enabling physicians with modest computer science backgrounds to better comprehend and use AI algorithms in clinical practice.

Table 1. The main topic points of recent studies.

Reference no.	Authors	Subjects	Main theme
Ref [1]	Xu et al.	gastric cancer	The agent gets incentives or punishments to achieve the desired results.
Ref [2]	Montull et al.	sports monitoring	The machine learning method involves an agent learning to make choices via environmental interaction.
Ref [4]	Attia et al.	left ventricular dysfunction in COVID-19	AI ECG has been demonstrated to identify ventricular dysfunction in a broad general population, which may be beneficial for COVID-19 screening.
Ref [5]	Yao et al.	patients with low ejection fraction	In primary care, an AI system based on ECGs may detect poor EF early.
Ref [7]	Kwon et al.	anaemia patients	Anaemia was discovered by a DLA utilising raw ECG data. ECGs with AI might check for anaemia.
Ref [8]	Ko et al.	hypertrophic cardiomyopathy	AI-based ECG-based HCM detection is effective, especially in younger patients.
Ref [9]	Kwon et al.	pulmonary hypertension	Using 12-lead and single-lead ECGs, the AI programme predicted PH accurately.
Ref [10]	Cho et al.	human-computer interaction	This simple and systematic heuristic assessment technique may be utilised at different phases of system development to decrease the time and expense of proving a system's usefulness before wider adoption.
Ref [11]	Emile et al.	COVID-19	Machine learning is used in AI to identify tiny correlations in data, eliminating the need for human encoding.
Ref [12]	Zhu et al.	biomedical computation	Unsupervised learning classifies samples using data analysis for a large number of samples without category information, such as clustering and association rule-learning algorithms.
Ref [13]	Yadav et al.	a case study of India	Reinforcement learning combines supervised and unsupervised learning, enabling failures and trials to improve algorithm accuracy.
Ref [14]	Kahr et al.	machine learning with synthetically generated data	Deep learning (DL), artificial neural networks (ANN), and support vector machines (SVM) are the most often used algorithms in medicine.
Ref [15]	Muller et al.	neuromorphic hardware	ANNs are better at ECG analysis.
Ref [16]	Yadav et al.	complex disease biology	SVMs improve illness stratification.
Ref [17]	De Mattos et al.	extreme learning machine	Over-ftting, under-ftting, and misspecification prevented ANNs and SVMs from disposing of all situations equally.
Ref [20]	Vaid et al.	right and left ventricular dysfunction	ECG-DL can build cheap screening, diagnostic, and prognostic tools for LV and RV dysfunction.

Ref [23]	Shrivastava et al.	patients with dilated cardiomyopathy	High sensitivity and negative predictive value for DC identification made AI-ECG a simple and cost-effective screening technique for first-degree relatives of DC patients.
Ref [24]	Elias et al.	left-sided valvular heart disease	Deep learning ECG analysis can correctly identify AS, AR, and MR in this multicenter population, which might fuel a valvular heart disease screening programme.
Ref [25]	Siontis et al.	cardiovascular disease management	Decision-support technologies may provide evidence-based recommendations, identify mistakes, and propose patient-specific treatment strategies.
Ref [26]	Attia et al.	Electrocardiograms	AI algorithms can analyse genomes, proteomics, and molecular pathways to find new drug targets, optimise therapeutic candidates, and speed up CV drug development.
Ref [29]	Kwon et al.	aortic stenosis	AI-powered decision support systems may provide evidence-based CVD therapy recommendations.
Ref [30]	Cohen-Shelly et al.	aortic stenosis	AI algorithms can analyze massive databases of patient outcomes, treatment responses, and clinical characteristics to create customized VHD treatment regimens.
Ref [32]	Davidson et al.	atrial fibrillation	AI is used to detect, diagnose, and treat AF, a common heart arrhythmia.
Ref [33]	Khurshid et al.	atrial fbrillation	AI models may predict AF and its consequences, such as stroke or HF, using demographics, medical history, and comorbidities.
Ref [34]	Noseworthy et al.	atrial fibrillation	AI-driven risk prediction techniques may improve AF management and tailored therapy by identifying high-risk patients who may benefit from preventative treatments or closer monitoring.
Ref [35]	Sun et al.	cardiovascular diseases	AI systems may combine ECG, imaging, laboratory, and electronic health record data to enhance AF clinical decision-making.
Ref [38]	Lin et al.	coronary artery disease	AI algorithms can identify ischemia and other cardiac irregularities in ECG records caused by CAD.
Ref [39]	Yan et al.	atrial fibrillation	AI systems may combine clinical data, imaging results, laboratory tests, and other factors to provide evidence-based CAD care recommendations.
Ref [41]	Khursid et al.	left ventricular mass and hypertrophy from 12-lead ECGs	AI-driven prediction models may help genetic CM patients make tailored treatment choices, interpret genetic testing and counselling, and understand disease pathophysiology by combining genetic, clinical, and imaging data.
Ref [43]	Arnaout et al.	complex congenital heart disease	AI algorithms can enhance CM therapy choices by analysing patient-specific data such as symptoms, test findings, medication history, and comorbidities.
Ref [52]	Reel et al.	hypertension subtypes	By considering genetic variability, biomarker profiles, comorbidities, and treatment history, AI-driven prediction models can estimate therapeutic efficacy, adverse effects, and treatment failure,

			allowing clinicians to tailor treatment regimens to maximise benefit and minimise harm.
Ref [57]	De Souza et al.	coronary artery disease	AI-driven risk stratification models may identify high-risk patients and lead customised therapies to minimise risk factors and enhance outcomes by assessing demographics, medical history, biomarkers, and other data.
Ref [58]	Backhaus et al.	acute myocardial infarction	Data from large patient cohorts may help AI-driven disease progression models predict illness exacerbations, comorbidities, and functional decline.
Ref [60]	Min et al.	coronary stent underexpansion	Clinicians may use these predictive models to forecast disease trajectories, adapt therapy, and improve patient care to avoid poor consequences.
Ref [62]	Kilic et al.	aortic valve replacement	AI algorithms may anticipate varied CVD therapy responses.
Ref [63]	Sherman et al.	cardiac surgery	In individual individuals, AI models may be able to predict MI, stroke, and HF aggravation in individuals.

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