



Editorial

Artificial intelligence in cardiology: The past, present and future



1. Introduction

Artificial intelligence (AI) belongs to the discipline of computer science which lays focus on developing programs to allow machines to understand and mimic human behavior and thinking. It often refers to “a machine's ability to generalize learning in order to efficiently achieve complex tasks autonomously”.¹ This broad concept was first proposed in 1956 by John McCarthy and include two major domains viz. machine learning (ML) and deep learning.² ML refers to the specialized domain of AI wherein using complex computing and statistical algorithms, computers analyze datasets in a fast and efficient manner. ML can be divided into three different types based on the manner the predictive algorithms learns and trains itself into analyzing complex datasets. These include (1) supervised learning which is based on analyzing previously human labelled datasets to develop models for future event prediction, (2) unsupervised learning wherein the training dataset has not been previously categorized and the models seeks to determine hidden relations in the dataset and (3) reinforcement learning which is a reward-based system wherein interactions with the system environment leads to generation of either a positive or negative reinforcement.³ Based on the repetitive interactions with positive reinforcements, the AI model learns to perform best in a given environment through trial and error. In recent times, it is actually the deep learning domain of AI which has garnered maximum attention. Deep learning is akin to a human brain and uses neural networks to extract meaningful patterns from complex datasets. Neural networks, akin to the human neuronal circuits, form the core of deep learning and makes it a high-performance recognition-based system.² Convolutional neural network (CNN), the most popular deep learning system, is often considered to be the standard for image recognition and uses feature extraction to build networks responding to visual inputs similar to the visual cortex in humans.²

2. AI in cardiology

Though the concept of AI was first proposed in the 1950s, its application in the healthcare sector has expanded only in the recent times. The utility of AI stems from the fact that it is able to process a significant volume of data and has found its application in cardiology for risk prediction, cardiovascular imaging and electrophysiology.³ AI is going to have a tremendous impact leading to a paradigm shift in the diagnosis and management of CV diseases in the near future (Fig. 1).

3. AI in preventive cardiology

One of the exciting areas where AI has a potential role is in the field of preventive cardiology wherein ML based models can be used for risk stratification. This data-driven approach can identify patients who are at high risk of complications thereby strengthening preventive cardiology. Since ML algorithms can use far larger number of variables, does not require preselection of important variables, and avoids prior assumptions, it is best suited for development of clinical risk prediction models.⁴ ML models can incorporate both traditional as well as nontraditional and unknown risk factors for proper risk stratification. Multiple ML models such as Naïve Bayes, k-nearest neighbors (KNN), decision tree, random forest and XGBoost have been used previously for risk prediction of adverse cardiac events following STEMI.⁵ The recently proposed MERC model among patients with STEMI in low-and-middle income countries had an improved 30-day mortality prediction as compared to traditional logistic regression-based models.⁴

4. AI in diagnostic CV imaging

AI has played a significant role in CV imaging by integrating huge amount of data. AI has a major impact on CV imaging beginning from the right patient selection to identify the patient who would benefit the most to learning various imaging features associated with one particular diagnosis.² Deep learning domain of AI can help in the analysis of echocardiograms, cardiac computed tomograms (CT) and cardiac magnetic resonance imaging (CMR). The current application AI in CV imaging includes identification and segmentation of various cardiac structures, lesion identification and classification of images associated with different conditions.⁶ AI has found its utility in all CV imaging modalities including Echocardiography, Cardiac CT and MRI as well as nuclear imaging. Echocardiography is the most commonly utilized CV imaging modality with both diagnostic and point of care applications. Since acquisition and interpretation of echocardiographic images are highly operator dependent, there occurs considerable variation in quality as well as diagnostic interpretability of the images. This leads to AI playing a significant role in improving diagnostic imaging capabilities of echocardiography.⁷ AI helps in the automated quantification of cardiac chamber dimensions and volumes, detection of regional wall motion abnormalities, valvular abnormalities and strain imaging.^{8,9} Additionally, AI has found significant utility in point of care, echocardiographic diagnostics, especially in developing countries such as India where trained and qualified manpower might not be available. AI based echocardiographic interpretation are more

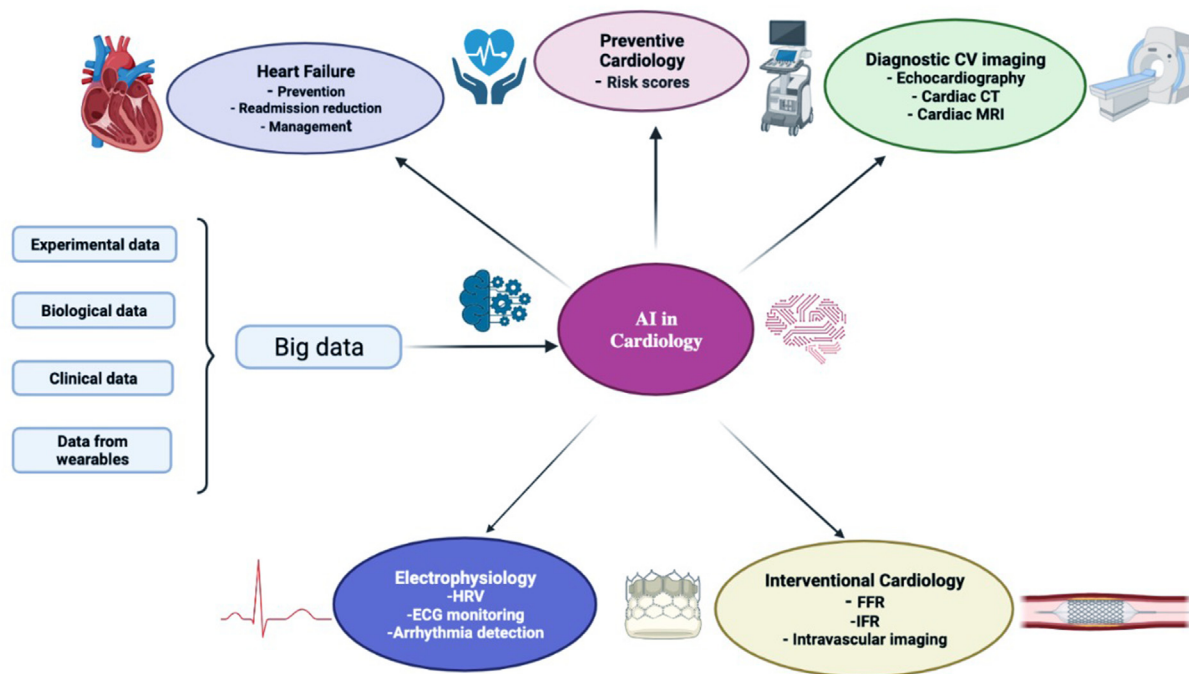


Fig. 1. Diagrammatic representation showing the various applications of Artificial Intelligence in Cardiology.

reproducible with enhanced diagnostic confidence, greater reproducibility and lesser processing time required than the traditional methods.⁶ This has been shown with use of the automated Heart Model A.I. software (Philips, Andover, MA) wherein the total time saved for image acquisition and analysis was 82% versus manual 3D measurements using QLAB.¹⁰ Cardiac CT is often used to determine the location and extent of atheromatous plaques in the coronary vasculature as well as for calcium scoring. AI models using CNN based estimation of Hounsfield units in the coronary vasculature have been used for coronary calcium scoring.¹¹ Lessman and colleagues developed a CNN model for screening and detection of high-risk individuals based on estimation of coronary calcium scores.¹² Recently, a multicentric study developed and validated a deep learning system for CCTA-derived measures of plaque volume and stenosis severity.¹³ Similarly, CNN has also been used for automatic estimation of CT coronary angiography based fractional flow reserve (FFR) with good agreement between ML derived values and those which were invasively measured.¹⁴ In recent times, CMR has emerged as a promising CV imaging modality with a wide variety of clinical application. AI models based on CNN have been used for automated segmentation of cardiac chambers for cardiac volume estimation.¹⁵ Additionally, automated ventricular function assessment based on CNN have shown good correlation with manually obtained left and right ventricular functions.¹⁶ In the field of nuclear imaging, Myocardial perfusion imaging (MPI) using Single-photon emission CT (SPECT) helps in assessment of coronary perfusion and detection of CAD. ML models using deep learning algorithms have been used for risk prediction for CAD based on MPI. ML models have also incorporated clinical and imaging data for better risk prediction following MPI. This allows for better prediction of the risk of CAD, the need for revascularization and development of major adverse cardiovascular events (MACE).^{3,6}

5. AI in electrocardiography

Electrocardiograph, one of the simple non-invasive tests forms the core of cardiovascular practice. Studies have previously shown

that ML models tend to fare better than humans in identifying various ECG based conditions such as long QT and atrial fibrillation.^{17,18} Automated ECG analysis using AI facilitates an early diagnosis of various arrhythmias and ST-segment abnormalities.¹⁹ AI through automated ECG analysis based on ML algorithms would empower primary care physicians as well as non-cardiologists for a confident and prompt decision making regarding the need for specialized cardiac care.³ These ML based ECG algorithms can not only distinguish between a normal and abnormal ECG but can confidently make a diagnosis of AF, VT and MI. Studies using AI for ECG based AF detection have shown good sensitivity (79%) and specificity (79.5%).²⁰ Additionally, AI based models have been used for detection of decreased ejection fraction based on the ECG analyses with a good sensitivity (86.3%) and specificity (85.7%).²¹ Recently, ECG based AI model has also found its application in heart rate variability (HRV) monitoring among COVID-19 recovered patients.²² Furthermore, AI finds a greater deal of application in smart wearable devices such as Apple smartwatch for routine ECG monitoring and arrhythmia detection in the general population.²³

6. AI in heart failure (HF)

HF is a major cardiovascular disorder with significant morbidity and mortality. Early recognition of HF and its prompt treatment remains the cornerstone of HF management strategies. AI plays an important role in both HF prevention, HF readmission reduction, and HF population-based management. Novel ML algorithms have shown a superior predictive ability of future HF events.²⁴ Incorporation of this algorithms in the electronic medical record system can automatically provide risk information to the physician and need for further intervention. AI can be seamlessly integrated into the Clinical Decision Support System (CDSS) which is a health information technology enabling physicians in appropriate clinical decision making. A recent study among patients presenting with dyspnea to the outpatient department reported that Artificial Intelligence based Clinical Decision Support System (AI-CDSS) had a

remarkably high diagnostic accuracy for HF compared to non-HF specialists and similar diagnostic accuracy when compared to HF specialists. AI-CDSS might be helpful for making a diagnosis of HF in these subsets of patients especially in resource limited low- and middle-income countries.²⁵ Additionally, AI based modalities can serve as an inexpensive, non-invasive, point-of-care screening tool for earlier diagnosis of HF. This was evident in the AI-ECG study wherein an AI based algorithm applied to a single-lead ECG recorded during ECG-enabled stethoscope examination reported good diagnostic accuracy for detection of LVEF <40%.²⁶ Apart from identification of at-risk patients, AI based system can also play a part in hospitalization prevention. Traditional statistical models for readmission prediction have marked limitations and ML algorithms tend to better identify those at risk for HF readmission. Additionally, AI based models can identify patients with need for a particular HF therapy such as patients with low LVEF and prolonged QRS duration requiring cardiac resynchronization therapy. AI based models can help in identification of responders and non-responders to CRT therapies as was evident in two recent studies.^{27–29}

7. AI in interventional cardiology

Interventional cardiology of late has been at the forefront of many technological advancements especially in the domains of intravascular imaging, hemodynamics and robotics. AI too has found novel applications in the field of interventional cardiology. The role of AI in clinical decision-making tools have been recently explored with AI based self-learning systems using ML algorithms and pattern recognition tend to mimic the human thought processes. This has been shown in the CEREBRIA-1 (Machine Learning vs Expert Human Opinion to Determine Physiologically Optimized

Coronary Revascularization Strategies) trial³⁰ wherein an ML algorithm based on computational interpretation of instantaneous wave-free ratio (IFR) traces was compared to human interpretation in patients with stable CAD. Findings of the study showed that the ML algorithms were non-inferior to expert consensus opinion in determining both appropriateness for PCI as well as the optimal PCI strategy. Similarly, a recent study using AI based FFR (Autocath FFR) for prediction of hemodynamically significant lesions reported excellent accuracy in prediction of wire based FFR.³¹ Other aspects for application of AI in the catheterization laboratory is in the field of intravascular imaging. ML algorithms have been used for automatic calculation of vascular luminal area and the plaque burden on intravascular ultrasound images.³²

8. The future ahead

The application of AI in Cardiology is still in its infancy with the current technology facing hurdles with respect to clinical validation, implementation as well as regulation. AI is definitely seen as a game-changer especially in the fields of preventive cardiology with better risk stratification. The advantage of AI is that it is constantly learning and improving on existing data thereby creating a positive feedback loop which tends to make the AI based prediction models more and more accurate with increased usage. Improvements in technology in the field of AI would lead to development of digital and computational biomarkers for risk prediction and early targeted interventions for disease prevention or halting the progress of the disease. In future, AI based tools would cut the redundancy in clinical decision making thereby reducing the physician's workload and improve work efficiency. The table summarizes current evidence of application of AI in various fields of Cardiology (Table 1).

Table 1
Summary of the studies involving Artificial Intelligence in cardiology.

| Cardiology Domain | Diagnostic modality/type of data used | Author/ Study name | Study application | Study conclusion |
|-----------------------------|---------------------------------------|--|--|--|
| Preventive Cardiology | MERC model in NORIN-STEMI patients | Shetty et al. ⁴ / NORIN-STEMI | Risk prediction following STEMI | ML models - improved mortality prediction following STEMI compared to traditional logistic regression (Extra Tree ML model best predictive ability -sensitivity: 85%, AUC: 79.7%, and Accuracy: 75%) |
| | Praise score in ACS patients | D'Ascenzo et al. ⁵ | ML model to predict all-cause death, recurrent acute myocardial infarction, and major bleeding after ACS | PRAISE score - accurate discriminative capabilities for prediction of all-cause death, myocardial infarction and major bleeding |
| Diagnostic CV Imaging | Echocardiography | Madani et al. ⁸ | Identification of echocardiographic views | CNN model distinguished between 15 standard echocardiographic views – accuracy: 97.8% |
| | Cardiac CT- CCTA | Zhang et al. ⁹ | Fully automated echocardiogram interpretation and detection of selected clinical condition | CNN model detected multiple clinical conditions (cardiomyopathy, cardiac amyloidosis and PAH - C statistics of 0.93, 0.87 and 0.85, respectively) |
| | Cardiac CT-FFR | Lin A et al. ¹³ | Develop and validate a deep learning system for CCTA-derived measures of plaque volume and stenosis severity | Deep learning system -rapid measurements of plaque volume and stenosis severity from CCTA |
| | CMR | Morais et al. ¹⁴ | Evaluate diagnostic performance of CT-FFR for detection of significant CAD in contrast to invasive FFR | ML-based CT-FFR: good diagnostic performance for detection of CAD |
| Electrocardiography | Arrhythmia classification | Bai et al. ¹⁵ | Segmentation of heart structures, automatic measurement of LV end-diastolic volume and other values | CNN model - able to perform highly accurate automatic measurements and delineation of heart structures |
| | | Wang et al. ¹⁶ | AI Based CMR Assessment of Biventricular Function | Good agreement between automated and expert-derived LVEF |
| | AF detection | Hannun et al. ¹⁹ | Automated arrhythmia classification | Classified 12 different arrhythmias with an average AUC of 0.97 and an F1 score of 0.84, exceeding that of an average cardiologist (0.78) |
| | | Attia ZI et al. ²⁰ | Detection of paroxysmal AF based on 10 s recording of 12-lead ECG taken in sinus rhythm | AI-enabled ECG acquired during normal sinus rhythm permits AF detection |
| Asymptomatic LV dysfunction | | | Detected LV dysfunction- AUC of 0.93 | |

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Table 1 (continued)

| Cardiology Domain | Diagnostic modality/type of data used | Author/ Study name | Study application | Study conclusion |
|---------------------------|---|---|---|--|
| | HRV | Attia et al. ²¹ Shah B et al. ²² | Detection of asymptomatic LV dysfunction from ECG Evaluate an AI model to identify time domain HRV measures in COVID-19 recovered subjects | AI model was able to distinguish between COVID-19 recovered patients and healthy controls based on HRV |
| | AF detection | Perez et al. ²³ | Smartwatch identification of AF | Participants receiving notification of an irregular pulse: 34% had AF on subsequent ECG patch readings and 84% of notifications were concordant with AF |
| Heart Failure | Artificial Intelligence–Clinical Decision Support System for HF diagnosis | Choi et al. ²⁵ | Evaluate the diagnostic accuracy of an AI-CDSS for heart failure | AI-CDSS - high diagnostic accuracy for HF: concordance rate between AI-CDSS and heart failure specialists - 98% |
| | AI algorithm applied to a single-lead ECG recorded during ECG-enabled stethoscope examination | Bachtiger P et al. ²⁶ | Validate a potential point-of-care screening tool (ECG-enabled stethoscope) for LVEF of 40% or lower | AI-ECG-enabled stethoscope can detect LVEF of ≤40% with good accuracy- AUROC: 0.91, sensitivity: 91.9% and specificity: 80.2% |
| | Predicting response to therapy (CRT) | AI-ECG, | Predicting CRT outcomes | Predicted death or HF hospitalization within 12 months - AUC of 0.74 |
| | Novel characterization of HF phenogroups | Kalscheur et al. ²⁷ | Predicting CRT outcomes | Predicted echocardiographic CRT response better than current guidelines (AUC: 0.70 vs. 0.65) - greater discrimination of long-term survival (c-index: 0.61 vs. 0.56) |
| | | Feeny et al. ²⁸ | Heart failure phenogroups in CRT | Four phenogroups identified with significantly different clinical and echocardiographic characteristics - two phenogroups substantially better treatment response to CRT therapy |
| Interventional Cardiology | IFR | Cikes et al. ²⁹ Davies J. ³⁰ CEREBRIA-1 | Comparison of AI with human intelligence for interpretation of IFR pullback data in stable CAD | ML algorithms were non-inferior to expert consensus opinion in determining both appropriateness for PCI as well as optimal PCI strategy |
| | FFR | Rougin A et al. ³¹ | Feasibility of AI based FFR (Autocath FFR) for prediction of hemodynamically significant lesions based on cineangiography images | Autocath FFR has excellent accuracy in prediction of wire based FFR |

Abbreviations: ACS: acute coronary syndrome; AF: atrial fibrillation; AI: artificial intelligence; AI-CDSS: Artificial Intelligence–Clinical Decision Support System; AUC: area under the curve; CAD: coronary artery disease; CNN: convoluted neural network; CMR: cardiac magnetic resonance imaging; CRT: cardiac resynchronization therapy; CV: cardiovascular; CT: computed tomography; CCTA: Coronary computed tomography angiography; ECG: electrocardiogram; FFR: fractional flow reserve; HF: heart failure; HRV: heart rate variability; IFR: instantaneous wave free ratio; LV: left ventricle; LVEF: left ventricular ejection fraction; ML: machine learning; North India ST-Elevation Myocardial Infarction (NORIN-STEMI); STEMI: ST-Elevation Myocardial Infarction.

9. Current limitations of AI

AI with its rapid progress can replicate few qualities of the human brain however, it can never outperform it. Even in the field of diagnostic CV imaging wherein AI has taken giant strides, the reproducibility of AI has not been better than the expert human observation. It must be clearly understood that both AI and ML should act to support and not replace the physician and his clinical skills.³³ ML algorithms can identify patterns based on the huge volume of data and often tends to identify the average characteristics of a patient and often ignores the outliers. However, in medicine every individual case is different and AI might be error prone in these cases especially if they are outliers. AI as a tool in cardiology should act as an aid in decision making and not actually make those decisions.² However, a proper combination of human intelligence and AI can reduce the number of clinical errors. Additionally, no AI algorithm is full proof and can be faulty if the ML algorithm has not been properly trained. It has often been seen that AI algorithms have a higher sensitivity but a poor specificity which increases the risk of overdiagnosis and further evaluation. Another issue which crops up with the use of AI and ML is the legal and ethical concerns when large volumes of data are being processed. There is an especially when huge volumes of data are being evaluated. This calls for greater transparency about the types of data which are being shared and to whom and to clarify the purpose of it being shared.¹ Additionally, there is a need for introduction

of strict regulations such as the General Data Protection Regulation (GDPR) in Europe for proper safety and privacy of the data being shared and accessed.²

AI and its vast spectrum of analytics has found tremendous application in modern medicine especially in the field of Cardiology. AI tends to improve the work efficiency, detect patterns behind an observed data and play a role in predicting future events. In the race between human brains and the machines, it must be kept in mind that AI is just one of the supplementary tools to improve clinical judgment, provide precise diagnosis however, it cannot replace the role of a physician. There is a need for greater awareness among the clinicians regarding the role and the application of AI in modern medicine.

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