Artificial Intelligence in Cardiovascular Imaging

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ABSTRACT: The number of cardiovascular imaging studies is growing exponentially, and so is the need to improve clinical workflow efficiency and avoid missed diagnoses. With the availability and use of large datasets, artificial intelligence (AI) has the potential to improve patient care at every stage of the imaging chain. Current literature indicates that in the short-term, AI has the capacity to reduce human error and save time in the clinical workflow through automated segmentation of cardiac structures. In the future, AI may expand the informational value of diagnostic images based on images alone or a combination of images and clinical variables, thus facilitating disease detection, prognosis, and decision making. This review describes the role of AI, specifically machine learning, in multimodality imaging, including echocardiography, nuclear imaging, computed tomography, and cardiac magnetic resonance, and highlights current uses of AI as well as potential challenges to its widespread implementation.

INTRODUCTION

In its broadest sense, artificial intelligence (AI) refers to the ability of computers to mimic human cognitive function, performing tasks such as learning, problem-solving, and autonomous decision making based on collected data.[1] In medicine and cardiology, the goal of AI is to predict a diagnosis or outcome or select the best treatment.[2] More and more cardiac imaging investigations are being performed each year, significantly increasing overall health care costs.[3] However, imaging studies provide a particularly rich data source that, when combined with clinical information from electronic health records and mobile health devices, can offer abundant opportunities for data-driven discovery and research. Despite the richness of data derived by cardiovascular imaging, traditional statistical approaches often struggle to process and model imaging data in its raw form; this is partly due to the large number and complexity of inputs (or high-dimensional data) that comprise images and videos. Because AI can better handle data with a large number of inputs, it has the potential to advance cardiovascular imaging by facilitating each step of the imaging process, including image acquisition, quantification, analysis, and reporting. Thus, AI improves efficiency while reducing cost.

This review describes the role of AI in cardiovascular imaging, including echocardiography, nuclear imaging, computed tomography (CT), and cardiac magnetic resonance (CMR); outlines current uses of AI such as automation, disease recognition, and prediction; and discusses potential challenges for AI in the future.

TERMINOLOGY AND COMPUTATIONAL APPROACHES

Whereas AI describes the concept of using computers to mimic human cognitive tasks,[1] machine learning (ML) describes the category of algorithms that enable most current applications described as AI.[4] ML algorithms differ in several ways from traditional "rule-based" computer algorithms. First, ML algorithms can "learn" patterns from training data to perform a task of interest without being given specific instructions. Second, many ML algorithms can automatically identify components or groupings from the input data ("features") that are helpful to perform the task. In imaging, input data for ML can range from a matrix of raw pixel values within an image to summary variables derived from that raw image data, such as measurements or clinically generated reports.[5] Generally, the more raw input data and more complex tasks require more complex algorithms and more data. Therefore, building appropriate features to use as inputs into the algorithm may decrease the amount of data and complexity of the model required, presuming the correct a priori assumptions are used to generate the features.

The two general approaches used to train ML algorithms are supervised and unsupervised learning (Table 1).[6-17] In supervised learning, the ML algorithm learns based on training data that has been labeled for the task of interest. Prominent examples of supervised ML algorithms include regression (logistic, ridge, elastic net, and LASSO), support vector machines, tree-based methods (random forests and gradient boosted trees), and convolutional neural networks.[18,19] Deep learning (DL) refers to the use of neural networks that are composed of more than 3 layers, otherwise called deep neural networks.[5] Figure 1 demonstrates how DL can be used for disease detection in cardiovascular imaging, specifically echocardiography.

After a supervised ML algorithm has been trained, it is important to assess how the algorithm performs on unseen data. Typically, a dataset is separated into "training" (ie, for algorithm

TYPE OF MACHINE LEARNING (ML)	DESCRIPTION	COMPUTATIONAL TECHNIQUES	EXAMPLES IN CARDIOVASCULAR IMAGING AND DATA SOURCES
Supervised learning	The data is labeled for the outcome of interest. The ML algorithm learns what features from the data drive prediction of the outcome.	Regression analysis, support vector machines, tree-based methods, neural networks (deep learning)	Madani et al. (echocardiographic data, deep learning)[6] Zhang et al. (echocardiographic data, deep learning)[7] Tabassian et al. (rest and stress echocardiographic data)[8] Narula et al. (echocardiographic data)[9] Sengupta et al. (speckle tracking echocardiographic data)[10] Kusunose et al. (echocardiographic data, deep learning)[11] Samad et al. (echocardiographic data)[14] Kang et al. (cardiac computed tomography)[15] Motwani et al. (cardiac computed tomography)[16] Haro Alonso et al. (myocardial perfusion data)[17]
Unsupervised learning	Key relationships and similarities are identified in a dataset without prior labels or annotations.	Principal component analysis, cluster analysis	Shah et al. (echocardiographic data)[12] Lancaster et al. (echocardiographic data)[13]

Table 1.
Types of machine learning and examples in cardiovascular imaging.[6-17]

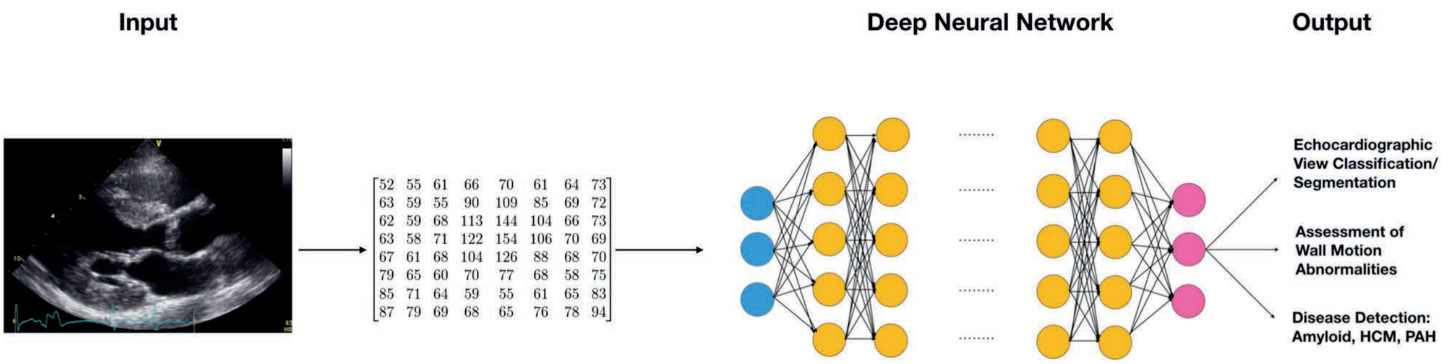

Figure 1.
Schematic of a deep neural network for imaging data. The input data often is down-sampled to a fixed height and width and nonimaging related data removed to prevent information about the target label from entering the training data. The input image data is represented to the algorithm as a fixed-size matrix corresponding to the image's pixel intensities in standard color channels (ie, red, green, blue). Each matrix (or set of matrices for a color image) represents an image that is fed into the first layer of the neural network (blue nodes). Subsequent layers of the neural network (yellow nodes) can be customized to perform a wide range of functions to the input matrix, transforming the data in a highly flexible way before feeding the data to the next layer of nodes. Deeper layers of nodes tend to learn complex interactions and higher level "features" derived from the input matrix. Each node in each layer of the network adjusts its weights during training, and the entire network is trained using the provided output labels in the training data. Different neural network architectures can be used to achieve object detection, disease classification or segmentation. HCM: hypertrophic cardiomyopathy; PAH: pulmonary arterial hypertension

development) and "testing" subsets (ie, for algorithm testing). It often is helpful to retain a separate subset of the training dataset for algorithm optimization or tuning. Data used for algorithm training should not be used for testing.[4] The generalizability of an algorithm to unseen data depends on several factors, including how well the sampled dataset represents the target data from the intended application and how well the algorithm is optimized to limit overfitting, which occurs when the algorithm learns the noise in the training data, decreasing its performance on new unseen data.[4]

In unsupervised learning (Table 1), pattern recognition occurs freely within unlabeled data. While less commonly used in medical applications, unsupervised learning has broad potential, particularly in medicine, where the process of annotating data for supervised learning is time-consuming and expensive. Examples of unsupervised learning ML algorithms include clustering algorithms ("k-means" or hierarchical clustering) and principal component analysis.[20]

IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE IN CARDIOVASCULAR IMAGING

Echocardiography

Echocardiography is the most widely used imaging modality in cardiology. Ultrasound has many advantages, including availability in most hospital and outpatient settings, portability, and affordability. However, accurate interpretation of echocardiographic data depends on intensive operator training.[21] Madani et al. have shown that a DL algorithm performs view classification with the same accuracy as a board-certified echocardiographer.[6] Moreover, in a study by Zhang et al., convolutional neural network algorithms were able to perform automated segmentation of cardiac chambers across five common views (Figure 2)[7] and, consequently, quantify chamber volumes/mass, ascertain ejection fraction, and determine longitudinal strain through speckle tracking. Measurements of cardiac structure were in line with the study report and commercial software-derived values.[7]

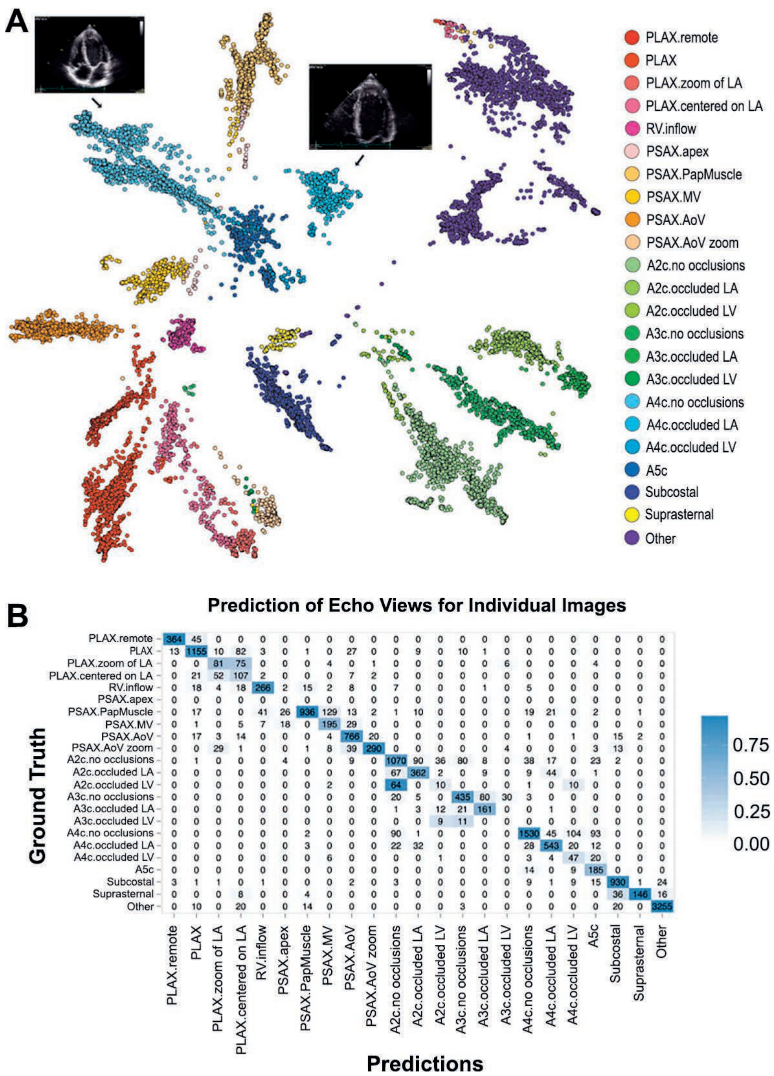

Figure 2.
Successful discrimination of echocardiographic views using convolutional neural networks. (A) Each cluster of test images corresponds to one of 23 different echocardiographic views, including apical views with or without occlusion of the left atrium. Echocardiographic still images provide examples of a 4-chamber view with and without occlusion of the left atrium. (B) Successful and unsuccessful view classifications within a matrix representation of the test data set. Successful classifications are shown as numbers along the diagonal, whereas misclassifications are indicated as off-diagonal entries. A2c: apical 2-chamber; A3c: apical 3-chamber; A4c: apical 4-chamber; echo: echocardiogram; LV: left ventricular; PLAX: parasternal long axis. Image reproduced from Zhang et al. (Open Access).[7]

In addition to automated analysis, AI has shown promising results for the classification or diagnosis of several cardiac pathologies. A support vector machine was the most accurate in determining the severity of mitral regurgitation (accuracy > 99% for every degree of severity).[22] AI is 87% accurate in identifying myocardial infarction using strain rate curves and segmental deformation.[8] Athlete's heart and hypertrophic cardiomyopathy can be distinguished using AI with three different classifiers.[9] Similarly, an associative memory classifier trained with features from speckle tracking echocardiography generated an area under the receiver-operating characteristic curve (AUC) of 0.96 (by adding four echocardiographic features) to distinguish patients with known restrictive cardiomyopathy and constrictive pericarditis.[10] In a DL algorithm, Zhang et al. trained convolutional neural networks to detect hypertrophic cardiomyopathy, cardiac amyloidosis, and pulmonary arterial hypertension with C statistics of 0.93, 0.87, and 0.85, respectively (Figure 1).[7] A study by Kusunose et al. using a DL algorithm to detect wall motion abnormalities found that the AUC produced by the algorithm was similar to that produced by the cardiologists and sonographer readers (0.99 vs 0.98, respectively; $P = .15$) and significantly higher than the AUC of the resident readers (0.99 vs 0.90, respectively; $P = .002$).[11]

Characterizing the phenotype of heart failure with preserved ejection fraction (HFpEF) is yet another diagnostic domain for AI implementation. The heterogeneous profile of HFpEF and lack of a true standard definition make it challenging to manage these patients.[23] In a study by Tabassian et al. of patients with HFpEF as well as healthy but hypertensive/breathless control subjects, an ML algorithm was 81% accurate in classifying the patients with HFpEF, with classification based on spatial-temporal rest-exercise features.[24] In another study that used imaging and clinical variables to classify and predict outcomes in patients with HFpEF, unsupervised phenomapping of HFpEF patients generated three different phenotypes with significantly different end points of cardiovascular hospitalization or death (AUC was 0.70-0.76 during validation).[12] A study by Lancaster et al. using clustering to identify HFpEF patients with high-risk phenotypes found that the clustering groups were more effective at predicting all-cause and cardiac mortality compared with conventional classification of diastolic function.[13]

In a large cohort of > 170,000 patients, Samad and colleagues predicted all-cause mortality by integrating high-dimensional echocardiographic measurements and electronic medical information into an ML algorithm. Compared with common clinical risk scores (AUC 0.69-0.79), these random forest algorithms had superior prediction accuracy (all AUC = 0.82) and outperformed logistic regression algorithms ($P < .001$).[14]

Computed Tomography

The number of ML-based studies of cardiac CT has multiplied over the last decade. Wolterink et al. developed and validated a DL method to obtain CT images with reduced radiation doses,[25] while a similar approach was used to calculate the calcium score from regular coronary CT angiography (CTA), also reducing radiation exposure for the patient.[26] In the context of image post-processing, Zreik et al. showed that automated segmentation of the left ventricle (LV) with coronary CTA and convolutional neural networks is feasible and reliable.[27] With regard to diagnosing coronary artery disease (CAD), various CTA-derived features have been used for modeling, including physiological features, quantitative plaque measurements, calculations from different spatially connected clusters of heart segmentation, and geometric features of the coronary anatomy (Figure 3).[28-33] In a study by Kang et al., an ML algorithm that detected coronary artery stenosis ≥ 25% in CT studies from 42 patient datasets achieved 93% sensitivity, 95% specificity, and 95% accuracy compared to three expert readers (AUC = 0.94).[15]

In addition to automated analysis and CAD diagnosis, AI has been used for prognostic purposes in cardiac CT. Motwani et al. used an ML algorithm to predict all-cause 5-year mortality in > 10,000 patients with suspected CAD and found that the algorithm displayed a higher AUC (0.79) compared to conventional cardiac metrics ($P < .001$).[16] Similarly, another study using AI with CT variables to predict major cardiovascular events in patients with suspected CAD reported that the AUC for the ML algorithm was superior to CT severity scores (0.77 vs 0.68-0.70, $P < .001$).[34]

Magnetic Resonance Imaging

In CMR, AI has mainly been used for segmentation of cardiac structures and infarct tissue. Winther et al. used DL for automated segmentation of the right and left ventricular endo- and epicardium to calculate cardiac mass and function parameters from a number of datasets.[35] Although small sample sizes resulted in limited findings, the ML algorithm achieved outcomes similar to or higher than those predicted by human experts. Tan et al. used a convolutional neural network to automate LV segmentation in all short-axis slices and phases in publicly available datasets.[36] In another study by Baessler et al., ML algorithms helped select the most important cine-image-derived texture features to distinguish between patients with myocardial infarction and control subjects. In multiple logistic regression, the use of two texture features generated a 0.92 AUC.[37] Implementing this algorithm in clinical practice could potentially expand the eligible patient population and reduce costs since it would preclude

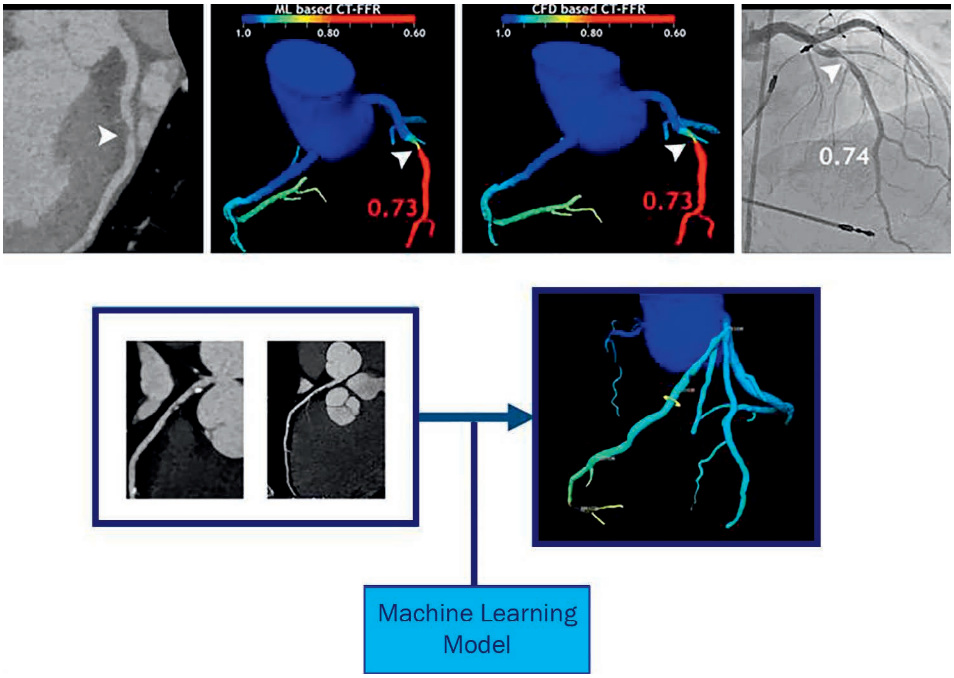

Figure 3.
Coronary stenosis (arrowheads) are displayed in different imaging methods. (a) Coronary computed tomography (CT). (b) Calculation of fractional flow reserve (FFR) with a machine learning (ML) algorithm. (c) FFR calculated with computational fluid dynamics. (d) Measurement of the stenosis during invasive coronary angiography. (e) From coronary CT to an AI-based 3-dimensional algorithm of the coronary tree displaying the FFR at different locations along the coronary arteries. Image reproduced from Siegersma et al. (Open Access).[33] AI: artificial intelligence

the need for gadolinium-enhanced CMR.

Predictive modeling using AI was performed in two CMR studies. In one study, principal component analysis was able to predict 4-year survival in patients with pulmonary hypertension using 3-dimensional (3D) cardiac motion of the right ventricle as an input. This method showed an AUC of 0.73 for including 3D-CMR features in the algorithm in addition to clinical, functional, and regular CMR features and features derived from right-sided heart catheterization (AUC 0.60 without 3D-CMR features).[38] In the second study, a predictive algorithm that evaluated deteriorated LV function in patients with a repaired tetralogy of Fallot showed that ML algorithms can be useful for planning early intervention in high-risk patients (AUC 0.87 for major deterioration).[39]

Nuclear Imaging

AI-based algorithms have been used to classify normal and abnormal myocardium in CAD with accuracy similar to expert human analysis of myocardial perfusion single-photon emission computed tomography (SPECT) images.[40] Other studies have used AI-based algorithms to detect locations with abnormal myocardium. For example, Nakajima and colleagues found that a neural network trained with expert interpretations of SPECT images was better able to identify stress (AUC 0.92), rest defects (AUC 0.97), and stress-induced ischemia (AUC 0.97) compared with conventional scoring; the AUCs of the summed stress, summed difference, and summed rest scores were 0.82, 0.75 and 0.91, respectively.[41]

Integrating clinical data with quantitative imaging features in an ML algorithm has been shown to increase the accuracy of SPECT. Arsanjani et al. improved the detection of obstructive CAD with an integrative algorithm that generated a marginally better result than one with solely clinical features (79% vs 76%). Algorithm performance was similar to that of one experienced reader (78%) and better than another (73%).[42] Betancur et al. used DL algorithms trained with raw and quantitative perfusion polar maps to predict obstructive CAD more accurately than the current clinical method (AUC 0.80 vs 0.78).[43] Another study merged SPECT data with functional and clinical features and showed that ML was comparable to or better than two experienced readers in predicting the need for revascularization.[44] Yet another study of major adverse cardiovascular events found that an ML algorithm combining clinical information with myocardial perfusion SPECT data had an AUC higher than the algorithm with only imaging features (0.81 vs 0.78).[45]

Additionally, Haro Alonso et al. explored the use of AI in predicting cardiac death. Selecting patients who had undergone myocardial perfusion SPECT and using imaging parameters for modeling, the researchers showed that all ML algorithms outperformed baseline logistic regression, with the support vector machine generating the highest AUC (0.77 vs 0.83).[17]

CHALLENGES IN ARTIFICIAL INTELLIGENCE APPLIED TO CARDIOVASCULAR IMAGING

Although the initial results of AI applications in cardiovascular imaging are promising, some issues must be resolved to implement AI in overall health care. First, further studies are needed to demonstrate that AI leads to higher quality of care, lower health care costs, and improved patient outcomes. Second, standardized methods must be implemented to assure patient privacy and secure information storage or extraction from the electronic health record. Finally, efforts are ongoing to improve comparability of imaging modes. Automated segmentation or extraction of imaging features is likely to be solved first, thus accelerating the analysis of large datasets and the diagnostic and prognostic capabilities of AI.

CONCLUSIONS AND FUTURE DIRECTIONS

AI applications in cardiovascular imaging are rapidly growing. In the short term, AI has the potential to reduce human error and save time in the clinical workflow through automated segmentation of cardiac structures. In the future, AI may expand the informational value of diagnostic images based on images alone or a combination of images and clinical variables, thus facilitating disease detection, prognosis, and decision making. There is also an opportunity to combine biomarker, genomics, proteomics, and metabolomics with imaging data to ultimately improve the predictive value of ML algorithms and create personalized health care for patients.

KEY POINTS

- Whereas artificial intelligence (AI) describes the concept of using computers to mimic human cognitive tasks, machine learning (ML) describes the category of algorithms that enable most current AI applications.
- The two general approaches used to train ML algorithms are supervised and unsupervised learning. In supervised learning, the ML algorithm learns based on training data that has been labeled for the task of interest. In unsupervised learning, pattern recognition occurs freely within unlabeled data.
- AI applications in echocardiography, nuclear imaging, computed tomography, and cardiac magnetic resonance include automation, disease recognition, and prediction of cardiovascular outcomes.

Conflict of Interest Disclosure:
The authors have completed and submitted the *Methodist DeBakey Cardiovascular Journal* Conflict of Interest Statement and none were reported.

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artificial intelligence, machine learning, cardiac imaging

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