The Role of Artificial Intelligence in Cardiac Imaging

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KEYWORDS

• Artificial intelligence • Cardiac imaging • Machine learning • Deep learning • Cardiac computed tomography • Cardiac magnetic resonance • Clinical workflow

KEY POINTS

- Main areas of artificial intelligence (AI) applicability in cardiac imaging are detection, quantification, and characterization of cardiac disease.
- AI has been successfully used to perform time-consuming tasks, such as segmentation and post-processing, optimization of data acquisition and reconstruction, and grading of disease severity.
- AI can aid physicians in better understanding the patient's cardiac health.
- Integration of AI applications into clinical workflow will have a great impact on costs, wider usability, and optimization of workflow efficiency.

INTRODUCTION

Cardiovascular disease (CVD) remains the number one cause of death worldwide, and the number of annual deaths is expected to increase in the near future[1]; thus it is not surprising that a great deal of effort is being put forth to advance cardiac imaging. Simultaneously, artificial intelligence (AI) has made great advances in the medical imaging field.

The 2 main approaches that have been used in medical imaging, including cardiac applications, are machine learning (ML) and deep learning (DL). ML uses computer algorithms to identify patterns in large data sets with a multitude of variables. ML is usually built from test inputs, makes data-driven predictions, and has been used for diagnostic or prognostic outcomes prediction. ML relies on the principle that a set of weak base classifier can be combined in a single strong classifier when their weighting is adjusted. Thus, a series of base classifier predictions and a weighting distribution are produced. The predictions are subsequently combined by weighted majority voting with a resulting overall classifier as a continuous estimate of predicted risk. ML requires 3 steps: training, where it learns characteristics of

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data; validation, where it validates the learned characteristics in a separate data set; and testing, where the accuracy of the ML model is evaluated.

DL methods, a subgroup of ML, are more advanced AI methods that, unlike classic ML that requires hand-engineered feature extraction, directly interrogates the data, learns the features by which to classify it, and performs tasks such as segmentation, classification, detection, or outcome prediction. DL works through multilayered neural networks to transform input images into outputs; it uses weighted connections between nodes that are iteratively adjusted through exposure to training data by back-propagating a corrective error signal through the network.[2,3] DL, being at its core represented by convolutional neural networks (CNNs), lends itself to be particularly suitable for large data sets with many features, such as imaging data sets, and it has been widely applied to radiology. Within cardiac imaging (**Table 1**), CNNs have been used to perform detection tasks, such as coronary plaque. CNN uses a bounding box that searches for the target in the input images, then another CNN model discriminates if the subimages found are true or false targets, and then coordinates of true detected targets are given as output. CNN has also been applied to segmentation, for example, segmentation of cardiac chambers, coronary arteries, or atherosclerotic plaques, by using encoder-decoder–based neural networks, and classification, where CNN gives category labels as outputs.

GENERAL ARTIFICIAL INTELLIGENCE APPLICATIONS

Image Acquisition and Reconstruction

Computed tomography (CT) and MR image acquisition and reconstruction can benefit from AI techniques. For example, AI can improve the image acquisition and reconstruction time in MR or improve the CT image quality at low-dose radiation.

CT exposes patients to radiation, and research has focused on the application of AI to reduce the dose. Low-dose CT ensures less radiation exposure, but it is characterized by intrinsic severe artifacts that undermine its reliability. CT vendors have introduced iterative reconstruction techniques to reduce dose and noise, but there are concerns over loss of anatomic details, and long reconstruction times. AI has been applied to overcome these problems that limit accuracy and feasibility. AI-based high-quality reconstruction methods have been developed, such as those based on CNN. Some of these AI-based image denoising methods based on CNN-quality enhancement have attained commercial availability.[4] Other approaches to denoise low-dose CT involve wavelet decomposition and processing by a neural network[5] and generative adversarial network, which uses DL to reduce image noise on both low-dose CT and non-enhanced cardiac CT, in order to obtain quality similar to conventional-dose CT.[6] Compared with iterative reconstruction, the strength of AI-based reconstruction relies on its ability to retrieve missing details and enhance the quality of output images, by learning from complex prior information. Greffier and colleagues[7] assessed the impact on quality and dose reduction of a DL-image reconstruction (DLIR) algorithm compared with a vendor's iterative reconstruction algorithm (adaptive statistical iterative reconstruction-V [ASiR-V] at 50% strength; GE Healthcare; Waukesha, WI, USA). They concluded that the DLIR reduced noise, improved spatial resolution, and optimized radiation dose, without perceived image alteration, commonly reported with iterative methods. Similarly, Bernard and colleagues[8] evaluated radiation dose and image quality of coronary CT angiography (CCTA) using a DLIR model compared with a hybrid iterative reconstruction algorithm: they showed that DLIR reduced radiation dose by about 40% and improved quality by about 50% (**Fig. 1**). Last, AI can perform image quality assessment evaluating the input image and producing a map, a metric of image quality, as output. CNNs are used to learn a similarity score between a reference and a reconstructed noisy image; the learned similarity is then considered a quality reference for the noisy image.[9]

With regards to cardiac magnetic resonance (CMR), optimal plane positioning is a crucial step to obtain high-diagnostic-quality images, and it traditionally required experienced technologists and time. Thus, AI-aided recognition of imaging planes has been developed to guide image scan, optimizing workflow and providing high-quality, highly reproducible images, with increased time efficiency and minimal user input.[10] Different studies have suggested AI models with acceptable accuracy,[11,12] and more recent studies have also shown reduced number of breath-holds.[13] Moreover, CMR acquisition time is long and often poorly tolerated by the patient; hence, effort has been put on developing AI technologies that could improve this aspect while maintaining a high spatiotemporal resolution. State-of-the-art software, such as compressed sensing (CS), is a widely used example of it, which, however, requires high computational power and is not always applicable to accelerated cine CMR images owing to motional changes in cardiac volume between frames.[14] To enable progress beyond CS-based

Table 1
Clinical applications of artificial intelligence in cardiac imaging

Clinical Application	Description	Advantage
Image acquisition		
Radiation dose reduction	DL-based reconstruction method	Improved image quality
CMR plane positioning	AI-aided plane recognition	High-quality, highly reproducible images
CMR acquisition time reduction	DL-aided acceleration of cine sequences	Reduced number of breath-holds
Image optimization		
Denoising	DL-based reduction of image noise and artifacts	Optimized image quality
Enhancement	Optimization of nonenhanced images	No need of contrast media
Outcome prediction		
MACE risk assessment	Integration of clinical and imaging data to ML	Better assessment than clinical and imaging data alone
Coronary artery disease		
Coronary calcium	Semiautomated and automated calcium scoring algorithms	Quantification of CAC from ECG- and non-ECG-gated CT
Plaque characterization	DL-based CAD-RADS assessment and high-risk features evaluation	Reduced postprocessing time and improved outcome prediction
CT-FFR	ML FFR calculation	Reduced processing time and costs
Epicardial fat	AI-based segmentation and quantification	Reduced postprocessing time and improved CV risk assessment
Evaluation of infarcted myocardium	AI-aided detection, segmentation, and analysis on noncontrast CMR images	No need of contrast media, reduced postprocessing time, and improved outcome prediction
Myocardial function		
Volume analysis	Automated segmentation	Reduced postprocessing time
Myocardial strain	Strain quantification from cine-to-tagged images	Wider availability and reduced processing time
Valve disease		
Classification	Grading of disease from phase-contrast CMR images	Reduced postprocessing time and improved outcome prediction
Cardiomyopathies		
Classification	Detection of diagnostic features and LGE evaluation	Improved prognostic prediction
Congenital heart disease		
Image acquisition	AI-aided acquisition and reconstruction	Reduced time of acquisition and postprocessing

reconstruction approach, DL methods have been proposed and have shown great performance in terms of quality and time, in a research setting. For example, CINENet[15] is a DL network that enabled highly accelerated cine sequences in a single breath-hold using spatiotemporal convolutions, and ESPIRiT,[16] another DL reconstruction framework, also showed higher image quality, contributing to improved segmentation.

Image Optimization

Image quality is central to diagnostic capabilities, and AI algorithms can assess it. This is particularly

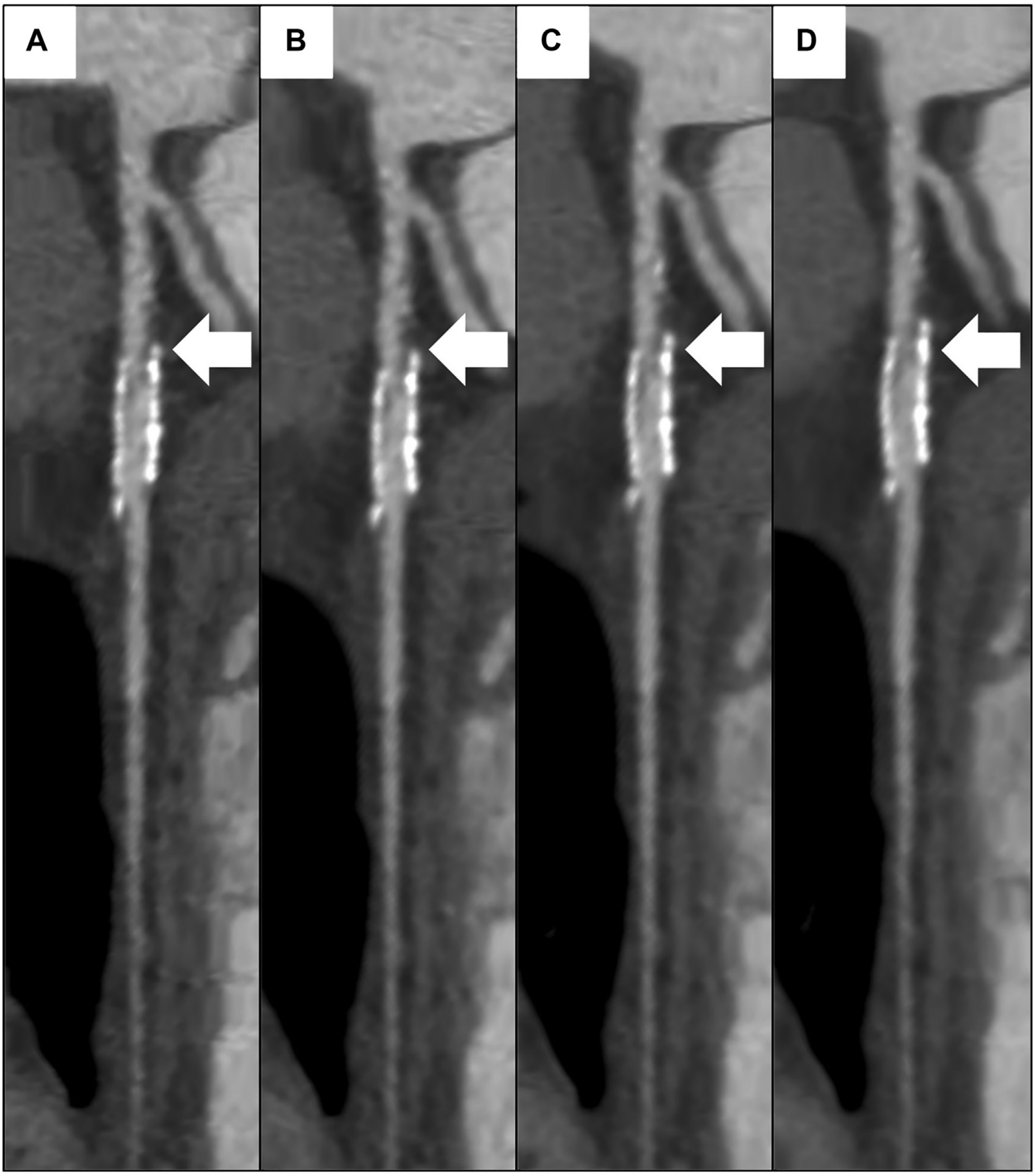

Fig. 1. A 57-year-old male patient who underwent CCTA following a positive stress ECG. CCTA shows severe in-stent restenosis (*arrow*) after previous stenting of the proximal left descending artery. Left descending artery is reconstructed using ASiR-V 50% (*A*), low-grade DLIR (*B*), medium-grade DLIR (*C*), and high-grade DLIR (*D*). DLIR reconstruction (GE Healthcare, Waukesha, WI, USA) is a DL algorithm reconstruction that allows the reduction of image noise. The DLIR application results in a significant reduction of the images noise without affecting the image signal and contrast. (*B–D*) A progressive reduction of the image noise can be appreciated.

true when it comes to noise, motion, or aliasing artifacts, which can negatively impact both CT and MR imaging quality. AI has been applied in this setting to optimize image quality. For example, CMR is deeply affected by motion artifacts, which can be caused by intended or accidental (respiration and cardiac motion) patient movement, and it can benefit from retrospective AI-aided artifact correction. A generative adversarial network has been used to pursue this goal, demonstrating feasibility resulting in near-realistic motion-free images.[17] A generative adversarial network combines 2 CNNs that work against each other to progressively refine their algorithms in order to give more accurate results. After the network has been trained with paired motion-free and motion-corrupted images, it can be a useful tool to remove motion artifacts from images.[18]

The ability of AI to reduce artifacts has been applied to CT as well. In particular, CNNs have proven to be useful in reducing metal artifacts in various settings, from cardiac CTs with artifacts and moving pacemakers[19] to ear CTs with artifacts from cochlear implants.[20] Metal artifact reduction methods based on DL are mostly supervised methods trained on synthetic-artifact CT images, which limit their applicability to unlabeled CTs. Both semisupervised[21] and fully unsupervised[22] methods have been developed to disentangle metal artifacts while addressing this problem, and they showed good generalizability for real-artifacts CT images.

Last, AI plays a promising role in contrast enhancement optimization. Recent studies focused on its ability to optimize image enhancement without the administration of contrast media. As shown by Zhang and colleagues,[23] virtual native enhancement, in the assessment of myocardial scar, demonstrated superior image quality compared with late gadolinium enhancement (LGE), excellent agreement between the 2 methods, and also with the histopathologic comparison. Thus, AI has proven useful to avoid gadolinium contrast administration with a dual advantage: reduced scan time and costs and reduced risks of contrast media adverse effects for patients.

ARTIFICIAL INTELLIGENCE APPLICATIONS IN CARDIAC COMPUTED TOMOGRAPHY

Coronary Artery Disease

Coronary calcium

Coronary artery calcium (CAC) score has been recognized as a predictor of future cardiovascular (CV) events and mortality.[24] Its measurement on cardiac CT can be obtained manually, with time-consuming segmentation, and semiautomatically or fully automatically, with DL-based algorithms. Several semiautomated and automated calcium scoring algorithms have been proposed,[25] and they have been applied to either electrocardiogram (ECG)-gated CT[26] or non-ECG-gated CT[27] scans with excellent accuracy comparable to expert readings and significant improvement in the workflow. The possibility to measure CAC score from noncontrast, non-ECG-gated CT scans has broadened the number of patients whose score, and consequent CV risk, can be evaluated without the need of dedicated cardiac CAC scan. In their study, van Velzen and colleagues[28] used a DL method for automatic calcium scoring across a wide variety of CT scan types, and they found that the method was robust with high performance. In addition, van Assen and colleagues[29] used a DL-based, fully automated calcium quantification on ECG and non-ECG-gated chest CT; they obtained good correlation compared with reference standards (manual evaluation and Agatston score) and shorter evaluation time. Other DL algorithms have been successfully applied to CCTA scans to measure CAC score avoiding additional scans and consequent additional radiation exposure.[30,31]

Plaque characterization

CCTA plays an important role in the noninvasive evaluation of coronary artery disease (CAD). Thanks to its high negative-predictive value, it allows us to effectively exclude the presence of obstructive CAD. Moreover, CCTA allows quantification of stenosis and grading according to the Coronary Artery Disease Reporting And Data System (CAD-RADS) and also allows assessment of high-risk plaque features,[32] included in the CAD-RADS 2.0.[33] AI has been applied to optimize the extraction of these features, thereby reducing postprocessing time by performing these tasks in an automated but accurate manner (**Fig. 2**). CNN-based models have been developed to classify CCTAs in the correct CAD-RADS category, using expert readers' grading as a reference standard. These CNN-based models have shown promising results, with performance similar to those achieved by the radiologist.[34–37] DL has also been applied to CCTA to increase its diagnostic performance and specificity in detecting functionally significant stenosis. DL models have been applied to identify patients with functionally significant stenoses who underwent CCTA and invasive coronary angiography (ICA) with fractional flow reserve (FFR) measurement, used as a reference standard. The DL model analyzed the presence of ischemic changes in the left ventricle myocardium and classified patients as having a nonsignificant or significant stenosis, resulting in improved discrimination compared with CCTA-based degree of stenosis only.[38,39] Recently, Lin and colleagues[40] showed that DL-based luminal stenosis severity has excellent agreement not only with expert readers but also with intravascular ultrasound, as well as DL-based CAD-RADS category agrees closely with expert CCTA read and ICA.

Beyond quantification of stenosis, CCTA also allows atherosclerotic plaque evaluation and vessel remodeling assessment. Several automated methods have been developed to perform these

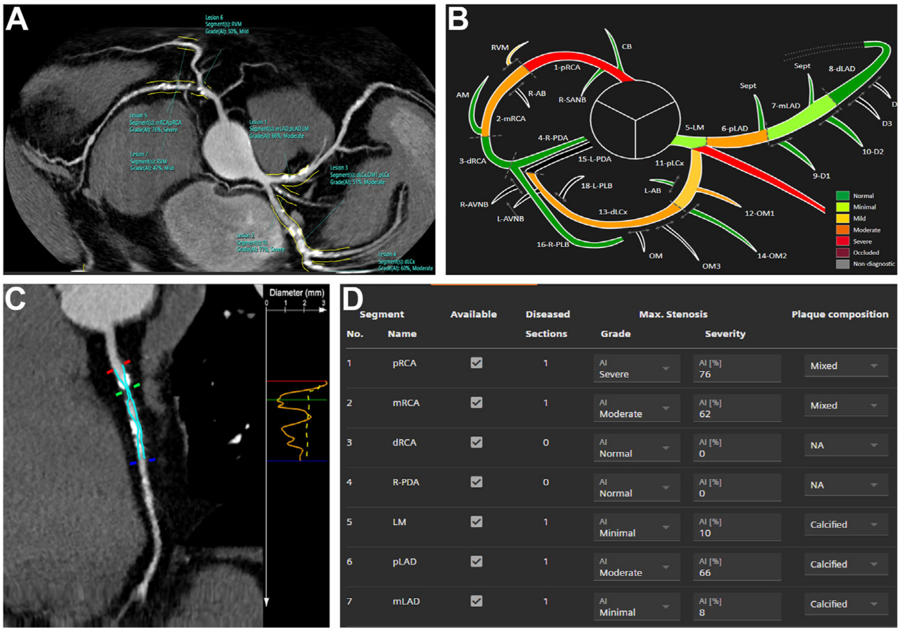

Fig. 2. CCTA plaque detection and automated CAD-RADS classification using AIHeart algorithm, an AI-based research prototype from Siemens Healthineers, Erlangen, Germany. (*A*) Identification of coronary plaque. (*B*) Classification of severity through a color-coded map. (*C*) Analysis of a single lesion, with a graph of the vessel diameter throughout. (*D*) Results of AIHeart analysis for all coronary segments, with plaque composition, stenosis grade and severity, and available manual correction. pRCA, proximal right coronary artery; mRCA, mid RCA; dRCA, distal RCA; R/L-PDA, posterior descending artery from the right/left; LM, left main; pLAD, proximal left anterior descending; mLAD, mid LAD, dLAD, distal LAD; D1-D3, diagonal branches 1 to 3; OM1-3, obtuse marginal branches 1 to 3; pLCx, proximal left circumflex; dLCx, distal LCx; AM, acute marginal branch; R-/L-PLB, posterior-lateral branch from the right/left; Sept, septal branches; R-/L-AB, right/left atrial branches; SANB, sinoatrial nodal branch; R-/L-AVNB, atrio-ventricular nodal branch from the right/left.

tasks, which would otherwise require time-consuming manual evaluation and challenging its clinical applicability to workflow.[41] AI-augmented software programs are able to automatically perform quantitative plaque analysis, with evaluation of plaque burden, calcified/noncalcified plaque, and high-risk features. Much of AI-assisted software has been validated against invasive or histologic data.[42] Total coronary plaque burden is a prognostic marker that correlates with disease severity, and noncalcified plaque burden is an indicator of more vulnerable/active plaque.[43] AI-based quantification methods allow for a rapid and standardized analysis of plaque burden, thereby reducing measurement variability that would affect the evaluation of plaque progression, another important prognostic factor.[44] Various software to perform AI-based plaque quantification has been developed and has obtained Food and Drug Administration approval.[45] For example, Cleerly (Cleerly Healthcare, New York, NY, USA) is a recent AI-assisted, fully automated software. It uses a series of validated CNN models to assess image quality, label, and segment and analyze the coronary tree and contours, outputting degree of stenosis, plaque volume, remodeling index, and plaque characteristics, such as low-density noncalcified plaque. Cleerly (Cleerly Healthcare, New York, NY, USA) recently showed high-diagnostic performance for stenosis severity and high correlation to quantitative coronary angiography, in accordance with the prior multicenter CLARIFY trial.[37,46] Another software is VascuCAP (Elucid Bioimaging, Wenham, MA, USA). It is a computer-assisted, semiautomated approach that performs structural and plaque component quantification, with evaluation of lipid-rich necrotic core, matrix, calcified plaque, as well as stenosis degree, plaque volume, and remodeling index (**Fig. 3**). Both of these examples allow the radiologist to perform quality control and manual adjustment if necessary.

Moreover, AI-based models were demonstrated to be useful in prognostic prediction: quantification of total, noncalcified, and low-attenuation plaque burden. These AI-based tools have been shown to significantly improve prediction of lesion-specific ischemia by FFR over stenosis grading alone.[47] AI-based plaque characterization has

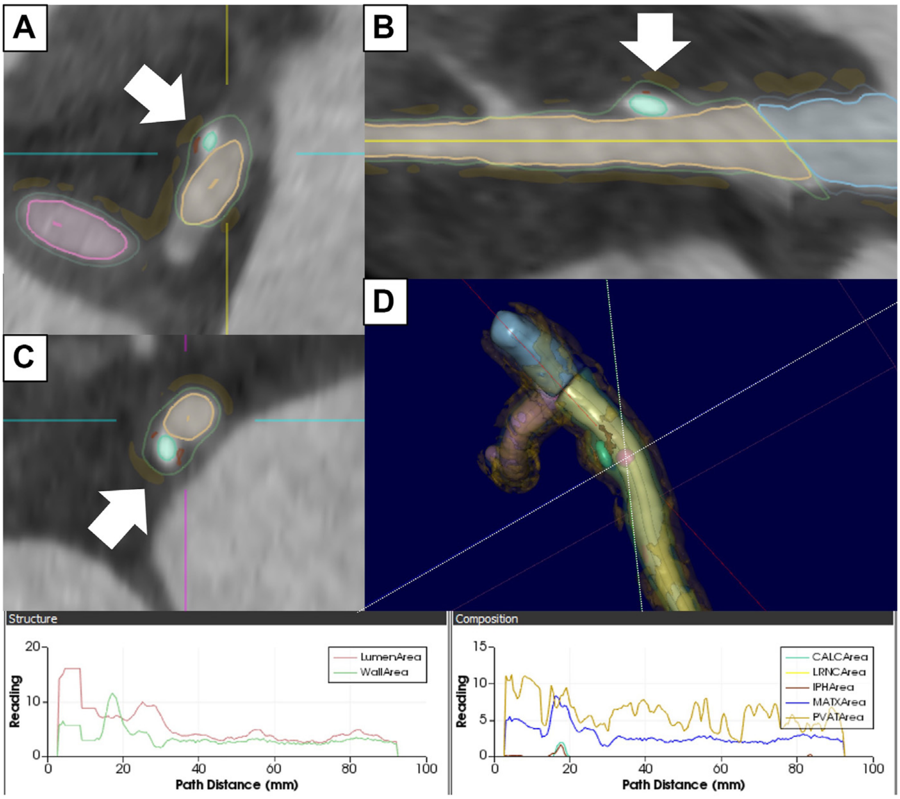

Fig. 3. A 61-year-old female patient with multiple CV risk factors who underwent CCTA. Analysis was performed via a DL-based software, Elucid Vascucap (Elucid Bioimaging, Wenham, MA, USA). (*A–C*) Cross-sectional images show color-coded plaque analysis of the left anterior descending artery (LAD): arrows pointing at a calcified plaque (*turquoise*) with spot of intraplaque hemorrhage (*brown*), and perivascular adipose tissue surrounding the vessel (*yellow*). (*D*) Color-coded 3D reconstruction of the vessel, with planes indicating the level at which images *A–C* were taken. Graphs showing structure and composition of the vessel.

also shown improved prognostic stratification, demonstrating better major adverse cardiovascular events (MACE) prognostication than clinical risk factors alone, increasing accuracy from 0.629 to 0.872.[48]

Computed tomography–fractional flow reserve

Even though CCTA mainly provides anatomic information, thanks to CT-FFR, it can provide functional assessment as well. However, it requires complex computer fluid dynamics computations, which are time-consuming and costly. ML has recently been applied to a CT-FFR calculation (FFR_{ML}) as opposed to a computational fluid dynamics (FFR_{CFD}) -based approach in order to shorten execution times (Fig. 4). As shown by Tesche and colleagues,[49] FFR_{ML} required significantly shorter processing time when compared with FFR_{CFD}, while performing equally in detecting ischemia. Moreover, FFR_{ML} closely reproduces FFR_{CFD} calculations, assesses the hemodynamic severity of coronary stenosis, correlating with invasive FFR results, and improves diagnostic accuracy and positive-predictive value of CCTA on a per-vessel and per-patient level.[50] However, CT reconstruction algorithms influence FFR_{ML} analysis results; thus, further studies are needed.[51] Recent studies have shown that FFR_{ML} can be useful in outcome prediction: the combined use of FFR_{ML} and CCTA-derived plaque features improves predictive value for MACE over stenosis grading alone.[52,53]

Epicardial fat

Epicardial adipose tissue (EAT) is the metabolically active fat depot that surrounds coronary arteries. It is known that it is related to CV events owing to its local proinflammatory, proatherogenic effect on vasculature.[54] AI can assist in segmentation and quantification of EAT. Semiautomated and fully automated models have been developed to measure epicardial fat from nonenhanced, calcium scoring CT.[55,56] This AI-based approach has proven to be a time-saving and reliable tool that

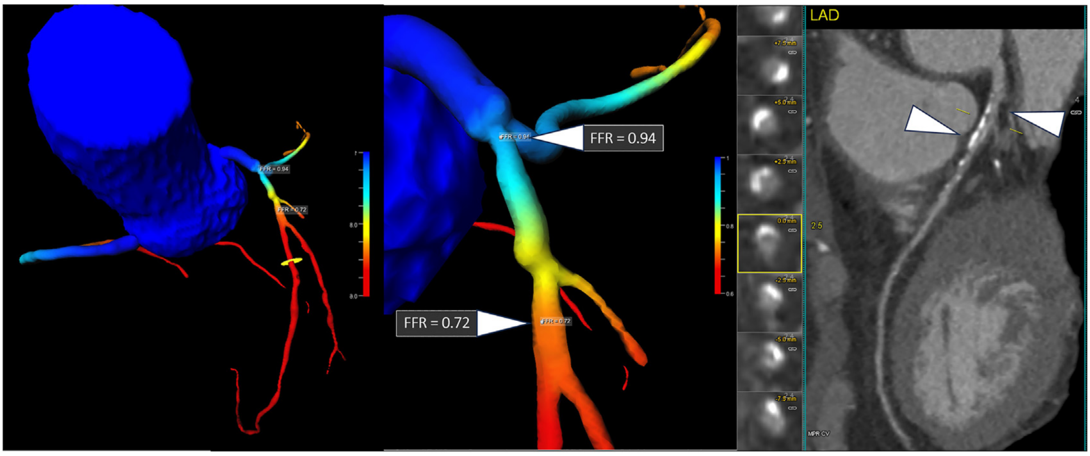

Fig. 4. Coronary CT-FFR analysis with ML-based research prototype from Siemens Healthineers, Erlangen, Germany. The analysis shows severe stenosis in the proximal LAD, with a drop of CT-FFR to 0.72, which is considered functionally significant (abnormal if less than 0.75). *Arrowheads* indicate the proximal and distal markers used for CT-FFR assessment. Normal value of CT-FFR proximally to the lesion (0.94) and abnormal value distally (0.72) can be observed.

may improve CV risk assessment.[57] Further studies are evaluating AI's applicability to pericoronary adipose tissue assessment—a part of EAT, in closer proximity to the artery, and hypothesized to be a more specific proinflammatory marker for CAD, but it is still under study.[58]

ARTIFICIAL INTELLIGENCE APPLICATIONS IN CARDIAC MR IMAGING

Volumes Analysis

One of the key advantages of CMR is to quantitatively assess cardiac function by measuring reproducible, less operator-dependent parameters, such as ejection fraction. Cardiac function evaluation is usually obtained from postprocessing analysis of cine CMR images. The use of AI, particularly DL, has significantly improved the postprocessing phase, and thus the radiology workflow, by performing time-consuming activities, such as manual segmentation (**Figs. 5** and **6**). Tao and colleagues[59] used CNN to perform fully automated quantification of left ventricle function from short-axis cine CMR images, and they obtained high accuracy when tested against a multivendor, multicenter data set. In addition, their trained CNN was able to process a complete cine CMR data set (approximately 300 images) in

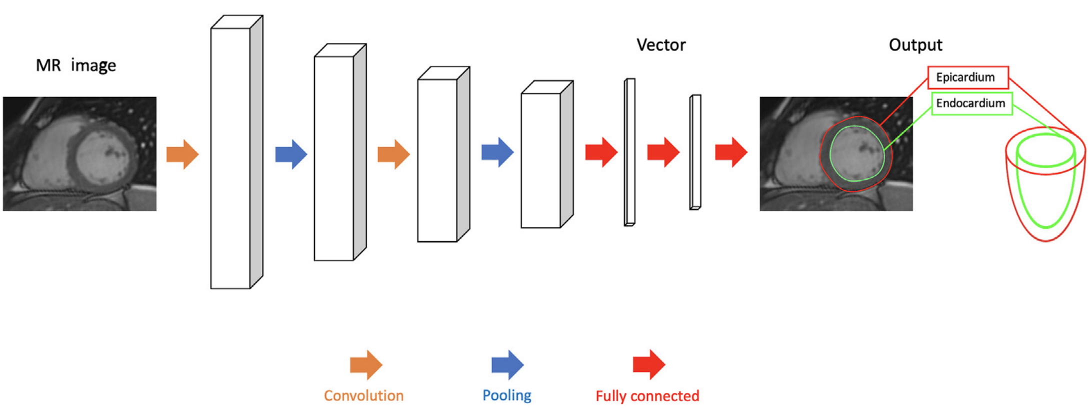

Fig. 5. A CNN for automated CMR ventricular segmentation. The CMR image is used as input by the CNN, which learns hierarchical features through a stack of convolution and pooling procedures, generating spatial features maps. These maps are flattened into a vector through fully connected layers, yielding the output, that is, the segmentation of the left ventricle (LV). As depicted in the output section, the algorithm learns the spatial features corresponding to endocardium and epicardium, thus obtaining a geometric model of the LV and performing automated segmentation.

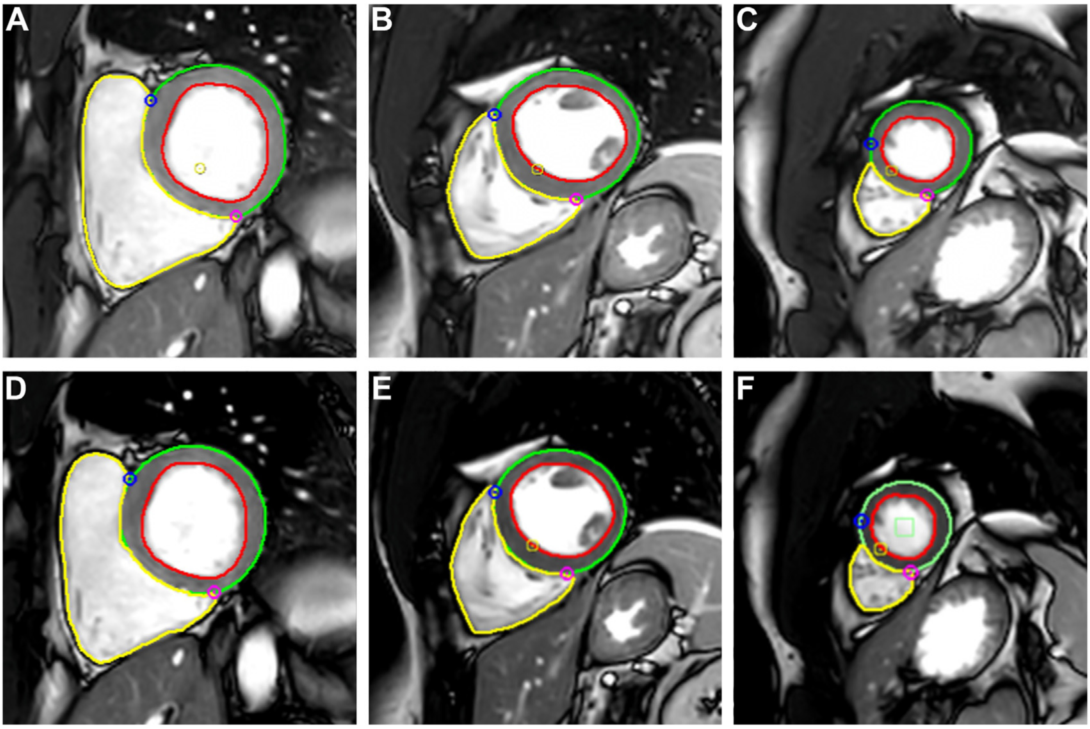

Fig. 6. Reconstruction of biventricular volumes obtained using a DL algorithm (Circle Cardiovascular Imaging,[42] Calgary, Canada) that automatically identified the best diastole, systole, the epicardial border of left ventricle, and the endocardial border of both left and right ventricle. Automated segmentation of left ventricle (epicardial border: *green*; endocardial border: *red*) and right ventricle (endocardial border: *yellow*) volumes and mass in diastole using DL reconstruction on basal (*A*), midventricle (*B*), and apical (*C*), in comparison with the myocardial borders manually drawn by human reader (*D–F*). The DL algorithm provides an accurate quantification of the ventricular volumes and mass in just a few seconds compared with several minutes from manual tracing.

approximately 1 second, free of any user intervention. Similarly, Ruijsink and colleagues[60] developed a fully automated DL-based framework for quality-controlled cardiac function analysis, without the need for direct clinician action; more recently, Evertz and colleagues[61] showed that a fully automated biventricular volumetric assessment was able to efficiently predict risk of CV death in patients undergoing transcatheter aortic valve replacement when compared with manual approach, with a significant time saving, which would improve and optimize clinical management.

Volume and function assessment is not limited to the left ventricle. AI algorithms have been applied also to whole-heart segmentation tasks. Automated CNN models performed whole-heart segmentation on short axis, long-axis four-chamber view, and both sets of images together, with similar accuracy to manual analysis, indicating feasibility and time-saving advantage of this approach.[62,63] However, accuracy is shown to be slightly lower for right chambers and basal slices, mainly because of higher morphologic complexity and variability of this anatomic regions, which cause more difficulties in segmentation, even for expert clinicians.[64,65]

Moreover, recent studies have drawn attention to AI-based methods to assess myocardial strain, a prognostic and diagnostic marker of CVDs, which represents radial, circumferential, and longitudinal deformation of myocardium from relaxed to contractile state.[66] CMR-based strain is usually obtained from tagged images, which are not routinely included in the workflow because of their need of time-consuming analysis and specific software; however, AI has been a useful tool to speed the process and make myocardial strain more widely available.[67] Some studies have developed AI models that automate strain analysis from tagged images, but these models still require manual input for initialization of reference points.[68,69] More recently, Dhaene and colleagues[70] addressed this problem by developing a DL algorithm that segments the myocardium from tagged images obtained from cine images through a cine-to-tagged transformation, and they showed a performance comparable to existing networks for cine images.

Thus, AI has proven to be a reliable tool that improves operator-dependency, speeds postprocessing phase, and optimizes CMR images assessment. AI, and DL in particular, is being widely implemented to improve radiology workflows by performing volume analysis, an otherwise time-consuming task that would require the clinician a considerable amount of time.

Ischemic Heart Disease

Of the multiple clinical applications of AI, its use to assess and evaluate ischemic heart disease, the leading cause of death globally, is noteworthy. Particularly, AI is being used to detect, segment, and analyze infarcted myocardium, and its application in myocardial viability studies has shown advantages over the traditional diagnostic evaluation of LGE and T1 mapping.[71] Detection of viable myocardium is a key step for prognosis assessment, because it represents the muscle that can recover after revascularization. Recent studies[72,73] applied texture analysis to cardiac cine MR images in order to differentiate between infarcted nonviable, viable, remote, or normal myocardium. Texture analysis has been successfully applied to noncontrast CMR images as well, giving an alternative to LGE,[74] particularly important for those patients with severe renal impairment.

With regards to segmentation, AI has been used to perform semiautomated and fully automated segmentation of myocardial infarction (MI), mainly with the use of DL-based algorithms using CNN-based networks,[75,76] enabling quantification of disease severity without time-consuming manual image annotation. Zabihollahy and colleagues[77,78] showed that CNN provided fully automated segmentation of myocardial scar from 3-dimensional (3D) LGE images, outperforming alternative approaches, including the manual one. In addition, Kotu and colleagues[79,80] suggested an automatic scar segmentation method based on texture analysis and Bayes classification, and they found comparable results to manual segmentation.

Once the scar is detected and segmented, its analysis provides useful prognostic information. Scar burden with LGE has been shown to predict all-cause mortality,[81] sudden cardiac death, and ventricular arrhythmias, especially in patients with ventricular dysfunction.[82,83] AI has been applied to fibrosis analysis with the aim of improving processing time, variability, and generalizability. Moreover, ML-based LGE analysis, compared with human-based, has proven to predict MACE, especially when dense scar is detected.[84]

Valve Disease

CMR, thanks to phase-contrast sequences and the possibility of obtaining specific anatomic planes, has been used to evaluate valves' anatomy. AI has been applied in this setting to classify and grade valve diseases. Fries and colleagues[85] created a DL model that satisfactorily classified aortic valve malformations from phase-contrast CMR images. They used weak supervision to train a DL model and used it to classify bicuspid aortic valve in unlabeled MR imaging sequences from the UK Biobank. Using health outcome data, they found that the model identified individuals at increased risk of MACE. In addition, ML models have been used to identify different phenotypes of bicuspid valve-associated aortopathy (root, ascending, and arch) and their association with specific clinical findings.[86]

Moreover, advances in AI have improved automated processing of phase-contrast images. Bratt and colleagues[87] tested an ML model for aortic flow analysis using this type of sequence. The model tracked aortic valve borders to quantify aortic flow and was compared with manual segmentation; it successfully segmented in less than 0.01 minutes per case compared with 3.96 minutes per case of the manual approach. Aortic flow is particularly important to assess forward and regurgitant flow, enabling CMR diagnosis and grading of aortic regurgitation. Regarding mitral valve assessment, CMR uses 2 acquisition techniques to quantify mitral regurgitation: 2-dimensional phase-contrast across the aortic valve and short-axis cine of the left ventricle to obtain aortic forward flow and left ventricle stroke volume, respectively. The subtraction of the two indirectly gives a measurement of mitral regurgitant flow. AI, as previously mentioned, has been applied to both acquisition techniques in order to automatically segment and quantify flow and volume.

Cardiomyopathies

CMR plays an increasingly important role in the diagnosis, management planning, and prognosis of cardiomyopathies. AI has been applied to this setting for the detection of specific diagnostic features, and LGE evaluation, which has a prognostic relevance in diseases such as hypertrophic cardiomyopathy (HCM), and disease classification. Ammar and colleagues[88] used a DL network and a classifier ensemble to segment and classify images from CMR of healthy patients, HCM, dilated cardiomyopathy (DCM), abnormal right ventricle, and MI, and they reported excellent accuracy. Radiomic texture analysis combined with AI algorithms has played a role in cardiomyopathy classification as well. Its diagnostic ability has been shown to be high, as seen in the study by Neisius and colleagues,[89] which aimed to perform radiomic analysis of native T1 images in order to differentiate between hypertensive and HCMs. Moreover, Fahmy and colleagues[90] developed an AI-based screening model that uses radiomics and DL features to identify patients with HCM without scar before the administration of contrast; the combined DL-Radiomics model outperformed the DL or radiomics models alone, indicating the potential of the combination of these 2 approaches. Fahmy and colleagues[91] also developed a DL model that combined LGE and cine images to improve accuracy of scar quantification among patients with HCM.

Moreover, AI has been applied to prognostic evaluation and risk stratification. Chen and colleagues[92] used an ML model to effectively predict risk of CV events in patients with DCM at 1-year follow-up. Zhou and colleagues[93] applied DL to detect the risk of having a genetic mutation in patients with HCM, and the DL model, especially if combined with Toronto genotype score, improved mutation-risk prediction and showed high diagnostic performance. Finally, DL has been successfully used in the setting of other cardiomyopathies: detection and classification of cardiac amyloidosis,[94,95] aiding diagnosis of left ventricular noncompaction,[96] and arrhythmogenic right ventricular cardiomyopathy.[97]

Congenital Heart Disease

CMR is widely used in the evaluation of congenital heart disease (CHD), and many studies have applied AI in this setting for acquisition speed-up and image reconstruction, with the aim to make CMR more suitable for the pediatric population and image processing easier despite the complex anatomy of these patients. For example, Karimi-Bidhendi and colleagues[98] used a fully automated DL method to segment right and left ventricles in patients with CHD, and the model showed strong agreement with manual segmentation. One other study[99] aimed to reduce scan time by acquiring images at lower resolution and subsequently processed the images by an ML network that recovered the high-resolution features from the rapidly acquired whole-heart images. The authors found good recovery of features and high diagnostic accuracy and confidence.

OUTCOME PREDICTION

The significant number of imaging markers of CV risk, such as CAC score, plaque features, adipose tissue, and radiomics, are being incorporated to traditional clinical risk factors, in order to create predictive models that can increase the performance of current risk score and prognostic models. AI plays an important role in this process, enabling the consideration of clinical and imaging data together while including a larger number of clinical parameters. Several fusion models have been developed to combine multiple resources, and they have been successfully applied to CVD risk and severity assessment, acute CVD detection, and CVD phenotyping.[100] CNNs can be used to extract clinical data from electronic medical records, radiology notes, imaging studies, and clinical notes, whereas ML algorithms, by integrating clinical and imaging data, have been shown to improve prediction of disease and evaluate prognosis[101] (**Fig. 7**). ML has been used to predict 5-year all-cause mortality in patients undergoing CCTA; the ML risk score combining clinical and CCTA data exhibited a significantly higher

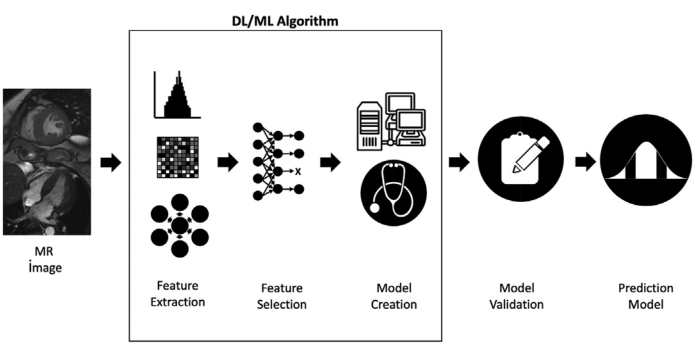

Fig. 7. A DL/ML algorithm based on CMR images texture analysis. The images are used as the input after being processed (eg, segmented and elaborated for analysis), and they are fed to the proposed algorithm, which automatically performs feature extraction, obtaining features of different orders. The features are subsequently selected and reduced, creating a radiomic signature model, possibly integrating such data also with electronic medical records (EMR). The model is further validated, thus creating finally a prediction model, the latter possibly being used to perform different tasks (eg, myocardial scar detection, pathology classification). ML and DL can be involved in different steps of the texture analysis process or automatize most of the workflow. The automated combination of advanced imaging features and EMR can provide more accurate and rapid prediction models to be applied in clinical practice.

area under the curve for outcome prediction when compared with the two alone.[102] The ML approach was also used to predict 3-year risk of MACE by combining myocardial perfusion single-photon emission CT data with clinical data, and it showed high predictive accuracy.[103] Fusion models are not limited to clinical and imaging data alone, but can include other types of data, such as genetic data, which can be used to predict 10-year risk of ischemic heart disease together with medical records.[104] Overall, a significant effort has been put into the development of various multimodality AI models that can improve patient care and CVD assessment.

SUMMARY

Continuous technical advancement is driving the implementation of AI into radiology, and recent literature has witnessed an increase in the number of publications regarding AI applicability in every field of imaging, including cardiac imaging. Literature shows that many AI-based algorithms are being applied to cardiac CT and MR and are partly already integrated into clinical application. The main areas of AI applicability are detection, quantification, and characterization of cardiac disease.

Although great progress has already been made, most of the AI models developed still present limitations, such as narrow focus and limited generalizability, that need to be addressed before AI can be clinically applied with confidence.[105] It is predicted that AI will aid radiologists by performing time-consuming tasks, saving resources that can be used for more difficult/rare cases where AI is expected to fail, therefore improving workflow. A limitation of AI is the lack of intuition, cognition, and reasoning—human skills that the radiologists will always apply to judge AI performance and to check for possible errors in difficult cases.

In summary, AI has been successfully used to perform time-consuming tasks, such as segmentation and postprocessing, optimization of data acquisition and reconstruction, and grading of disease severity. AI has been proven to show an improvement, in terms of time and accuracy, of human work, and therefore, serves as an aid to physicians in better understanding of the patient's cardiac health. Several AI applications in cardiac imaging demonstrate human-level performance, and it is likely that, in the near future, these applications will be further improved to be integrated into clinical workflow; this will have a great impact on costs, wider usability, and optimization of workflow efficiency.

CLINICS CARE POINTS

- Artificial intelligence can be applied to cardiac imaging postprocessing, significantly decreasing time and improving accuracy.
- Artificial intelligence can improve cardiac disease quantification and repeatability, directly impacting patients' cardiac health.
- Artificial intelligence solutions will improve clinical workflow and efficiency in cardiac imaging.

DISCLOSURE

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