Artificial Intelligence

Cardiovascular Imaging and Intervention Through the Lens of Artificial Intelligence

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Abstract

Artificial Intelligence (AI) is a broad term that implies the use of machines to mimic human behaviour and perform various actions with minimal human intervention.\(^1\,^2\) Machine learning (ML), a branch of AI, can analyse information and discover hidden patterns in data.\(^3\)

The treatment of cardiovascular disease has significantly evolved in interventional cardiology over the last 2 decades.\(^4\) Although percutaneous coronary intervention (PCI) is the cornerstone of the catherisation laboratory, many conditions can be treated there, including coronary artery disease (CAD), valvular heart disease, cardiac arrhythmias, pericardial disease, myocardial disease, congenital heart disease and heart failure.

With the emergence of transcatheter therapies, the clinical arena of interventional cardiology has greatly expanded. Non-invasive imaging is the critical gatekeeper in the assessment of cardiovascular diseases before cardiovascular intervention.\(^5\) AI technologies in imaging are demonstrating their capacity for image interpretation, quality control, diagnostics and improved workflow.\(^6\) AI and ML can help discover new variants or phenotypes present within large data in cardiovascular imaging, which can improve our understanding and lead to new therapeutic interventions in CAD.\(^7\) They can further aid in interventional cardiology as they can improve clinical decision-making, organise workflow in the catheterisation laboratory, facilitate catheter-based intervention through robotic application and predict proper placement to reduce or avoid paravalvular leakage.\(^4\,^8\)

Over the last few years, AI has substantially altered the landscape in clinical medicine by providing new insights and opportunities to improve therapy.\(^9\) While AI is evolving in other aspects of human life from self-driving cars to automated voice recognition systems, ML is expanding clinical pathways and opening new frontiers in cardiovascular medicine.\(^9\)\(^\text{–}\)\(^14\) In comparison, the application of ML in interventional cardiology (IC) has been less apparent.\(^15\)\(^\text{–}\)\(^16\) It is evident that AI progress in IC lags behind its counterparts but interest in it is still growing.\(^14\) As advances in stent technology and transcatheter aortic valve replacement (TAVR) or transcatheter mitral valve replacement (TMVR) continue, AI will be beneficial.\(^5\)

In this review, we will discuss how AI will improve the role of cardiovascular imaging and imaging in interventional cardiology.

Keywords

Artificial intelligence, cardiovascular imaging, interventional cardiology, diagnostic tool

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Table 1: Recent Examples of Machine Learning in Cardiology

| Study                    | ML Algorithm      | Field of Cardiology | Study Description                                                   |
|--------------------------|-------------------|---------------------|---------------------------------------------------------------------|
| Narula et al. 2016       | Supervised learning | Echo                | To differentiate between athlete’s heart and hypertrophic cardiomyopathy |
| Zhang et al. 2018        | Deep learning     | Echo                | To distinguish between different echocardiographic view classes     |
| Sengupta et al. 2016     | Supervised learning | Echo                | To discern between constrictive pericarditis and restrictive cardiomyopathy |
| Samad et al. 2019        | Deep learning     | Echo                | To predict survival from echo and EMR information                   |
| Betancur et al. 2018     | Deep learning     | MRI                 | To assess the prediction of CAD                                      |
| Betancur et al. 2019     | Deep learning     | MRI                 | To evaluate the prediction of CAD in semiupright and supine stress MPI |
| Arsajani et al. 2013     | Deep learning     | MRI                 | To compare accuracy of ML to expert readers for CAD                 |
| Arsajani et al. 2015     | Supervised learning | MRI                 | To determine the probability of revascularisation                    |
| Haro Alonso et al. 2019  | Supervised learning | MRI                 | To estimate the risk of cardiac death from SPECT and clinical information |
| Betancur et al. 2018     | Supervised learning | MRI                 | To predict MACE events from MRI data                                |
| van Rosandeal et al. 2018| Deep learning     | CT                  | To compare ML risk scores and current risk scores from CT angiography for CAD |
| Zrek et al. 2018         | Deep learning     | CT                  | To compare fractional flow reserve from CT angiography and invasive coronary angiography |
| Lessmann et al 2016      | Deep learning     | CT                  | The algorithm created bounding boxes around the heart to determine candidates for coronary artery calcium measurement |
| Santini et al. 2017      | Deep learning     | CT                  | To classify and segment lesions in cardiac CT                        |
| Ruijsink et al. 2020     | Deep learning     | CMR                 | To compare automatic ventricular measurements with manual findings from CMR |
| Tan et al. 2017          | Deep learning     | CMR                 | To automatically segment the left ventricle in different views from CMR |
| Cook et al. 2019         | AI algorithm      | IC                  | To compare AI with human experts for interpretation of instantaneous wave-free ratio (iFR) pressure–wire pullback traces |
| Azzalini et al. 2018     | Supervised learning | IC                  | To determine which contrast media was associated with contrast induced kidney injury following PCI |
| Hernandez-Suarez et al. 2019 | Multiple ML algorithms | TAVR           | To predict in-hospital mortality following TAVR by an array of ML algorithms |
| Ghaffar et al. 2019      | Unsupervised learning | TAVR              | To use ML to determine the 30-day adverse events following TAVR      |

AI = artificial intelligence; CMR = cardiac MRI; Echo = echocardiography; EMR = electronic medical records; IC = interventional cardiology; MACE = major adverse cardiovascular events; PCI = percutaneous coronary intervention; SPECT = single photon emission CT; TAVR = transcatheter aortic valve replacement.

Figure 1: Role of Artificial Intelligence in Cardiovascular Imaging and Interventional Cardiology

Types of Machine Learning
ML is a collective term that encompasses a variety of algorithms (Table 2). This includes supervised learning, unsupervised learning and reinforcement learning. The choice of algorithm depends on the indication and purpose of the investigation. Supervised learning uses specific labels or classes.9 Unsupervised learning analyses a database without labels.10 Semi-supervised learning is a combination of supervised and unsupervised learning.11 Reinforcement learning uses reward criteria similar to human psychology to perform actions.12 Deep learning is one of the most advanced ML algorithms available.13 Supervised and unsupervised learning have demonstrated tremendous potential in cardiovascular imaging, and deep learning (DL) is poised to make the evolutionary leap in ML for cardiovascular imaging.2 It does not require significant training to execute an action.1 It performs significantly better with larger and more complex data sets than other ML algorithms (Figure 2). It requires less domain knowledge to perform various tasks. Among the various algorithms available, DL has the most potential and prowess for prediction.13 It is being used in a variety of applications, including voice recognition systems, such as Amazon’s Alexa or Apple’s Siri, and image identification systems.10 DL may process complex information through several layers to process information. It is extracted through each part of the hierarchy and DL can recognise various hidden patterns.9 DL has tremendous capabilities, which are being used in various sectors by the commercial industry and information technology.9

Natural Language Processing
NLP is a branch of AI that comprehends the mechanics of human language.14 This method can be applied to electronic medical records (EMRs) for large-scale text analysis and data extraction. Similar to ML algorithms, it may be used to identify complications and postoperative
These aspects can be particularly
Furthermore, NLP can be used
The ML algorithm was
In several recent studies, ML algorithms have shown innovative
The random forest models demonstrated superior
testifies to identify 23 viewpoints and segmentation of cardiac chamber
algorithm, for automated image interpretation.
Similarly, Zhang et al. used a convolutional neural network (CNN), a DL
adverse drug event identification or patient selection for cardiac resynchronisation therapy, to name a few.

Computer Vision
Computer vision uses image processing and ML algorithms to detect features or pattern recognition in digital or video imaging. Computer vision algorithms coupled with deep learning can provide an automated interpretation of complex radiological images to assist or train cardiologists. This may play an important role in IC for identifying potential complications in the placement of valves and structural defects. Currently, there are troves of IC data that can be analysed by ML algorithms to predict adverse events.

Clinical Decision Support System
Clinical decision support systems use information in EMRs and present summaries and notification that are relevant to healthcare providers in implementing evidence-based clinical practice. They may provide information regarding risk factors, drug interaction information or information relevant to patients undergoing catheterisation. Because it relies on EMRs, NLP could be imperative to decision support systems. However, ML could also be used to interpret images for treatment approaches and aid in medical management.

Role of AI in Echocardiography
Echocardiography is the primary image modality in cardiology and plays a central role in most diagnostic pathways for several pathological entities. In several recent studies, ML algorithms have shown innovative applications in findings using echocardiographic parameters. Although echocardiography is widely used, its results can be heterogeneous. These variables can affect management and outcomes for the interventionist. Machine learning can produce rapid and consistent findings, which can help budding interventionists in clinical decision-making.

In our own experience, we have harnessed the capabilities of AI to identify differences between hypertrophic cardiomyopathy and athlete’s heart, and applied a supervised learning algorithm to differentiate between restrictive cardiomyopathy and constrictive pericarditis.

Similarly, Zhang et al. used a convolutional neural network (CNN), a DL algorithm, for automated image interpretation. The ML algorithm was trained to identify 23 viewpoints and segmentation of cardiac chamber

Machine learning
- Classification: It includes logistic regression, Bayesian networks, random forests, ridge regression, elastic net regression, least absolute shrinkage and selection operator (LASSO) regression, and artificial neural networks.
- Clustering: k-means clustering, and principal-component analysis.

Unsupervised learning
- It detects vital relationships and similarities in unlabeled datasets.

Semi-supervised learning
- Hybrid of supervised and unsupervised learning.

Reinforcement learning
- Based on behavioural psychology, uses reward function.

Table 2: Types of Machine Learning

| Types of Machine Learning | Description | Examples |
|---------------------------|-------------|----------|
| Supervised learning       | The data contains labels and outcomes | This includes logistic regression, Bayesian networks, random forests, ridge regression, elastic net regression, least absolute shrinkage and selection operator (LASSO) regression, and artificial neural networks. |
| Unsupervised learning     | It detects vital relationships and similarities in unlabeled datasets | It encompasses of hierarchical clustering, k-means clustering, and principal-component analysis. |
| Semi-supervised learning  | Hybrid of supervised and unsupervised learning. | It contains a combination of labelled and unlabelled outcomes and classes, used in image and speech recognition. |
| Reinforcement learning    | Based on behavioural psychology, uses reward function | Uses certain reward criteria, it is seen in medical imaging, analytics, disease screening, and prescription selection. |

Figure 2: Evolution of Artificial Intelligence in Cardiovascular Imaging

Artificial intelligence
- Supervised
- Unsupervised
- Semi-supervised
- Reinforcement

Role of AI in Nuclear Medicine
Myocardial perfusion imaging (MPI) has an important role in nuclear medicine and provides vital information in CAD. Single-photon emission CT (SPECT) enables physicians to identify perfusion defects. MPI is a non-invasive modality that has a paramount role in risk stratification for CAD. With ML algorithms, it can integrate clinical information and a large number of parameters to predict CAD, revascularisation and major adverse cardiovascular events (MACE). These aspects can be particularly useful for interventionists as they can assist in clinical management and patient selection for high-risk procedures.

Betancur et al. assessed the prediction of obstructive coronary artery disease (CAD) using myocardial perfusion imaging (MPI) by a DL algorithm. The ML algorithm demonstrated a higher area under the curve for CAD prediction (per patient 0.80 versus 0.78; per vessel 0.76 versus 0.73; p<0.01). Recently, Betancur et al. also assessed a deep learning algorithm for the prediction of obstructive CAD with a combination of semi-upright
and supine stress MPI in comparison with TPD.\textsuperscript{14} Similarly, the area under the receiver-operating curve for prediction of disease per patient and per vessel by the ML algorithm was better (per patient, 0.81 versus 0.78; per vessel 0.77 versus 0.73, p<0.001).\textsuperscript{15} Arsajani et al. evaluated the combination of clinical and imaging data to predict CAD using SPECT.\textsuperscript{16} The receiver-operating curve for the ML method was better than TPD and two readers with considerable significance (p<0.001).

Arsajani et al. examined clinical and imaging data to determine the probability of revascularisation in 713 patients with suspected CAD through a LogitBoost supervised learning algorithm.\textsuperscript{16} The specificity of the ML algorithm was better than both expert readers (p<0.05) and similar to total perfusion deficit (p<0.05). In addition, the receiver-operating curve for the ML architecture (0.81 ± 0.02) was similar to reader 1 (0.81 ± 0.02), but better than reader 2 (0.72 ± 0.02, p<0.01) and the standalone measure of perfusion (0.77 ± 0.02, p<0.01).

Alonso et al. used a supervised ML algorithm to estimate the risk of cardiac death, derived from an amalgamation of adenosine myocardial perfusion SPECT with clinical information in 8,321 patients and 551 cases of cardiac death.\textsuperscript{17} The logistic regression was outperformed by the ML algorithm (AUC 0.76; 14 features). It evidently showed superior accuracy (AUC 0.83; p<0.0001; 49 features). Nonetheless, the least absolute shrinkage and selection operator (LASSO) model required the least number of features (AUC 0.77; p=0.045; six features).

Betancur et al. explored the predictive value of patient information with SPECT MPI to predict MACE through a LogitBoost supervised learning ML algorithm in 2,619 patients.\textsuperscript{18} At around 3 years’ follow-up, 239 patients had experienced MACE. Interestingly, the ML combined achieved superior MACE prediction than ML imaging (AUC 0.81 versus 0.78; p<0.01). The ML also had higher MACE predictive accuracy when compared with an expert reader, automated stress total perfusion deficit and automated ischaemic perfusion deficit (AUC 0.81 versus 0.65 versus 0.73 versus 0.71; p<0.01 for all).

**Role of AI in Cardiac CT**

CT is a non-invasive approach for the identification of obstructive CAD. CT enables the depiction of the underlying coronary anatomy to visualise plaques or stenosis in the coronary artery tree.\textsuperscript{19} From an interventionalist point of view, cardiac CT plays an important role in appropriate selection for PCI. Among all non-invasive modalities, CT angiography closely mirrors invasive angiography. ML algorithms can greatly augment the possibilities of cardiac CT.

Lessmann et al. used a convolutional neural network (CNN), a deep learning algorithm, to create a bounding box around the heart that corresponds to certain Hounsfield units.\textsuperscript{20} They investigated the potential of an automated coronary calcium system that was able/would be to screen patients for high-risk cardiovascular events. Santini et al. explored the role of a CNN algorithm in classifying and segmenting lesions in cardiac CT imaging.\textsuperscript{21} After proper training of the CNN algorithm with various CT volumes, they were able to demonstrate a Pearson correlation measuring 0.983.

Zreik et al. used a CNN algorithm to automatically calculate the fractional flow reserve (FFR) from coronary CT angiography.\textsuperscript{22} Surprisingly, there was good agreement between the ML-derived values and invasively measured one, with the AUC being 0.74. Rosendaal et al. examined the role of a boost ensemble algorithm to compare ML-derived scores and current risk scores in CT angiography for CAD evaluation.\textsuperscript{23} The events expressed by the AUC was superior by the ML algorithm in reference to conventional scores (0.771 versus 0.685 to 0.701, p<0.001).

**Role of AI in Cardiac MRI**

Cardiovascular magnetic resonance (CMR) imaging has emerged as a robust diagnostic modality for assessing a variety of clinical conditions in cardiology. Of the various non-invasive approaches, it is the only option that permits tissue characterisation. CMR can be used by the interventionist to plan appropriate management for patients. During procedures, CMR imaging can be used to guide complex procedures because of the minimal risk of radiation.

Tan et al. assessed the role of the CNN algorithm for automatic segmentation of the left ventricle in short-axis slices in publicly available database.\textsuperscript{24} Interestingly, the ML algorithm achieved a Jaccard index of 0.77 for the left ventricle segmentation challenge dataset and obtained a continuously ranked probability score of 0.0124 for the Kaggle Second Annual Data Science Bowl.

Similarly, Ruijink et al. evaluated the role of the CNN framework for automated ventricular function assessment from cardiac CMR.\textsuperscript{25} The findings corroborated highly with manual analysis for left ventricular and right ventricular volumes (all r >0.95), strain (circumferential r = 0.89; longitudinal r >0.89) and ejection rates (all r ≥0.93).

**Can AI-integrated Cardiovascular Imaging Facilitate Interventional Therapies?**

Using the vast troves of cardiovascular imaging enables the possibilities of data-driven phenotypic differentiation.\textsuperscript{26} This has particular relevance in the field of IC and transcatheter therapies for enabling individualised therapies.\textsuperscript{5} Algorithms integrating ML and cardiovascular imaging can help generate patient-specific risk scores, which can yield diagnostic significance in procedural planning.\textsuperscript{14} Furthermore, ML may play a paramount role in automating cardiovascular imaging workflow for referral of patients to cardiac catheterisation laboratory by facilitating faster reading, interpretation and diagnosis.\textsuperscript{28} In addition, ML algorithms may help predict outcomes such as mortality or complications following interventional therapies.

**Role of AI in Percutaneous Coronary Intervention and Transcatheter Aortic Valve Replacement**

Although the potential of AI has not been fully harnessed in PCI, a few studies provide a glimpse of AI in the near future.\textsuperscript{26} One aspect of considerable variability in interpretation is physiologically guided coronary revascularisation.\textsuperscript{8} The consistency of results can be improved with AI.

Cook et al. compared an AI algorithm with 15 human experts for interpretation of 1,008 instantaneous wave-free ratio (iFR) pressure-wire pullback traces.\textsuperscript{31} In addition, a heart team interpretation was determined by a consensus of individual opinions. The median human expert had an 89.3% agreement with heart team response, while it was 89.4% with AI (p<0.01 for non-inferiority) for PCI haemodynamic appropriateness. Within the 372 cases evaluated for haemodynamic appropriateness, the AI framework had 89.7% agreement while the median human expert was 88.8% in agreement with the heart team response (p<0.01 for non-inferiority). Cook et al. confirmed that the AI algorithm was not inferior to the expert decision making for determining the appropriateness and strategy of PCI.\textsuperscript{23}

Azzalin et al. used a generalised boost regression to determine which contrast media among five types was associated with contrast-induced...
kidney injury following PCI in 2,648 patients. In a risk-adjusted analysis, Azzalini found no particular contrast type was associated with contrast-induced kidney injury when compared to ioxixanol.

Currently, few centres have explored the role of AI in TAVR. Hernandez-Suarez used ML algorithms to predict in-hospital mortality after TAVR in 10,883 patients using data derived from the national inpatient sample. The AUC for the ML algorithm was greater than 0.80. They were able to show ML could generate risk models capable of predicting in-hospital mortality.

Ghaffar explored the role of topological data analysis (TDA) network to predict 30-day complications and mortality following TAVR in 228 patients. Four clusters were identified. Cluster A had more frequent vascular intervention (p<0.016), while clusters B and D had a higher number of procedures before TAVR (p<0.04). Cluster C underwent TAVR. Major adverse complications were seen in the first week of complications in clusters C and D (p<0.05). Interestingly, there was no difference in the Society of Thoracic Surgeon’s risk scores between either cluster.

Role of AI in Robotics

Interest is surging in robotic technology for IC because it can deliver precise, efficient clinical care. Robotic technology has the capability to reduce variability in procedure time, accurately assess lesion length and decrease the number of stents used. Robots can be used in training young interventionists.

Though robotics has the potential to open new doors in IC, it is not without flaws. There are fundamental differences between interventionists and their accompanying robotic assistants. These systems do not recognise the underlying anatomy or understand the intentions of the operator. ML algorithms, computer vision and image interpretation can truly help in this process by bridging the gap between man and machine. They can enhance the underlying technology to possibly enable some degree of automation and possible decision-making. Future robotic systems may be able to assess previous procedures and provide feedback to intervention cardiologists.

Our Evolving Views on AI in Cardiovascular Imaging and Interventional Cardiology

Although AI has clearly caused paradigm shifts in cardiovascular imaging, the application of AI for IC is still in its early stages. AI is poised to create revolutionary progress in IC in years to come (Figure 3). AI offers the possibility of detecting patients with high-risk profiles and gauge treatment effects according to various factors. In the catheterisation laboratory, AI can assist in procedural guidance for angiography, intravascular imaging and provide any form of additional support to the operator during the procedure.

Shortly, AI could provide patient-specific, vessel-specific or even lesion-specific revascularisation strategies. Based on outcome data arising from national and international registries, this could be tapped by AI to create treatment strategies to improve short- and long-term outcomes.

Figure 3: Future of Artificial Intelligence in Interventional Cardiology and the Catheterisation Laboratory

Though AI may appear revolutionary, it is not without limitations. Several risks are associated with AI. Although AI and DL are extremely capable of extrapolating patterns from data, they can misinterpret information. This can lead to an inaccurate classification of information. Some changes can be minuscule and not noticed by human perception. This can perplex the best operating ML algorithms and can have severe ramifications in healthcare. There is a possibility of misinterpreting information as well.

Cardiologists must be cognisant of the risks of AI and be educated on its strengths and weaknesses. They must not blindly accept the actions of AI. By being aware of the risks, we can fully tap the potential of AI in IC.

Many echocardiographers have played a key role in the development of AI and ML algorithms in cardiovascular imaging. Similarly, interventionists must play an active role in the genesis and propagation of AI in IC. Interventionists can provide clinically relevant information to engineers regarding the nature of IC data. Engineers can use this data to create practical solutions in the field of IC. Such algorithms could benefit the interventionist, streamline the workflow and help to minimise error. Collaboration between interventionists and engineers needs to occur at national and international levels for AI to truly flourish in IC.

Conclusion

AI is playing a paramount role in diagnostic imaging by integrating vast amounts of information. Similarly, AI is beginning to take root in IC. It can expand options for procedural guidance, intraprocedural analysis, robotics and clinical judgement.

As interventionists learn to adopt AI in clinical practice, it will revolutionise IC treatment strategies. There may be some initial hurdles, and difficulties are inevitable in the path to progress. The trinity of human, machine and patient will be the focal point of IC along with imaging in years to come.
AI in Cardiac Imaging and IC

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