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Review Article

The relative effectiveness of AI-based imaging and ultrasound in the navigation of cardiac procedures

Anju Singh[1], Sibi Samuel[2], Shailendra Verma[3], Chandra Prabha Joshi[1], Dilpreet Kaur[4], Monalisha Pal[5]*

[1]Department of Medical Surgical Nursing, Rohilkhand College of Nursing Bareilly, Uttar Pradesh, India
[2]Department of Medical Surgical Nursing, Nightingale Institute of Nursing, Noida, Uttar Pradesh, India
[3]Department of Medical Surgical Nursing, Tirthankara Mahaveer University, Uttar Pradesh, India
[4]Department of Medical Surgical Nursing, Prakash Institute of Paramedical Rehabilitation Allied and Medical Sciences, Greater Noida, Uttar Pradesh, India
[5]Department of Community Health Nursing, School of Nursing, Noida International University, Uttar Pradesh, India

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***Correspondence:**
Dr. Monalisha Pal,
E-mail: monalishapal091@gmail.com

ABSTRACT

The exponential growth in cardiovascular imaging investigations underlines a vital need to optimise clinical workflow efficiency and diagnostic accuracy. Artificial intelligence (AI), particularly machine learning, has emerged as a transformational technology in this sector, giving the potential to expedite cardiac imaging operations and enhance patient outcomes. This review investigates how well AI-based imaging navigates cardiac operations in comparison to traditional ultrasonography. We investigate AI's ability to automate picture segmentation, minimise operator-dependent variability, and combine multimodal data, such as cardiac magnetic resonance imaging, computed tomography, nuclear imaging, and echocardiography, for a whole cardiac evaluation. AI-enhanced imaging provides more accuracy in illness identification, prognosis, and clinical decision-making, even though conventional ultrasound is still a vital component of real-time procedure guidance. The article also identifies the main obstacles to the widespread use of AI in clinical practice, as well as current applications and developing technology. The study offers a critical viewpoint on the developing role of AI in improving cardiovascular care by contrasting different modalities.

Keywords: Imaging, Ultrasound, Electrocardiography, Cardiac magnetic resonance, Computed tomography

INTRODUCTION

Cardiovascular diseases (CVDs) continue to be the world's leading cause of morbidity and mortality, requiring prompt and accurate diagnosis, intervention, and monitoring. Cardiac imaging is essential at every stage of cardiovascular care, from initial diagnosis and procedural planning to real-time navigation during interventions and long-term follow-up. Ultrasound, especially echocardiography, has long been the mainstay of cardiac evaluation among imaging modalities because of its accessibility, non-invasiveness, real-time imaging capability, and affordability. However, ultrasound is intrinsically operator-dependent, prone to interobserver variability, and has limited capacity to process and integrate large amounts of data for advanced decision support.[1]

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) algorithms, has become more popular in cardiovascular imaging due to the growing need for accuracy and speed in clinical processes. High-volume datasets may be processed by AI-based imaging systems, which can also automate complicated and routine image processing activities and combine multimodal data inputs to help doctors with real-time procedural advice.[2] These skills have the potential to predict clinical outcomes, personalise therapy approaches, and increase the accuracy of picture interpretation. AI, for example, can improve cardiac structure segmentation, identify minor problems, speed up diagnostic procedures, and help with difficult procedures like catheter ablation, valve replacement or repair, or closure of the left atrial appendage.[10] AI's incorporation into multimodality imaging, such as nuclear cardiology, magnetic resonance imaging (MRI), cardiac computed tomography (CT), and echocardiography, is changing the norm for cardiovascular treatment. While AI-based systems provide improved image interpretation, three-dimensional reconstruction, and even predictive analytics- all of which are crucial in complex or high-risk procedures- traditional ultrasound remains the primary tool for many cardiac procedures because of its portability and real-time capability.

Even with these developments, clinical use of AI-based imaging is still developing. Widespread integration is hampered by issues including algorithmic bias, the requirement for sizable, annotated datasets, expensive implementation costs, and a lack of standardised protocols. Furthermore, research on the moral and legal ramifications of AI-assisted decision-making in crucial cardiac surgeries is currently ongoing.[8]

COMPUTATIONAL METHODS FOR AI-POWERED HEART IMAGING

A strong foundation of computational techniques that allow automated picture capture, processing, interpretation, and decision support is necessary for the use of AI in cardiac imaging. These methods mostly fit within the frameworks of computer vision, deep learning, and machine learning (ML, DL), each of which has special features to deal with the difficulties of cardiac imaging. This section goes into further detail about these computational techniques, highlighting how they improve procedural navigation, especially when compared to conventional ultrasound modalities.[11]

Algorithms for machine learning

Machine learning (ML) is the term used to describe a class of algorithms that, without explicit task programming, learn from data patterns and generate predictions or choices. ML is used in cardiac imaging to separate cardiac structures, categorise disease states, and forecast clinical outcomes.

Learning under supervision

In supervised learning, algorithms are trained using labelled datasets with known valid outputs (diagnosis, anatomical boundaries, etc.), such annotated cardiac pictures. Typical algorithms consist of following.

Support vector machines

For binary classification tasks like identifying myocardial infarction or differentiating between healthy and sick tissues or support vector machines (SVMs), are utilised.

Random forests

Used for feature selection and classification, particularly when integrating clinical data (e.g., age, blood pressure, BMI) with features extracted from images.

Logistic regression

For forecasting binary outcomes, including procedure success or post-operative problems, logistic regression is utilised. Through the reduction of interobserver variability and the automation of measures such as valve gradients or ejection fraction, supervised learning enhances diagnostic reproducibility in echocardiography.[9]

Unsupervised learning

Hidden patterns in unlabelled data are discovered by unsupervised learning. Anatomical or functional metrics from imaging data can be used to stratify patients or find novel phenotypes in heart failure using clustering techniques like K-means and hierarchical clustering. Risk classification and pre-procedural planning are aided by these techniques.

CONVOLUTIONAL NEURAL NETWORKS AND DEEP LEARNING

A kind of machine learning called ‘deep learning (DL)’ employs multi-layered artificial neural networks to extract intricate characteristics from massive datasets. For image analysis, convolutional neural networks (CNNs) are very effective.

CNNs for segmenting images

The purpose of CNNs is to find spatial hierarchies in data. U-net topologies are frequently used in cardiac imaging to automatically partition the heart's chambers, valves, and vascular structures in CT, MRI, and ultrasound scans. Consistent segmentation and a large reduction in human labour are made possible by these models, which is essential for real-time image-guided treatments such as electrophysiological research or valve replacement.

Classification with CNNs

CNNs are capable of classifying problems including congenital heart abnormalities, pericardial effusion, and left ventricular hypertrophy since they have been trained on thousands of cardiac pictures. CNNs can also evaluate functional issues like as decreased wall motion or diastolic dysfunction when paired with time data from echocardiography (cine loops).

LONG SHORT-TERM MEMORY MODELS AND RECURRENT NEURAL NETWORKS

Time-series data is associated with cardiac imaging, particularly echocardiography. Such sequences are best analysed by long short-term memory (LSTM)s and recurrent neural networks (RNNs), which allow the model to "remember" previous frames and identify dynamic changes. LSTMs can help surgeons with ablation or device insertion procedures in intraoperative situations by tracking cardiac movement in real time. These models can also forecast trends in cardiac output or haemodynamic changes throughout the surgery when paired with Doppler ultrasonography data.[11,12]

RECONSTRUCTION OF IMAGES AND GENERATIVE MODELS

In cardiac imaging, generative adversarial networks (GANs) are used to improve picture quality, eliminate noise, and recreate lost views. Better visualisation of cardiac structures is made possible by GANs' ability to convert low-resolution ultrasound pictures into high-fidelity images. In order to lessen reliance on annotated clinical datasets, they are also employed in the creation of synthetic images for training.

MODELS FOR MULTIMODAL DATA FUSION AND INTEGRATION

For a more thorough patient evaluation, AI models are increasingly combining imaging data with genetic profiles, test findings, and electronic health records (EHR). AI can merge echocardiogram data with CT angiography and MRI for accurate anatomical and functional correlation thanks to multimodal deep learning. These integrated models facilitate personalised treatment planning in procedural navigation, including choosing the optimum access route, device kind, and size.[13]

PROCEDURE NAVIGATION USING REINFORCEMENT LEARNING

Through trial-and-error interactions with their surroundings, agents may learn to make decisions through reinforcement learning (RL). When doing cardiac procedures: (a) by simulating millions of procedural scenarios, RL agents can learn the best injection angles or catheter courses; and (b) RL offers potential for autonomous robotic help in image-guided cardiac procedures, while it is still mostly in the research stage.

COMPARING CONVENTIONAL ULTRASOUND METHODS

Although ultrasound is still essential because to its cost, mobility, and real-time imaging capabilities, picture collecting and interpretation are mostly handled by humans. AI-based imaging systems, on the other hand, use computer models to: (a) automate measurements (e.g., ejection fraction, ventricular volume); (b) ensure that interpretations are consistent across institutions; (c) reduce the variability between and between observers; and (d) boost spatial resolution and picture quality under noisy or less-than-ideal circumstances. Additionally, AI improves procedural safety by providing decision support tools that complement human judgement during high-risk cardiac operations, real-time feedback, and predictive alarms (such as an imminent tamponade or device dislocation).[14,15]

ARTIFICIAL INTELLIGENCE APPLICATION IN CARDIOVASCULAR IMAGING

A new study used 12-lead ECG data from a large prospective cohort to verify a deep learning model that predicts left ventricular ejection fraction (EF)$\leq$35%. With 82.5% sensitivity, 86.8% specificity, and an AUC of 0.918, the algorithm showed good diagnostic performance when tested on 16,056 patients at the Mayo Clinic, especially those who had echocardiograms within a month after ECG testing. Interestingly, a sizable fraction of false positives (39.8%) had somewhat lower EF (36-50%), suggesting possible subclinical impairment. Additionally, 3.5% of patients without previous echocardiograms had positive screenings marked, highlighting its ability to detect heart abnormalities that was previously unknown. The study recommends more validation to evaluate its effect on clinical outcomes and resource utilisation, and it believes that including biomarkers such as NT-pro-BNP might improve specificity.[3]

Recent developments in ML and AI have greatly improved cardiac CT diagnostic and prognostic capabilities, providing quick, accurate, and non-invasive evaluations of a range of cardiovascular disorders. The transformative impact of ML in six key areas- CT-derived fractional flow reserve (CT-FFR), atrial fibrillation (AF), aortic stenosis, coronary plaque characterisation, epicardial fat quantification, and coronary artery calcium scoring- is highlighted in a thorough review of 57 studies that were found through systematic searches in Medline, Embase, and the Cochrane Library up until November 2021. Accurate CT-FFR estimate has been made possible using ML algorithms, which may lessen the need for invasive coronary angiography. Additionally, computerised measurement of non-calcified plaques and coronary artery calcification has improved in accuracy and repeatability. Rapid and precise measurements of epicardial adipose tissue have been improved, providing information on cardiovascular risk classification. ML enables safe, optimal aortic annulus measurements to direct transcatheter aortic valve replacement (TAVR) in structural heart disease. ML-based left atrial segmentation in electrophysiology can predict AF recurrence following ablation with greater accuracy. Together, these advancements highlight the growing contribution of machine learning to improving the clinical usefulness and effectiveness of cardiac CT imaging.[4]

In recent developments within cardiac imaging, CNNs have demonstrated high efficacy in automating landmark detection in cardiac CMR, significantly enhancing the precision and speed of image interpretation. A retrospective study involving over 40,000 CMR images from more than 2,800 patients across two institutions reported robust performance of CNN models trained to identify key anatomical landmarks- such as mitral valve plane points, apical points on long-axis views, and right ventricular (RV) insertion and left ventricular (LV) center points on short-axis views- across cine, late gadolinium enhancement (LGE), and T1 mapping sequences. The CNN achieved near-perfect detection rates, ranging from 96.6% to 100%, with Euclidean distances between model-predicted and manually annotated landmarks consistently within 2 to 3.5 mm, reflecting high concordance with expert annotations. Importantly, no significant differences were observed between model outputs and expert assessments in derived anatomical parameters such as anterior RV insertion angle and LV length. Moreover, the rapid inference time- 610 milliseconds on a GPU- positions this CNN framework as a practical, real-time solution for clinical deployment, offering a promising avenue for standardized, reproducible CMR analysis.[5] This work used a Support Vector Machine (SVM) method to integrate numerous quantitative factors in order to improve the diagnostic accuracy of myocardial perfusion SPECT (MPS) for diagnosing coronary artery disease (CAD). Angiographic stenosis criteria were used to identify CAD in 957 rest-stress gated non-corrected MPS images. Total perfusion deficit (TPD), ischaemic changes (ISCH), and ejection fraction changes (EFC) were among the quantitative measures. The SVM was evaluated on 832 patients after being trained on 125. The findings demonstrated that SVM outperformed individual quantitative measures and visual evaluations in terms of sensitivity (84%) and specificity (88%). It performed noticeably better than TPD, ISCH, EFC, and even expert visual interpretation in terms of diagnosis accuracy (86%) and ROC AUC (0.92). These results show that CAD identification by MPS is much enhanced by SVM-based integration of perfusion and functional data.[6]

LITERATURE SEARCH

The relative efficacy of AI-based imaging and ultrasonography in cardiac procedure navigation is examined in this descriptive review. To find pertinent research contrasting various imaging modalities in interventional cardiology, a literature search was done. Books, journals, published research papers, systematic reviews, and clinical trial reports were among the secondary sources that were used to gather data. The terms artificial intelligence in cardiac imaging, AI in cardiology, image-guided cardiac interventions, echocardiography in interventions, AI verses ultrasound in cardiac navigation, and ultrasound-guided cardiac treatments were used.

DISCUSSION

This paper emphasises how ultrasonography and AI-based imaging are becoming more and more important in guiding cardiac operations. According to the gathered literature, AI-based imaging, especially in complicated cardiac treatments, provides improved diagnostic accuracy through automated image interpretation, real-time data processing, and predictive analytics. By reducing human error, enhancing decision-making, and providing comprehensive anatomical visualisation, these technologies help physicians. On the other hand, ultrasound- particularly echocardiography- continues to be a widely available, reasonably priced, and real-time imaging modality that is crucial for procedural guidance and bedside cardiac evaluations. However, in some therapeutic situations, operator dependence and picture quality frequently restrict its efficacy. Numerous studies have highlighted how AI integration is progressively complementing or improving conventional imaging, even if ultrasonography is still the first-line method for many cardiac procedures. Pre-procedural planning, intra-procedural navigation, and post-procedural result evaluation were all shown to be greatly aided by AI-based solutions. AI-powered echocardiography systems have also demonstrated promise in automating picture interpretation and lowering inter-observer variability. Overall, the research indicates that ultrasound and AI-based imaging both offer unique advantages. Ultrasound guarantees instant accessibility and dynamic imaging, while AI offers accuracy, automation, and sophisticated analytics. In contemporary clinical practice, the most complete support for cardiac procedure navigation may be provided by combining the two technologies.

CONCLUSION

To sum up, the incorporation of artificial intelligence into cardiac imaging represents a substantial breakthrough in procedural navigation and cardiovascular diagnostics. AI-based imaging methods offer significant benefits over conventional ultrasonography, including improved accuracy, automated image segmentation, and the capacity to combine data from other imaging modalities. These developments enhance the effectiveness and consistency of cardiac evaluations while lowering operator-dependent variability. Conventional ultrasound is still useful for real-time guidance, particularly in dynamic procedural settings, but AI-driven methods improve clinical decision-making and diagnostic accuracy. However, there are still significant obstacles to overcome before AI can be widely used in clinical practice, such as ethical, regulatory, and infrastructure issues. The strategic application of AI in cardiovascular imaging has enormous potential to improve patient outcomes and revolutionise the provision of cardiac care as technology develops.

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