Editorial

Artificial Intelligence in Echocardiography: The Future of Precision Diagnosis

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The integration of artificial intelligence (AI) into echocardiography ushers in a transformative era in cardiovascular imaging, offering greater diagnostic accuracy, workflow efficiency, and data integration. The emergence of AI-based technologies in various areas of cardiovascular imaging is redefining not only our field of expertise, but also the interaction between diagnostic medicine and clinical practice. This editorial aims to provide basic definitions of terms used in AI, summarized in Table 1,[1] and explore the growing role of AI in echocardiography, with emphasis on its applications in systolic and diastolic functions, mitral and aortic valve diseases, and the increasing use of point-of-care ultrasound (POCUS). Furthermore, it provides a final reflection on the advantages and disadvantages of using AI in diagnostic medicine.

AI and the Systolic Function

Ejection fraction (EF) is an essential parameter used to assess the systolic function; however, it has been historically subjected to interobserver variability and the level of experience of the examiner.[2] AI-based algorithms present solutions for EF, providing automated and reproducible calculations.[3–5] A pioneering study published by He et al.[6] evaluated a deep learning (DL) system comprised of convolutional neural networks (CNNs), called EchoNet-Dynamic flow, and compared EF assessments performed by AI with measurements performed by experienced sonographers. The reference cardiologists who checked these results were unable to differentiate between the sonographer and AI. Furthermore, the results demonstrated that the assessment by AI was not inferior to those performed by experts, with a difference of less than 5% in variability. Other advantages of this system were the speed of measurement and the possibility of averaging up to five heartbeats, thus improving the accuracy of the result in atrial fibrillation.

Another parameter widely used to assess systolic function in echocardiography is the Global Longitudinal Strain (GLS) analysis,[7] which not only aids in the diagnosis of cardiac function, but also reveals characteristic patterns of certain diseases, such as amyloidosis.[7] The GLS technique itself requires machine learning (ML) training of the equipment to identify acoustic window incidences and outline edges. However, AP techniques by CNR were able to assess GLS more quickly and with less variability when compared to a commercially established workstation used in echocardiography laboratories.[8] Recently, Kwan et al.[9] evaluated a CNR system used to assess GLS with images produced by equipment from two different companies, concluding that, in addition to having less variability and good reproducibility, this system was able to identify GLS patterns and differentiate between athlete's hypertrophy, amyloidosis, and hypertrophic cardiomyopathy. However, it important to understand that the quality of the images obtained for both GLS and EF assessments must be good, a factor that cannot yet be achieved by AI.

AI and the Diastolic Function

Assessment of left ventricular diastolic function plays an essential role in the diagnosis and prognosis of several heart diseases, especially heart failure with preserved EF. However, the multiple algorithms and complexity of echocardiographic parameters used to assess diastolic function make it difficult to adequately classify approximately 20% of all patients, even when experienced professionals perform the analysis.[10] In this group, classified as having indeterminate diastolic function, it is not possible to define the presence or absence of elevated filling pressures, an essential parameter in determining prognosis and aiding in treatment.[11]

In this scenario, electrocardiogram (ECG) data, detectable primarily through AI AP, emerges as a promising solution to detect patients with increased filling pressures. Lee et al.[12] analyzed more than 90,000 ECGs performed by AI in patients who underwent evaluation for diastolic function with a maximum difference of 14 days. By incorporating ECG into echocardiogram data, the accuracy for detecting elevated filling pressure was 91%, rivaling that of traditional echocardiographic assessments. Thus, the use of AI-assessed ECG can complement echocardiogram data, especially in situations where the number of parameters is quite large and where there is a lack of dichotomization. The ability to predict diastolic dysfunction and elevated filling pressures from a simple ECG underscores the role of AI in expanding diagnostic capacity in resource-limited settings and has now been incorporated into the echocardiogram report of the authors of the article.

AI in Mitral Valve Disease

Mitral regurgitation (MR) is highly prevalent in the population and is associated with a significant reduction in quality of life. Transthoracic echocardiography (TTE) plays an

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Table 1 – Definition of terms associated with AI.

Term	Abbreviation	Concept
Artificial Intelligence	AI	Technology that enables computer systems to imitate human cognitive functions, such as learning, reasoning, and problem-solving.
Convolutional Neural Network	CNN	A specialized architecture for analyzing visual images, within the category of deep neural networks, using convolutional layers to capture spatial patterns.
Deep Learning	DL	A subfield of ML that uses multilayer neural networks to learn from large data sets, especially effective for complex tasks, such as image recognition.
Deep Neural Network	DNN	A DL framework designed to analyze complex data patterns, using multiple layers of processing to improve prediction accuracy.
Large Language Model	LLM	Advanced DL models, such as GPT (exactly the model in GPT chat), trained on large volumes of textual data, effective in processing and producing natural language.
Machine Learning	ML	A branch of AI that develops algorithms to train computers to analyze data and make predictions, enabling autonomous learning from large volumes of data, such as recognizing an echocardiogram location of acoustic window.
Natural Language Processing	NLP	A field of AI that enables machines to understand and interpret human language, crucial for such applications as language translation and sentiment analysis.

Adapted from Lüscher et al.[1]

essential role in detecting the presence and quantification of MR. However, it is subject to significant interobserver variability regarding measurements of volume and regurgitant orifice. MR assessment by AI is challenging, since only a few images obtained during the examination contain the data that define severity. More recently, Long et al.[13] described an AP model capable of interpreting TTE video data and automatically classifying MR severity. This model integrates color Doppler video imaging, offering precise grading of MR on a scale ranging from mild to severe, with an accuracy of approximately 80%.

Furthermore, the predictive power of AI is highlighted by the development of risk stratification tools, such as the EuroSMR score,[14] designed to predict outcomes in patients undergoing transcatheter edge-to-edge repair for secondary CABG. This AI-derived tool has demonstrated robust performance in predicting mortality, aiding clinicians in making decisions together with the Heart Team. This score can be accessed online at www.eurosmr.com.

AI and Aortic Valve Disease

Aortic stenosis (AS) is a very prevalent and lethal valve disease, especially in elderly patients. Once again, the method of choice to assess AS is TTE, integrated with Doppler parameters and analysis of the left ventricular outflow tract. However, there is a need for numerous variables, which in addition to being time-consuming to analyze, are subject to intra- and interobserver variability. Fully automated AI systems have been developed to address these challenges. In the study by Krishna et al.,[5] AP algorithms with CNR were applied to a cohort of patients with different degrees of AS. The result was an excellent correlation, with measurements made by experienced cardiologists, with the advantage of substantially reducing analysis time.

The role of AI in the assessment of AS is not only limited to improving measurement accuracy, but it also extends to the identification of early markers of the disease. These technologies are especially promising in screening programs, where the rapid and accurate assessment of valve function is essential.

AI in POCUS

The introduction of AI in POCUS has opened up new possibilities for real-time diagnostic assessments, especially in low-resource settings. AI-enabled POCUS devices assist non-specialists by automating image acquisition and interpretation, reducing the learning curve. For example, AI can guide the operator in obtaining the correct acoustic windows, significantly reducing the learning curve in POCUS.[15]

AI applications in POCUS are particularly beneficial in emergency scenarios, where rapid decision-making is essential. The use of AI can facilitate lung ultrasound for the consistent detection of congestion and pleural effusion. Furthermore, in rural and remote areas, where access to expert interpretation is limited, AI can provide real-time diagnostic support, making access to advanced technologies more democratic.[16]

Reflections on AI in cardiovascular imaging

AI streamlines and simplifies image evaluation, optimizing the workflow in echocardiography laboratories. However, image acquisition is still performed manually, and for CNR analysis to be accurate, the images must be of high quality, making the human component indispensable. In addition, another limitation of AI is the need for a significant volume of images to properly train the CNR model.

We can reflect on two opposing points of view. According to Yuval Harari, AI is not a passive technology, but rather a system that learns autonomously, which can lead to a decrease in human empowerment, as described in his book ***Nexus: A Brief History of Information Networks*** (2024). By contrast, Kai Fu Lee, one of the leading scholars of AI since its inception and author of several works on the subject, argues that AI will not replace humans, but rather humans who use AI will replace those who do not use it.

Conclusion

AI is poised to play a central role in the future of echocardiography, improving diagnostic accuracy, increasing efficiency, and optimizing workflow in echocardiography laboratories. However, with these advancements also come challenges, including the need for robust validation in diverse populations and rigorous regulatory oversight. As the field advances, collaboration among AI developers, cardiovascular imaging experts, and regulators will be crucial to ensuring the safe and effective integration of AI into clinical practice.

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