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PERSPECTIVE

Artificial intelligence-enhanced echocardiography in the emergency department

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Abstract

A focused cardiac ultrasound performed by an emergency physician is becoming part of the standard assessment of patients in a variety of clinical situations. The development of inexpensive, portable handheld devices promises to make point-of-care ultrasound even more accessible over the coming decades. Many of these handheld devices are beginning to integrate artificial intelligence (AI) for image analysis. The integration of AI into focused cardiac ultrasound will have a number of implications for emergency physicians. This perspective presents an overview of the current state of AI research in echocardiography relevant to the emergency physician, as well as the future possibilities, challenges and risks of this technology.

Key words: *artificial intelligence, echocardiography, emergency medicine.*

Background

There is a growing body of evidence supporting emergency physician-performed focused cardiac ultrasound (FoCUS) in the ED.[1] A FoCUS examination is becoming part of the standard assessment of patients in a variety of clinical situations such as undifferentiated shock and cardiac arrest. Emergency physician-performed FoCUS can identify clinical findings and can also exclude clinically important pathologies such as pericardial effusion and is more accurate than physical examination for assessing left ventricular (LV) function and valvular disease.[1,2] Consequently, FoCUS is becoming integrated into emergency medicine specialist training programmes worldwide.[3]

The development of inexpensive, portable handheld devices promises to make point-of-care ultrasound even more accessible over the coming decades.[4] Images obtained from modern small handheld ultrasound machines can provide enough detail to answer the targeted clinical questions of a FoCUS examination.[4] Many of these handheld devices are beginning to integrate artificial intelligence (AI) for image analysis.[4] Several AI algorithms have already been approved in the United States and other countries for use in echocardiography.[5] The integration of AI into FoCUS will have a number of implications for emergency physicians.

Artificial intelligence

AI can be defined as the theory and development of computer systems able to perform tasks normally requiring human intelligence.[6] AI research has achieved impressive successes in image analysis and medical applications in the last decade.[7] Deep learning (DL) algorithms are behind much of this success. DL algorithms can iteratively learn patterns from the training data provided to them, rather than requiring hand-coded rules.[8] DL algorithm training benefits from large training datasets, and especially from datasets that are labelled with a 'ground truth' that the DL algorithm can then compare its predictions against. Once trained, the DL algorithm can then be used to analyse new data. Echocardiography appears particularly well suited to DL applications due to standardised views, multiple measurements and the existence of large databases of echocardiograms that have been labelled by human experts from many institutions. There is enthusiasm for AI-enhanced echocardiography from clinicians, researchers and industry.[9,10] AI can assist at every stage of the use of echocardiography in the ED.

Image acquisition

Commercially available AI-based technologies that guide novices to acquire echocardiogram images already exist.[11] These algorithms can analyse the current image and probe position, then provide instructions to the user to move the probe in a way predicted to optimise the image.[12] The algorithms can also use DL to assess image quality and provide feedback to the user through a real-time quality metre.[12] The image can be automatically recorded and

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measurements were taken once the quality metre passes a threshold.

Narang *et al.* studied eight nurses without ultrasound experience using an AI-guided system to each scan 30 patients.[12] Expert echocardiographers blindly reviewed the scans and found them to be of diagnostic quality for the assessment of LV size and function, right ventricle size and function, and presence of pericardial effusion in over 90% of cases.[12] Results were consistent across a range of body mass indexes and cardiac pathologies.[12]

Another study by Schneider *et al.* had 19 first-year medical students without ultrasound experience scan patients with AI guidance to acquire parasternal long axis, apical four-chamber (AP4) and apical two-chamber (AP2) views.[13] These views were compared to scans conducted on the same patients by experts. The medical students were more often able to obtain diagnostic quality views in the AP4 (86%) compared to AP2 (68%) and parasternal long axis (58%); however overall, at least one diagnostic quality view was obtained in 91% of the attempts.[13]

Echocardiographic measurements are prone to errors if there are errors in image acquisition. For example, left ventricular ejection fraction (LVEF) estimation can be considerably affected by apical foreshortening. Smistad *et al.* developed an AI system capable of automatically providing a warning when apical foreshortening is present.[14] The integration of real time AI image analysis into FoCUS examination may be able to ensure that images obtained are of diagnostic quality.

Image quality

Traditionally, image quality has been a limitation of portable handheld ultrasound devices. AI may help to overcome this limitation. DL has been applied to ultrasound images to reduce artefact and to enhance the image quality.[10] Generative adversarial neural networks can improve image quality through mapping low-quality ultrasound images to corresponding, high-quality images, and so have the potential to transform the image quality of point-of-care ultrasound to that of a high-end machine.[15,16]

Image augmentation

AI has been used to automatically segment anatomy in ultrasound images.[17] This can allow for real time highlighting of relevant anatomy or pathology.

Automatic calculation and assessment

It is conceivable that all aspects/ measurements of current echocardiography assessment could be automated by DL algorithms. Automated measurement will save time, avoid interoperator variability in manual calculations, and may increase accuracy. LVEF is an important indicator of cardiac output, however, is difficult and time consuming for the novice provider to accurately calculate, especially in the emergency setting.

Asch *et al.* hypothesised that a fully automated machine learning algorithm would be able to estimate the degree of ventricular contraction without first needing to identify endocardial borders or measuring LV volumes at end-systole and end-diastole.[18] This approach mimics the human expert's eye. This algorithm was trained on over 50 000 echocardiogram studies that had been acquired on different machines over a period of 10 years. When tested on an independent group of 99 patients, the automated estimation of LVEF was found to be feasible, and the automatically calculated LVEF values showed high consistency and excellent agreement with the reference values. Others have also demonstrated DL systems are able to automatically calculate LVEF and such tools are increasingly available on many systems.[13,14]

Regional wall motion abnormalities are an important sign of cardiac, but their assessment can be challenging. Kusunose *et al.* developed a deep convolutional neural network that was able to detect both presence of a regional wall motion abnormality, and territory affected achieving an area under the receiver operating characteristic curve similar to that produced by cardiologists and sonographers, and significantly outperformed residents.[19] Huang *et al.* used DL model for echo view selection, segmentation of the LV wall, and evaluation of segments for wall motion abnormality, achieving an area under the receiver operating characteristic curve of 0.891 in external validation at an independent hospital.[20]

AI algorithms can also be applied to echocardiogram data to predict findings that usually require other echocardiographic measurements, such as predicting aortic stenosis without using LV outflow tract measurements (which are usually required for the continuity equation to calculate aortic valve area).[21]

Future possibilities

Inexpensive personal handheld ultrasound devices are likely to become commonplace over the coming decade, hence insonation will become more widespread. Currently, calculating various echo parameters is complex and time consuming. Automated calculation of echo parameters such as LVEF would make echocardiogram parameters more accessible in the ED setting, and multiple parameters could be calculated in parallel rather than from sequential manual measurements. Novel AI-based scores that integrate demographics, patient history, investigations and echocardiogram images to directly predict patient orientated outcomes could be developed.

Currently, training in echocardiography is labour intensive, requiring an expert practitioner to train a novice. AI-guided image acquisition could be a useful training tool for novice scanners. Automatic analysis of the probe movements of an operator, combined with the quality of images obtained may allow for an automated analysis of operator skill and assist with credentialing. Such systems are currently in development.[22] Real time anatomy segmentation and highlighting could also help orientate the novice practitioner.

Challenges and risks

Despite promising research, there remain multiple challenges and risks. Evidence of the clinical benefit of AI-enhanced echocardiography on patient orientated outcomes remains unassessed. There has also been no assessment of the impact of these devices on clinical decision making. Algorithms must be assessed to ensure they can generalise to unwell patients with acute pathology.

Datasets used in most studies have been relatively small by modern DL standards. Few studies have assessed generalisability or conducted external validation. The handheld ultrasound market is fast growing and competitive. There are likely significant financial incentives for early commercialisation of AI technologies. It is important that any AI-based models have appropriate external validation before they are used in a clinical setting. Cloud-based image storage is offered by companies as a convenient solution to limited storage of portable devices. The implications of such services on patient privacy and data ownership must be clarified, including the ethical issues that arise if companies are using patients' data to train their commercial algorithms without patients' knowledge or consent.

Regulation of software as a medical device is an evolving area, and regulation of AI devices is a recognised challenge.[23] Performance of such devices may change over time as algorithms are trained on more data, and updates may affect performance in unpredictable ways. It will be important to ensure any algorithms used in clinical practice have appropriate governance and stewardship.[24]

AI-based tools will occasionally fail, just as humans do. The ultimate responsibility for diagnostic decisions will remain with the emergency physician. AI-enhanced echocardiography will be a tool to be used in the appropriate clinical context.

Conclusion

AI-based algorithms are able to assist with echocardiogram image acquisition, assess and enhance image quality, and automatically calculate clinically relevant echocardiogram parameters. AI-enabled echocardiography is likely to play an increasing role in the ED in the future.

Author contributions

JES drafted the manuscript. All authors were involved in critical revision, editing and approval of the final manuscript.

Competing interests

None declared.

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