

(Deep) learning your left from your right.

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Remembering which is your left and which is your right can be a skill that people have to proactively ‘*learn*’¹. In 1953, Critchley in an early description of neurological left-right differentiation problems commented ‘...*the recruit is notorious for often mixing up the right and the left or at least being hesitant in making the correct response when the command ‘left’ or ‘right’ is given*’². In this 2019 issue of *JACC Cardiovasc Imaging*, Kusonose *et al*³ have tested out the latest ‘*recruit*’ to echocardiography – artificial intelligence (AI) systems - to see whether they can learn their left from their right in the setting of coronary disease.

Coronary artery disease remains the leading cause of cardiovascular mortality and morbidity with early detection being essential to prevent progression to myocardial infarction and heart failure. The first imaging modality most patients with suspected heart disease encounter is echocardiography⁴ and therefore echocardiographers have an opportunity to diagnose - or suspect - coronary disease very early in the patient pathway. To identify a coronary stenosis with echocardiography the operator usually needs to see the downstream sequelae of the artery occlusion, namely, wall motion abnormalities. As left and right coronary systems have distinct myocardial territories, ‘regionality’ of wall motion impairment is a hallmark of disease, which helps pinpoint the blockage and differentiate from other pathologies, which cause global declines in myocardial function⁵.

Regional wall motion abnormalities are typically identified by subjective visual assessment and this reliance on operator expertise is a weakness that could be overcome if automated and quantifiable regional wall motion assessment was possible. Automated measures of global function, such as ejection fraction, have gained acceptance as clinical tools but robust automation of ultrasound analysis at a regional or wall-specific level has proved more

challenging⁵. Significant variability in image appearances between different patients, combined with a need to cope with myocardial motion both within the cardiac cycle and within the image, as well as variability in operator-selected image planes, has meant systems struggle with reproducibility when tested in clinical settings^{6,7}. This is exemplified by strain imaging, which has gained prominence as a technique for automatic characterisation of myocardial function but, while global measures have translated into clinical care⁵, widespread use of regional or segmental wall motion abnormalities has remained less widely adopted^{8,9}. AI systems provide a new way to automate medical image identification tasks. The AI programme is shown a large number of scans with predefined abnormalities and the programme determines the combination of image-derived features that most closely associates with the different diseases. When the same pattern of parameters is encountered in a new image the scan can be automatically categorised into the most appropriate class^{10,11}.

Ultrasound ‘machine learning’ has been of academic interest^{12,13} since at least the 1980s but the power of the statistical approaches has changed dramatically in recent years¹⁴. Kusunose et al³ have now tested the latest image processing networks (or programmes) to understand whether they can be trained to differentiate left coronary from right coronary patterns of disease in echocardiograms. To achieve this they needed to simplify the ultrasound acquisition considerably using only single frame, short axis views, pre-processed for uniformity of appearance. They also had experts select examples of disease that were severe enough to be associated with a significant coronary lesion and had resulted in a persistent wall motion abnormality at rest. This pre-selection probably explains the very high accuracy that was also achieved by the human readers. Nevertheless, they convincingly show it is possible to train the deep learning networks to recognise scans that have regional abnormalities and differentiate left from right coronary disease.

Importantly, their deep learning approach does not require image segmentation.

Commercially available systems usually rely on automatic identification of endocardial borders (segmentation) to quantify ejection fraction or to track wall motion and then infer diagnosis from the measures⁶. In the deep learning approach the whole image was fed into the network and patterns in the whole image used for training. This does mean it is not entirely clear what, exactly, the network is using to differentiate patterns of disease. It is possible the features have nothing to do with wall motion but reflect image contrast, intensity, position of the heart in the scan, meta-data tags, type of machine¹². There are significant differences in degree of left ventricular dysfunction related to the three coronary territories so it is possible there were aspects of the severity of cardiac dysfunction, even something as simple as ejection fraction or left ventricular volume, being used by the programme to differentiate. Knowing what drives the differentiation will help understand whether the same programme would cope at identifying normal wall motion in a patient who may have non-coronary heart disease that has altered image parameters.

Designing the right trial to validate clinical AI is also now being recognised as critically important. The AI system in the paper by Kusonose et al tended to be better than humans at identifying normal function³ but this could reflect a tendency for human readers to identify disease in normal images when placed under ‘test’ conditions. There are other clinical translational hurdles. Only short axis views were used so the system will never identify apical or basal abnormalities. No formal quality threshold testing was undertaken so we do not know how the system copes with off-axis views. Or perhaps more clinically-relevant pertinent, just how off-axis can a view be before the training starts to fail? Finally, even if an

AI system can automatically identify a regional wall motion abnormality does this technique have a definable, positive, patient benefit that justifies incorporation into clinical practice?

Caution within the field is essential at this stage in development of AI imaging applications. Publications based on small or selected datasets, which are prone to over-fitting, can deliver ‘eye-catching’ high accuracies, which will fail to deliver expectations when the generated algorithms are applied more generally into clinical practice¹³. However, discussions about how to generate ‘clinical grade’ AI are now appearing¹⁵, which reflects a slow movement on from ‘proof-of-principle’ studies to an age of development, verification, validation and implementation. Both the statistical methods and large-scale datasets needed to effectively train echocardiography models are now available and the AI ‘*recruit*’ may soon be entering active duty.

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