

**ARTIFICIAL INTELLIGENCE: A NEW CLINICAL SUPPORT TOOL FOR STRESS
ECHOCARDIOGRAPHY**

¹Alsharqi M, ²Upton R, ²Mumith J.A, ¹Leeson P.

¹Oxford Cardiovascular Clinical Research Facility, Division of Cardiovascular Medicine,
Radcliffe Department of Medicine, University of Oxford, Oxford, UK

²Ultramics Ltd, Oxford Science Park, Magdalen Centre, Robert Robinson Ave, Oxford OX4
4GA, UK

Key words: Echocardiography – Stress echocardiography – Artificial intelligence – Machine
learning – Automated analysis.

Correspondence to: Prof Paul Leeson, Oxford Cardiovascular Clinical Research Facility,
Division of Cardiovascular Medicine, Radcliffe Department of Medicine, University of
Oxford. John Radcliffe Hospital, Oxford, UK OX3 9DU.

Email: paul.leeson@cardiov.ox.ac.uk Tel: +44(0)1865226839 Fax: +44(0)1865572840

1. INTRODUCTION

Echocardiography remains the imaging modality of choice for the early detection and diagnosis of cardiovascular disease because it is portable, non-invasive, radiation-free and allows real time imaging of the heart. Furthermore, echocardiography is relatively inexpensive when compared with other imaging modalities and so is accessible in the majority of healthcare settings around the world (1). However, accurate diagnosis using echocardiography requires a high level of clinical skill and operator training to ensure good quality image acquisition, optimisation and interpretation. Wide implementation of echocardiography guidelines have helped standardise these processes and ensured reproducible echocardiographic parameters. However interpretation remains dependent on operator experience and a limited set of echocardiography parameters (2). Computational tools that allow complex, standardised analysis and quantification of images have emerged, which provide more comprehensive characterisation of cardiac structure and function (3, 4). However, it is the combination of these approaches with artificial intelligence tools, such as deep learning, which can form the foundations of a new era of consistent and accurate echocardiography image interpretation.

2. WHAT IS ARTIFICIAL INTELLIGENCE?

The first applications of artificial intelligence in healthcare were reported over three decades ago (5). However it is only in the last few years, as artificial intelligence has become embedded within multiple areas of life, that there has been an exponential growth of interest in whether it can assist in automated diagnosis and personalised patient management. Artificial intelligence includes computational techniques that ‘learn’ from existing data to make future decisions. Deep learning is a method composed of many layers of highly interconnected processing

elements, which are able to represent high levels of abstraction. The use of deep learning with imaging data is usually based on convolutional neural networks that mimic, to some extent, how the human ventral stream is structured (6). These techniques facilitate rapid analysis of massive amounts of data (7). Less fluid computational approaches are also possible such as support vector machines and random forests (8-10). However, the objective of all these methods is to learn patterns from existing sets of clinical data, such as clinical notes, blood test results or images, to allow future sets of data to be automatically processed (5). In medicine, applications of artificial intelligence have been innovative, particularly in medical imaging (11). Medical images contain large sets of data that require intensive training and experience in order to detect abnormalities (6). For clinical adoption, it is important the true impact of artificial intelligence systems, compared to operator-led analysis, on patient outcomes, including how changes in workflow and test accuracy impact on health economic costs, needs to be validated in clinical trials. However, machine-assisted interpretation of medical images offers the potential for more consistent decision-making that could improve patient outcome (11).

3. ARTIFICIAL INTELLIGENCE IN ECHOCARDIOGRAPHY

The application of artificial intelligence in the clinical practice of echocardiography has been less advanced than in some other areas of medical imaging. Every echocardiogram generates multifaceted and complex information within the image, which is mostly filtered by the eye of the operator when being interpreted or measured. Therefore, potentially useful data that could be used for quantification of cardiac structure and function, or used for diagnosis, may be missed or overlooked (8). Recent applications of artificial intelligence in echocardiography have shown promise in the field of automated image selection and quantification. The left

ventricle appears in multiple echocardiographic views and a deep learning model was able to recognise 15 major transthoracic echocardiography views accurately, including continuous and pulsed wave Doppler traces (12). Automated quantification or border recognition of left and right ventricular function could then be possible using demonstrated techniques (13, 14). Valvular morphological quantification also appears to be possible using automated machine learning analysis of 3D transoesophageal echocardiography images of the mitral valve. From this analysis it was feasible to achieve reproducible measurements of mitral valve annulus without significant user intervention (15). Image interpretation is a distinct task that may also be tackled with artificial intelligence approaches. Machine learning models have provided efficient differentiation of cardiovascular hypertrophic phenotypes including those with hypertrophic cardiomyopathy and athletes (8). Classification of constrictive pericarditis and restrictive cardiomyopathy has been shown to be possible particularly when conventional echocardiography parameters were combined with parameters obtained using speckle tracking echocardiography (10).

4. A NEW MEDICAL DEVICE FOR STRESS ECHOCARDIOGRAPHY?

Stress echocardiography is a specific test that studies how cardiac function changes after a patient is exposed to a stressor, either exercise or drugs such as dobutamine (16). Stress echocardiography is the most widely used functional test for coronary artery disease with nearly 4 million performed in the United States every year (17). Current interpretation is based on visual assessment of the images by an experienced operator. The test typically has a sensitivity and specificity of around 80% for identification of functionally significant coronary artery disease when assessed by angiography or clinical outcome (18). Machine learning algorithms hold the potential to utilise the whole dataset from each echocardiography image,

and detect abnormal myocardial segment patterns to ensure more accurate and consistent results. Thereby, these systems might help to reduce the number of inconclusive test results also leading to potential time, effort and cost savings for the patients, as well as the clinical care team. Attempts to apply machine learning techniques to stress echocardiography have shown promise. These included approaches to automate quantification of wall motion with machine learning classification (19) or to extract and categorise information from processed data such as principal strain maps (20). These methods were able to achieve sensitivity or specificity comparable with human operators (18). However, a limitation in improving the accuracy of these methods further and, ultimately, translating these techniques into a medical device has been a lack of sufficient high quality data for both training and validation. Over the last 7 years, we have been compiling image datasets from patients undergoing stress echocardiography linked with longitudinal clinical outcome data, as part of an ongoing clinical research study (16). Advances in machine learning and, in particular, deep learning, during this time have meant it has become possible to use a multi-parametric assessment of cardiac function, based on 1000s of image-derived features at rest and stress, to predict patient outcome in longitudinal clinical datasets of sufficient quality and size for medical device development.

5. CONCLUSIONS

Echocardiography remains the main imaging modality in the diagnosis of cardiovascular diseases. The application of artificial intelligence into echocardiography offers the potential for accurate and reliable image identification, quantification and interpretation. Machine learning systems may reduce image analysis time, expedite clinical decision-making and provide iterative feedback to train less-experienced clinicians (11). The first tangible clinical applications of artificial intelligence in echocardiography are now emerging, particularly in the

126 field of quantification. Over the next year we expect the first applications of artificial
127 intelligence in stress echocardiography to emerge as a new clinical decision support medical
128 device.

129

130

131 **6. ACKNOWLEDGEMENTS**

132 Professor Paul Leeson acknowledges support from the British Heart Foundation, Oxford BHF
133 Centre for Research Excellence and NIHR Oxford Biomedical Research Centre.

7. REFERENCES

Papers of special note have been highlighted as either of interest (*) or of considerable interest (**) to readers.

1. Douglas PS, Garcia MJ, Haines DE, et al. ACCF/AHA/ASA/ASNC/HFSA/HRS/SCAI/SCCM/SCCT/SCMR 2011 Appropriate Use Criteria for Echocardiography. A Report of the American College of Cardiology Foundation Appropriate Use Criteria Task Force, American Society of Echocardiography, American Heart Association, American Society of Nuclear Cardiology, Heart Failure Society of America, Heart Rhythm Society, Society for Cardiovascular Angiography and Interventions, Society of Critical Care Medicine, Society of Cardiovascular Computed Tomography, Society for Cardiovascular Magnetic Resonance American College of Chest Physicians. Journal of the American Society of Echocardiography : official publication of the American Society of Echocardiography. 2011;24(3):229-67.
2. Cobey FC, Patel V, Gosling A, et al. The Emperor Has No Clothes: Recognizing the Limits of Current Echocardiographic Technology in Perioperative Quantification of Mitral Regurgitation. Journal of cardiothoracic and vascular anesthesia. 2017;31(5):1692-4.
3. Lewandowski AJ, Augustine D, Lamata P, et al. Preterm heart in adult life: cardiovascular magnetic resonance reveals distinct differences in left ventricular mass, geometry, and function. Circulation.127(2):197-206.
* Key publication that demonstrated ability of computational atlases and simple unsupervised learning methods to identify subtle changes in left ventricular geometry and function.
4. Aye CYL, Lewandowski AJ, Lamata P, et al. Disproportionate cardiac hypertrophy during early postnatal development in infants born preterm. Pediatric Research. 2017;In press.
** Application of computational statistical shape modelling to ultrasound to analyse left ventricular morphology.
5. Szolovits P, Patil RS, Schwartz WB. Artificial intelligence in medical diagnosis. Annals of internal medicine. 1988;108(1):80-7.
6. Lee JG, Jun S, Cho YW, et al. Deep Learning in Medical Imaging: General Overview. Korean journal of radiology. 2017;18(4):570-84.
7. Mayr A, Binder H, Gefeller O, et al. The evolution of boosting algorithms. From machine learning to statistical modelling. Methods of information in medicine. 2014;53(6):419-27.

178 8. Narula S, Shameer K, Salem Omar AM, et al. Machine-Learning Algorithms to
179 Automate Morphological and Functional Assessments in 2D Echocardiography. Journal of
180 the American College of Cardiology. 2016;68(21):2287-95.
181 ** Key early study of application of machine learning models to aid in echocardiography
182 interpretation.

183

184 9. Meherwar Fatima MP. Survey of Machine Learning Algorithms for Disease
185 Diagnostic. Journal of Intelligent Learning Systems and Applications. 2017;9(1):1-16.
186

187

188 10. Mahmoud A, Bansal M, Sengupta PP. New Cardiac Imaging Algorithms to Diagnose
189 Constrictive Pericarditis Versus Restrictive Cardiomyopathy. Current cardiology reports.
190 2017;19(5):43.
191 * Detailed review that summerises AI-aided echocardiography interpretaion applications to
192 differentiate between constrictive pericarditis and restrictive cardiomyopathy.

193

194 11. Darcy AM, Louie AK, Roberts LW. Machine Learning and the Profession of Medicine.
195 Jama. 2016;315(6):551-2.
196

197 12. Madani A, Arnaout R, Mofrad M, et al. Fast and accurate view classification of
198 echocardiograms using deep learning. npj Digital Medicine. 2018;1(1).
199 ** Key study applying deep learning echocardiography to recognise 15 different
200 echocardiography views.

201

202 13. Domingos JS, Stebbing RV, Leeson P, et al. Structured Random Forests for
203 Myocardium Delineation in 3D Echocardiography2014; Cham: Springer International
204 Publishing.

205

206 14. Stebbing RV, Namburete AI, Upton R, et al. Data-driven shape parameterization for
207 segmentation of the right ventricle from 3D+t echocardiography. Medical image analysis.
208 2015;21(1):29-39.
209

210

211 15. Jeganathan J, Knio Z, Amador Y, et al. Artificial intelligence in mitral valve analysis.
212 Annals of cardiac anaesthesia. 2017;20(2):129-34.
213

214 16. Augustine D, Ayers LV, Lima E, et al. Dynamic release and clearance of circulating
215 microparticles during cardiac stress. Circulation research. 2014;114(1):109-13.
216

217 17. Ladapo JA, Blecker S, Douglas PS. Physician decision making and trends in the use of
218 cardiac stress testing in the United States: an analysis of repeated cross-sectional data.
219 Annals of internal medicine. 2014;161(7):482-90.
220

221 18. Geleijnse ML, Krenning BJ, van Dalen BM, et al. Factors affecting sensitivity and
222 specificity of diagnostic testing: dobutamine stress echocardiography. Journal of the
223 American Society of Echocardiography : official publication of the American Society of
224 Echocardiography. 2009;22(11):1199-208

225 *Important meta-analysis summarising publications on current state of the art human
 226 operator-based interpretation of stress echocardiography.
 227
 228 19. Chykeyuk K, Clifton DA, Noble JA, editors. Feature extraction and wall motion
 229 classification of 2D stress echocardiography with relevance vector machines. Proceedings -
 230 International Symposium on Biomedical Imaging; 2011.
 231
 232 20. Omar HA, Domingos J, Patra A, et al. Quantification of cardiac bull's-eye map based
 233 on principal strain analysis for myocardial wall motion assessment in stress
 234 echocardiography,. IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018);
 235 Washington, DC,2018. p. 1195-8.
 236