ESC European Society of Cardiology

European Heart Journal - Imaging Methods and Practice (2023) **1**, 1–3
https://doi.org/10.1093/ehjimp/qyad043

LETTER TO THE EDITOR

Deep learning-based computed tomography quantification of left ventricular mass

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Online publish-ahead-of-print 8 December 2023

Introduction

Left ventricular (LV) mass is a well-established predictor of major adverse cardiovascular events.[1] Cardiovascular magnetic resonance (CMR) is the gold standard for LV mass measurement; however, its use is limited by availability and may be contraindicated in patients with metallic foreign bodies. Cardiac computed tomography angiography (CCTA) is a readily available and validated modality for accurate measurement of LV mass, which has been shown to have prognostic value, reliably predicting major adverse cardiac events and all-cause death.[2] However, conventional methods for CCTA-derived LV mass are time-consuming, limiting clinical translation. Deep learning (DL), a recent advancement of artificial intelligence (AI), enables computers to independently learn and process annotated imaging with minimal operator input. In this study, we aim to develop, validate, and test a fully automated DL-based system capable of quantifying LV mass on CCTA.

Methods

A DL system using a convolutional neural network-based U-Net architecture was developed and trained using 86 multi-vendor CCTA LV image data sets. The system was then validated on 13 LV image data sets, improving its performance by tuning. The model is a 2D U-Net architecture, input images were rescaled to the size of 384 × 384, and the output is a binary mask of the same size. The model segments the LV on individual CT slices, and the 2D masks are then stacked together to form a final 3D mask. Conventional segmentation was analysed using commercially available software Medviso Segment CT v3.0 (Medviso, AB, Lund Sweden) by two independent and blinded expert readers to determine the LV mass. The average of the two expert readers was calculated to create a final result that was deemed the ground truth. Both the expert readers and the DL system were blinded to the patient's details. A final testing data set was analysed independently by both the DL system and conventional manual analysis to derive LV mass.

Results

A total of 82 randomly selected multi-vendor data sets were used for testing the performance of the DL system. The mean age of the cohort was 58 ± 11 years, 75% were male, and the mean LV mass of the cohort was 126.8 ± 39.4 g. Excellent correlation was seen for the DL system as compared with conventional techniques in detecting LV mass ($r = 0.96$, $P < 0.0001$) (*Figure 1A*). Bland–Altman analysis reported a bias of −6.2 g (95% limits of agreement −28.4, 16.1) for the DL method (*Figure 1B*). Intra-class correlation coefficient was 0.98. The Sorensen–Dice coefficient for image segmentation was 0.92. The average DL system analysis time was 21.3 ± 6.49 s. An example of our DL system segmentation is seen in *Figure 2*.

Discussion

In this study, we sought to develop, validate, and test a fully automated DL system capable of quantifying LV mass on CCTA. Our model showed excellent correlation compared with expert readers with minimal bias.

The use of AI-based assessment of LV mass has been employed with success in CMR and has shown good correlation with clinical outcomes and improved inter and intra-observer variability as compared with conventional techniques.[3] A previous study by Rockenbach *et al.* pointed out that AI systems utilizing CCTA image data set have limited ability to generalize across multiple sites, particularly when the data are acquired using different scanners.[4] This means that a model developed and tested at one site may not perform well when applied to data from a different site. To address this issue, they used transfer learning to

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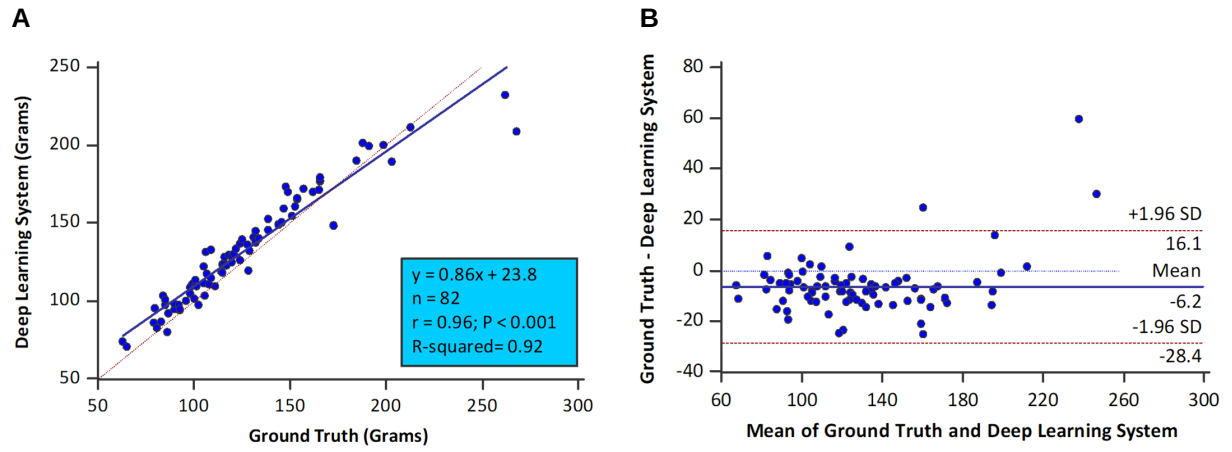

Figure 1 (*A*) Linear regression plot of LV mass detected by the DL system. Line of equality ($y = x$) represented by dashed line. (*B*) Bland–Altman plot of the ground truth as compared with the DL system for LV mass detection, with 95% limits of agreement.

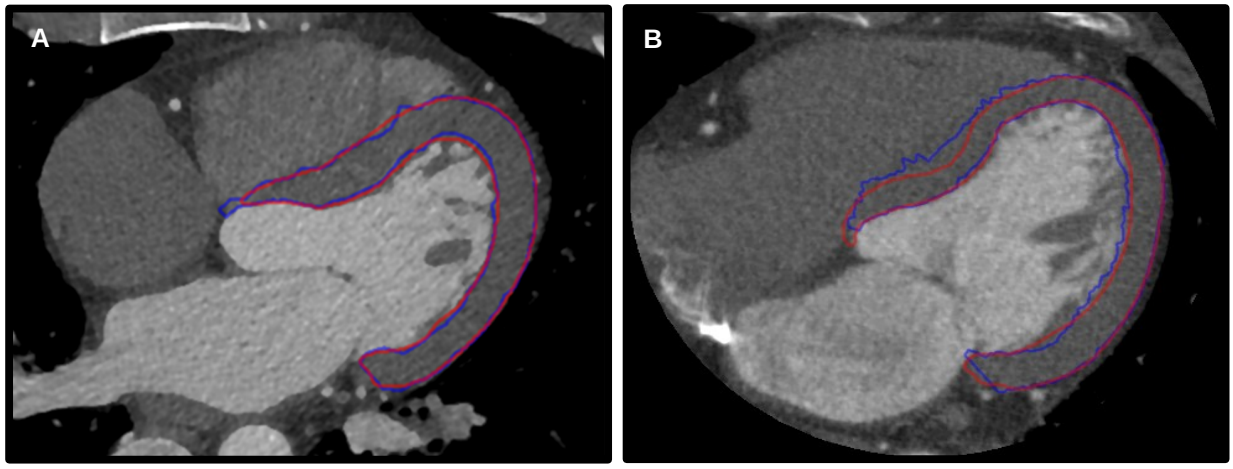

Figure 2 Cardiac CT four-chamber views of the LV with the ground truth (blue outline) and DL model (red outline) segmentation contours overlayed. The left image (*A*) demonstrates an example of good correlation of the DL model with ground truth, whereas the right image (*B*) demonstrates an example of poor correlation.

train an AI model on time series images and detect LV mass on CCTA data sets from two different sites.[4] Our DL system, on the other hand, was developed using multi-vendor scanners from different sites and trained on single-phase data. This approach eliminates the need to re-train the model for individual sites. Importantly, our DL system achieved similar accuracy and correlation with ground truth as the AI model trained with transfer learning.[4] Conventional semi-automatic techniques of LV mass assessment on CCTA can typically take 2–3 min, our system can complete this in 21.3 s, rapidly providing accurate results to enhance the reporting process and improve clinical translation.[5] The limitations of our study include the modest sample size and lack of clinical outcomes. Although our testing sample size was only 82 data sets, each of these data sets is comprised of multiple of 2D slices, considerably expanding the actual number of individual samples.

A fully automated quantification of LV mass on CCTA is feasible using a DL-based system.

Author contributions

A.S., A.H., J.A., J.K., J.J., J.F., S.K., B.J.W.C., B.K., M.R., A.R.I., and G.D. contributed to writing, reviewing, and editing the manuscript. A.R.I. and G.D. are the corresponding authors.

Consent

Written informed consent was waived by the Institutional Review Board. Institutional Review Board approval was obtained by the Bellberry Limited 2020-06-533.

Conflict of interest. J.A., J.K., J.J., J.F., A.R.I., and G.D. have equity in Artrya Ltd. J.J., J.F., and S.K. are employees of Artrya Ltd. A.R.I. has speaker bureau from Boston Scientific, Abbott Medical, and Janssen. G.D. has speaker bureau for Janssen, Amgen, Pfizer, and AstraZeneca. For the remaining authors, none were declared.

Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

Lead author biography

Doctor Amro Sehly is a Cardiology Registrar working in Perth, Western Australia. He graduated from the University of Western Australia Medical School with Honours in 2016 and completed Basic Physician Training with the Royal Australasian College of Physicians in 2021. He is currently undertaking a Master of Clinical Research with the University of Western Australia. His research interests lie in cardiac imaging and artificial intelligence.

References

1. Bluemke DA, Kronmal RA, Lima JAC, Liu K, Olson J, Burke GL *et al.* The relationship of left ventricular mass and geometry to incident cardiovascular events. *J Am Coll Cardiol* 2008;**52**:2148–55.
2. Klein R, Ametepe ES, Yam Y, Dwivedi G, Chow BJ. Cardiac CT assessment of left ventricular mass in mid-diastasis and its prognostic value. *Eur Heart J Cardiovasc Imaging* 2017;**18**:95–102.
3. Wang S, Patel H, Miller T, Ameyaw K, Narang A, Chauhan D *et al.* AI based CMR assessment of biventricular function: clinical significance of intervendor variability and measurement errors. *JACC Cardiovasc Imaging* 2022; **15**:413–27.
4. Rockenbach MABC, Buch V, Gupta V, Kotecha GK, Laur O, Erdal BS *et al.* Automatic detection of decreased ejection fraction and left ventricular hypertrophy on 4D cardiac CTA: use of artificial intelligence with transfer learning to facilitate multi-site operations. *Intell-Based Med* 2022;**6**:100051.
5. Akram K, Anderson HD, Voros S. Quantification of left ventricular parameters obtained by automated software for 64-slice multidetector computed tomography and comparison with magnetic resonance imaging. *Cardiovasc Intervent Radiol* 2009;**32**: 1154–60.