Fully automated contrast and non-contrast cardiac view detection in echocardiography a multi-centre, multi-vendor study

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Background: Correctly identifying views acquired in a 2D echocardiographic examination is paramount to post-processing and quantification steps often performed as part of most clinical workflows. In many exams, particularly in stress echocardiography, microbubble contrast is used which greatly affects the appearance of the cardiac views. Here we present a bespoke, fully automated convolutional neural network (CNN) which identifies apical 2, 3, and 4 chamber, and short axis (SAX) views acquired with and without contrast. The CNN was tested in a completely independent, external dataset with the data acquired in a different country than that used to train the neural network.

Methods: Training data comprised of 2D echocardiograms was taken from 1014 subjects from a prospective multisite, multi-vendor, UK trial with the number of frames in each view greater than 17,500. Prior to view classification model training, images were processed using standard techniques to ensure homogenous and normalised image inputs to the training pipeline. A bespoke CNN was built using the minimum number of convolutional layers required with batch normalisation, and including dropout for reducing overfitting. Before processing, the data was split into 90% for model training (211,958 frames), and 10% used as a validation dataset (23,946 frames). Image frames from different subjects were separated out entirely amongst the training and validation datasets. Further, a separate trial dataset of 240 studies acquired in the USA was used as an independent test dataset (39,401 frames).

Results: Figure 1 shows the confusion matrices for both validation data (left) and independent test data (right), with an overall accuracy of 96% and 95% for the validation and test datasets respectively. The accuracy for the non-contrast cardiac views of >99% exceeds that seen in other works. The combined datasets included images acquired across ultrasound manufacturers and models from 12 clinical sites.

Conclusion: We have developed a CNN capable of automatically accurately identifying all relevant cardiac views used in "real world" echo exams, including views acquired with contrast. Use of the CNN in a routine clinical workflow could improve efficiency of quantification steps performed after image acquisition. This was tested on an independent dataset acquired in a different country to that used to train the model and was found to perform similarly thus indicating the generalisability of the model.

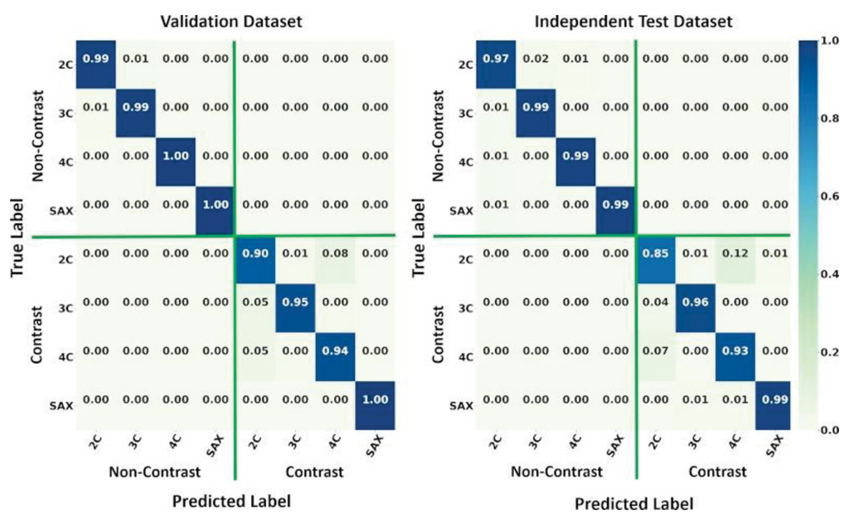

Figure 1. Confusion matrices