Iowa Initiative for Artificial Intelligence

Final Report

Project title:	Evaluation of left atrial strain using machine learning techniques	
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Date:		
Were specific aims fulfilled:	Yes, they were partially fulfilled	
Readiness for extramural proposal?	No	
If yes … Planned submission date		
Funding agency		
Grant mechanism		
If no … Why not? What went wrong?	The development of the approach to calculate the LA peak systolic strain proved to be extremely difficult and took longer than expected. The final product shows good automatic tracing of the LA borders, however, implementation into a larger dataset has not been accomplished. This needs to be done prior to seeking external funding.	

Brief summary of accomplished results:

We have developed a deep learning-based method to automatically predict the lengths (strains) of left atrium (LA) walls from neonatal echocardiogram images. After creating probability maps of the LA walls using an ensemble approach of 3 convolutional neural networks, the lengths were measured by thresholding the probability maps, followed by skeletonization. The R^2 value of the LA wall length between ground truth and our prediction is 0.825 with 52 echocardiograms (2,576 frames).

Research report:

Aims (provided by PI):

The goal is to develop automated techniques for left atrial strain analysis in neonates across multiple gestational age stratifications. The specific objectives are to

- (i) Use machine learning-based image segmentation approach to automate border detection of the LA in the 2D 4-chamber view over 2 cardiac cycles,
- (ii) Use the automated approach [from Aim 1] to calculate the LA peak systolic strain (reservoir) in EchoPac to form a larger training dataset,
- (iii) Develop a machine learning-based technique for calculating LA peak systolic strain trained on LA echocardiogram images without the need to trace myocardial borders utilizing peak strain truth obtained in Aim 2 and determine the resulting accuracy.

To ensure our dataset is representative across gestational ages, only one echocardiogram per patient will be used for analysis.

Data:

52 neonatal echocardiograms (4-chamber view, 2,576 frames, 1016 × 708 pixels, DICOM) and 52 corresponding movies (673 × 504 pixels, AVI) of LA strain measurements were used to train 3 convolutional neural networks, and 47 echocardiograms were used to test them. The ground truth of a LA wall centerline in the echocardiogram image was created by extracting color landmarks from the movie of LA strain measurements, detecting the landmarks by finding the points with the local maximum intensities from a response of square (5 x 5 pixels) pattern matching, and drawing a line with the thickness of 1 pixel after transforming the landmarks into the echocardiogram image (Fig. 1). Additionally, the ground truth of a LA wall region was created by drawing a line with the thickness of 32 pixels.

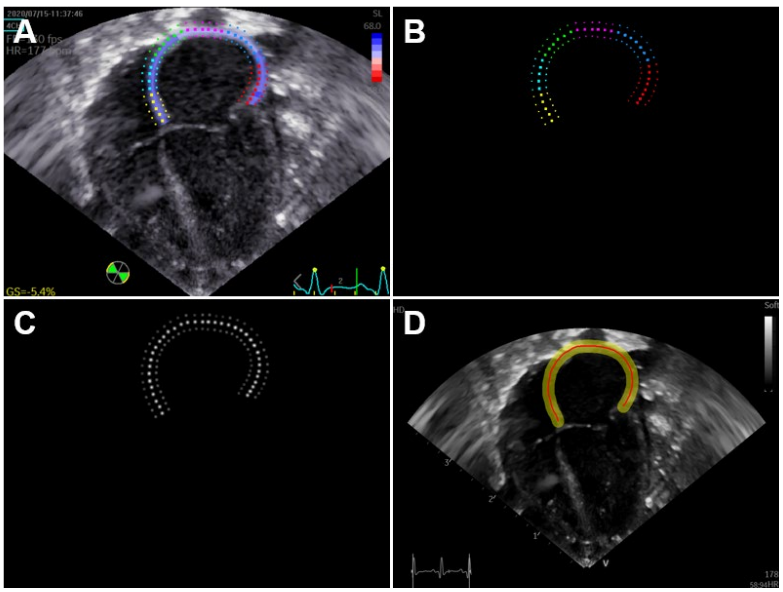

Figure 1. Ground truth creation of the LA wall centerline and region. (A) Movie of LA strain measurements. (B) Extracted color landmarks. (C) Response of square (5 x 5 pixels) pattern matching. (D) Echocardiogram image overlaid with the LA wall centerline (red) and region (yellow).

AI/ML Approach:

An ensemble approach of U-Net architectures, convolutional neural networks developed for image segmentation, with backbones of ‘original [1]’, ‘resnet34 [2]’, and ‘inceptionv3 [3]’ was used to automatically create the probability maps of LA wall regions from neonatal echocardiograms (Fig. 2). Three consecutive frames, down-sampled to 128 × 128 pixels, of an echocardiogram were used as an input for the U-Net architectures which were trained using the following hyperparameters.

- Optimizer: Adam with the learning rate of 0.0001
- Loss: Binary cross entropy and Dice loss
- Maximum number of epochs: 100

The ‘original’ neural network did not have any trained weight, but the ‘resnet34’ and ‘inceptionv3’ had weights trained on 2012 ILSVRC ImageNet dataset. The same ensemble approach was utilized to improve the probability maps of the LA wall regions by using the first probability maps as an input. Finally, the lengths of the LA walls were measured by thresholding the second probability maps, followed by skeletonization.

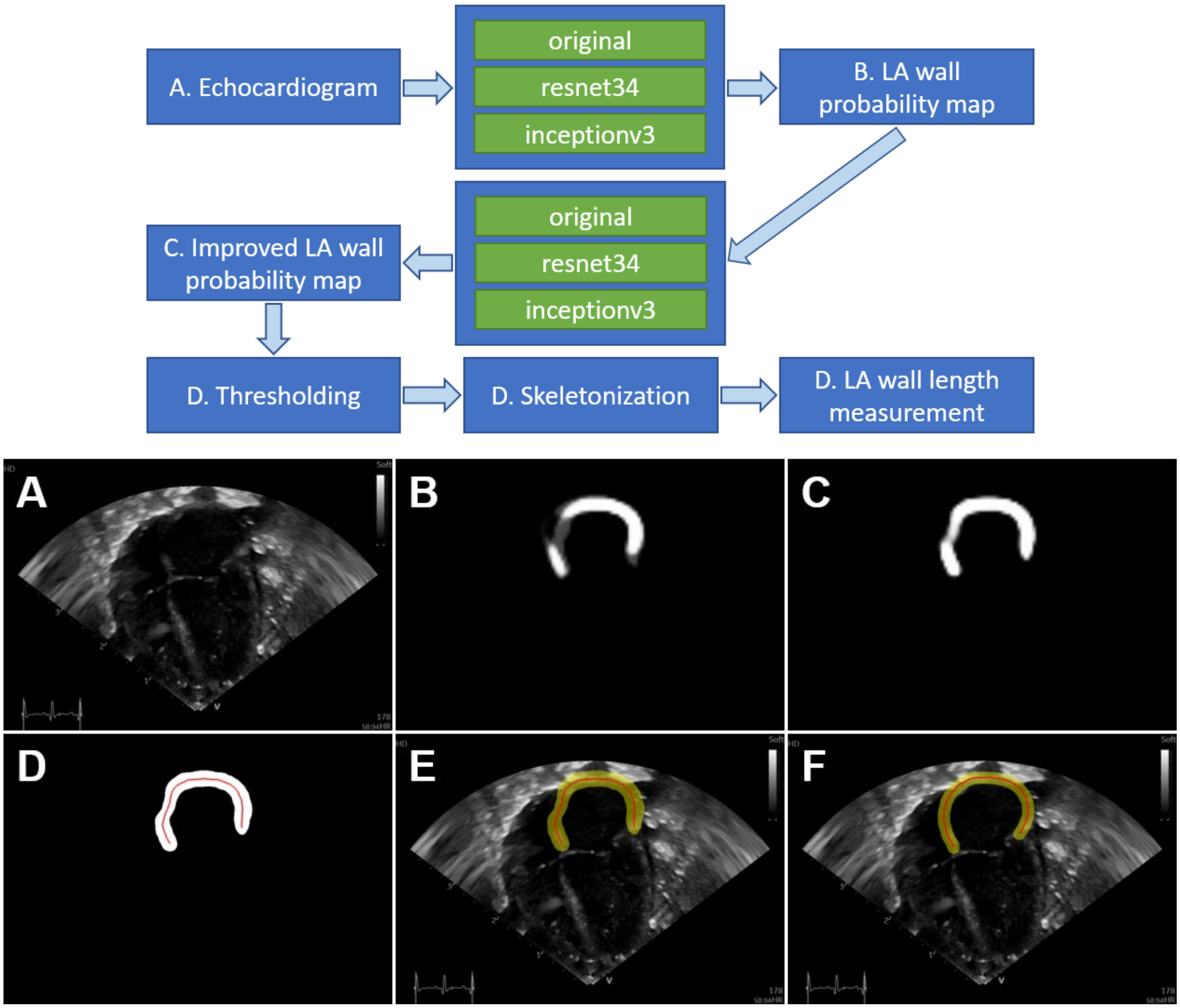

Figure 2. Our framework for automated length prediction of LA walls from neonatal echocardiograms. (A) Original echocardiogram image. (B) Probability map obtained from the first ensemble approach. (C) Probability map obtained from the second ensemble approach. (D) LA wall centerline (red) obtained by skeletonizing the second probability map thresholded. (E) Image (A) overlaid with the segmented LA wall centerline and region (yellow). (F) Image (A) overlaid with the ground truth.

Experimental methods, validation approach:

To validate our proposed method, 13-fold cross validation was performed with a training dataset of 48 echocardiograms and a validation dataset of 4 echocardiograms. The segmentation accuracy of LA wall regions was estimated by the Dice coefficient showing a spatial overlap between ground truth (A) and our segmentation result (B), D = 2 · |A ∩ B| / (|A| + |B|). To binarize LA wall probability maps, 50 threshold levels ($t = 0.02 \times n$, $0 \le n < 50$) were used, and the threshold level having the maximum Dice coefficient was selected. The prediction performance of LA wall lengths is displayed using a scatter plot between ground truths and our prediction results with a regression line and a R^2 value.

Results:

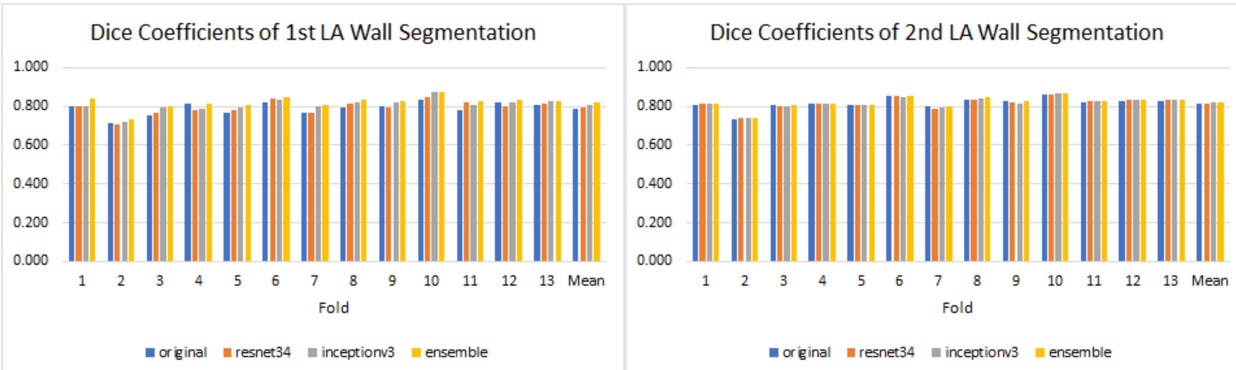

Figure 3. Dice coefficients of the first and second LA wall region segmentations using ‘original’, ‘resnet34’, ‘inceptionv3’, and ‘ensemble’ neural networks for 13-fold cross validation.

Fig. 3 shows dice coefficients of the first and second LA wall region segmentations using ‘original’, ‘resnet34’, ‘inceptionv3’, and ‘ensemble’ neural networks for 13-fold cross validation. For the first LA wall region segmentation, the mean Dice coefficients of ‘original’, ‘resnet34’, ‘inceptionv3’, and ‘ensemble’ are 0.791, 0.796, 0.809, and 0.821, respectively. For the second LA wall region segmentation, the mean Dice coefficients are 0.818, 0.817, 0.819, and 0.822, respectively.

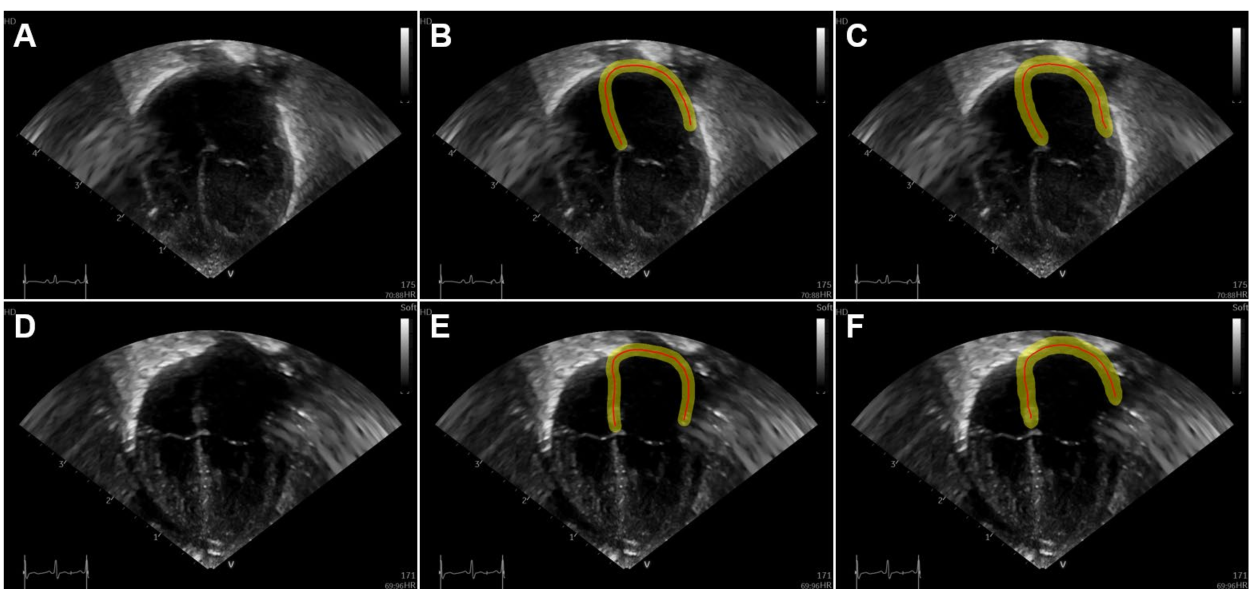

Figure 4. Our good and bad segmentation results of the LA wall centerlines and regions. (A, D) Original echocardiogram images. (B, E) Images (A, D) overlaid with ground truths. (C, F) Images (A, D) overlaid with our good and bad segmentation results.

Fig. 4 shows the LA wall centerlines and regions obtained by ground truth and our proposed method. While Fig. 4C shows a reliable segmentation result, Fig. 4F shows a local segmentation failure because of the obscure right LA wall.

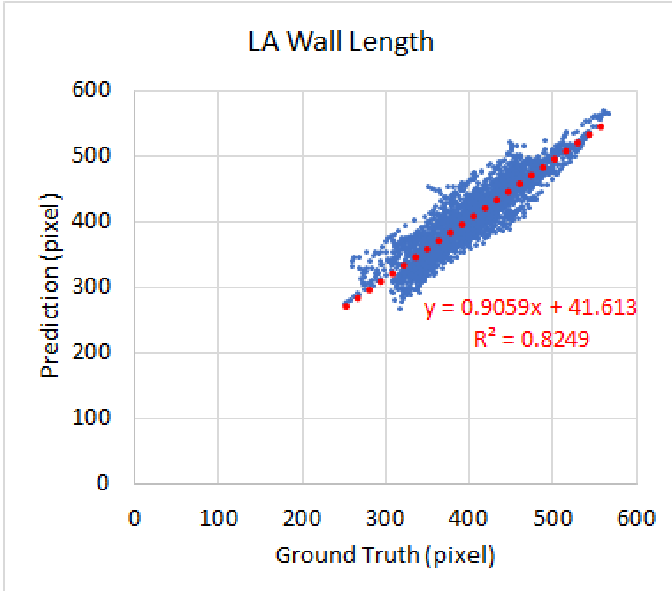

Figure 5. Scatter plot of the LA wall lengths of 52 neonatal echocardiograms (2,576 frames) between ground truths and our predictions. The dotted line is a regression line.

For 52 neonatal echocardiograms (2,576 frames), the mean LA wall lengths of ground truths and our predictions are 404.1 ± 55.4 pixels and 407.7 ± 55.2 pixels, respectively. Fig. 5 shows a scatter plot of the LA wall lengths between the ground truths and our predictions, and the R^2 value is 0.825.

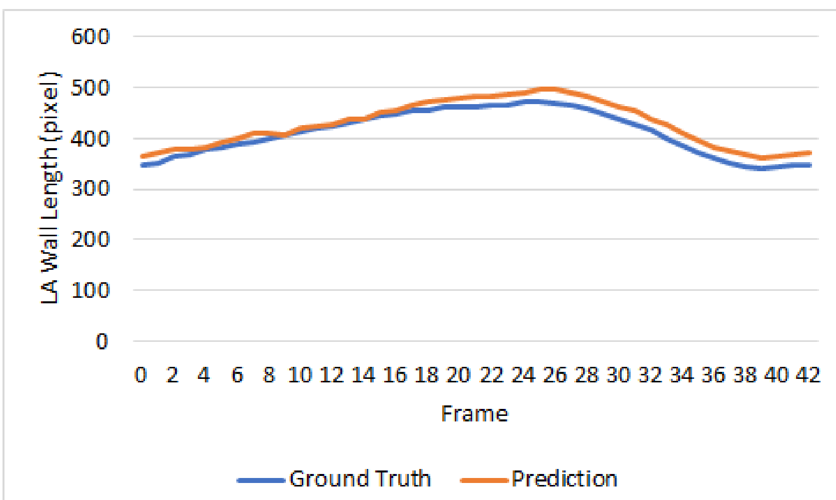

Figure 6. Typical graph showing the LA wall length changes of ground truth and our prediction over frame for an individual echocardiogram.

Fig. 6 represents a typical graph showing the LA wall length changes of ground truth and our prediction over frame for an individual echocardiogram. All 52 graphs are in a separate Excel file.

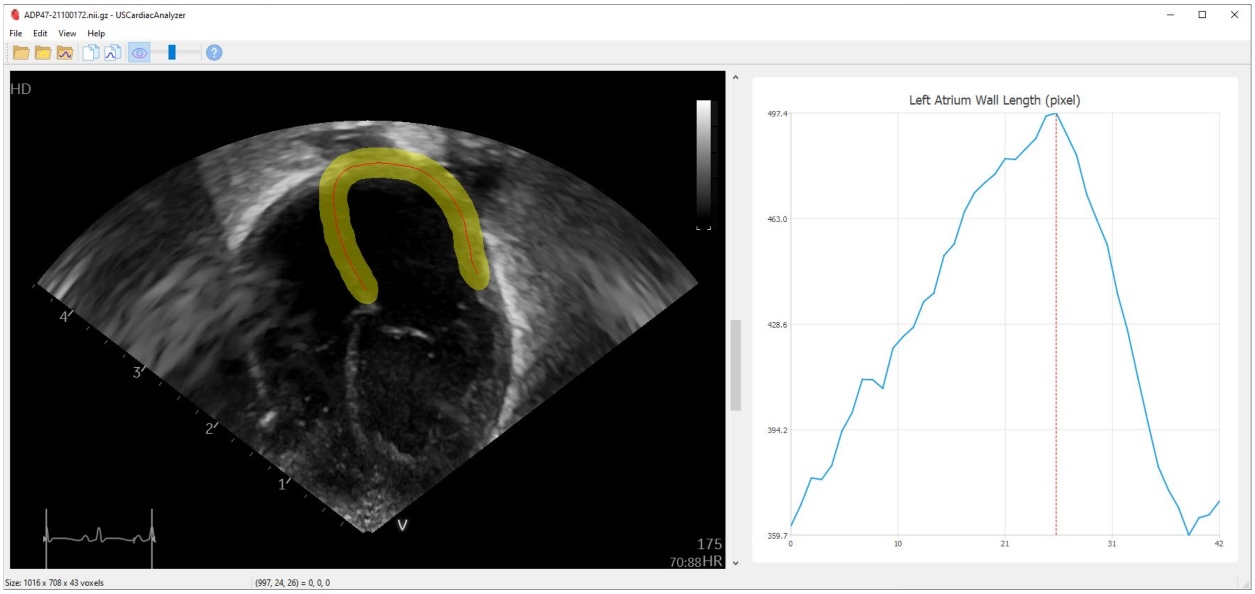

Figure 7. Custom software for visualization of the LA wall centerline/region on the echocardiogram and the length change of the LA wall centerlines over frame.

Additionally, we developed custom software for visualization of the LA wall centerline/region on the echocardiogram and the length change of the LA wall centerlines over frame (Fig. 7).

Ideas/aims for future extramural project:

More reliable and robust length prediction of LA wall centerlines would be possible by training our proposed neural network models with more datasets including a variety of neonatal heart shapes and diseases.

Publications resulting from project:

None to date.

The plan is to expand the use of this technology into a larger dataset with varied pathological states. The preliminary data will be used to prepare a manuscript to illustrate the technique developed.

References:

1. Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation. arXiv. 2015;1505.04597.
2. He K, Zhang X, Ren S, Sun J. Deep Residual Learning for Image Recognition. arXiv. 2015;1512.03385.
3. Szegedy C, Wei L, Yangqing J, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A. Going deeper with convolutions. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2015;1-9.