



ARTERYS

DeepVentricle

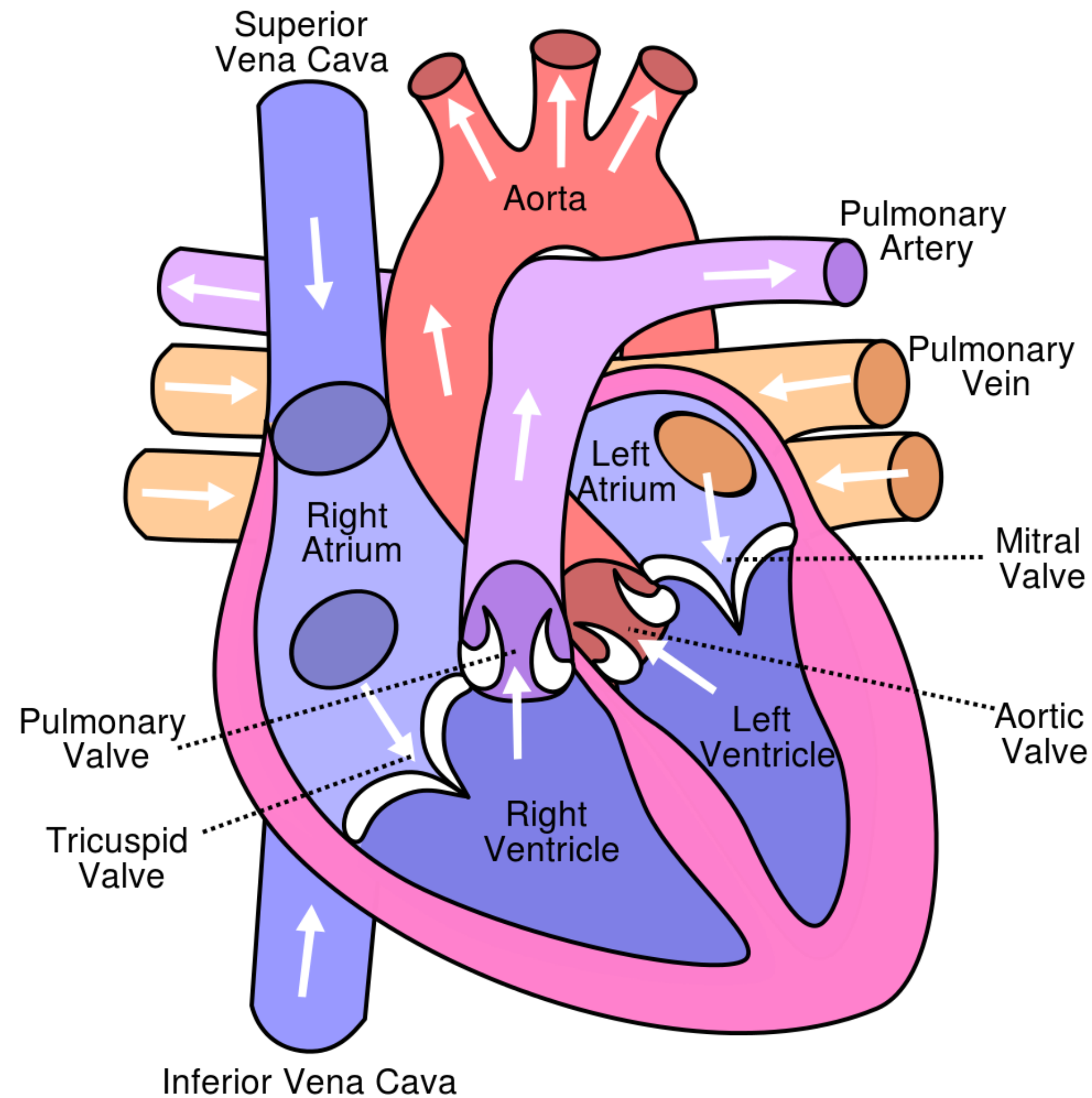
Automated Cardiac MRI Ventricle Segmentation
using Deep Learning (S7654)

Daniel Golden, Director of Machine Learning

- May 9, 2017 -

GPU TECHNOLOGY
CONFERENCE

Background



5.7M US adults have heart failure

Reduced cardiac function

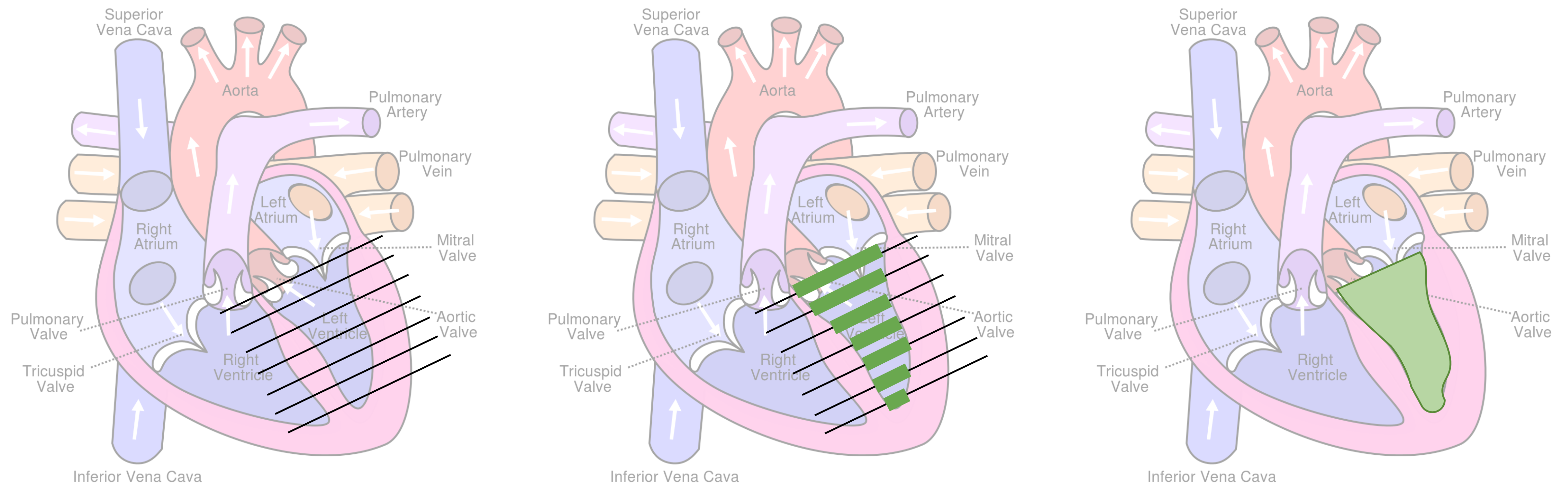
Ejection Fraction (EF): Fraction of blood ejected from heart in one cardiac cycle

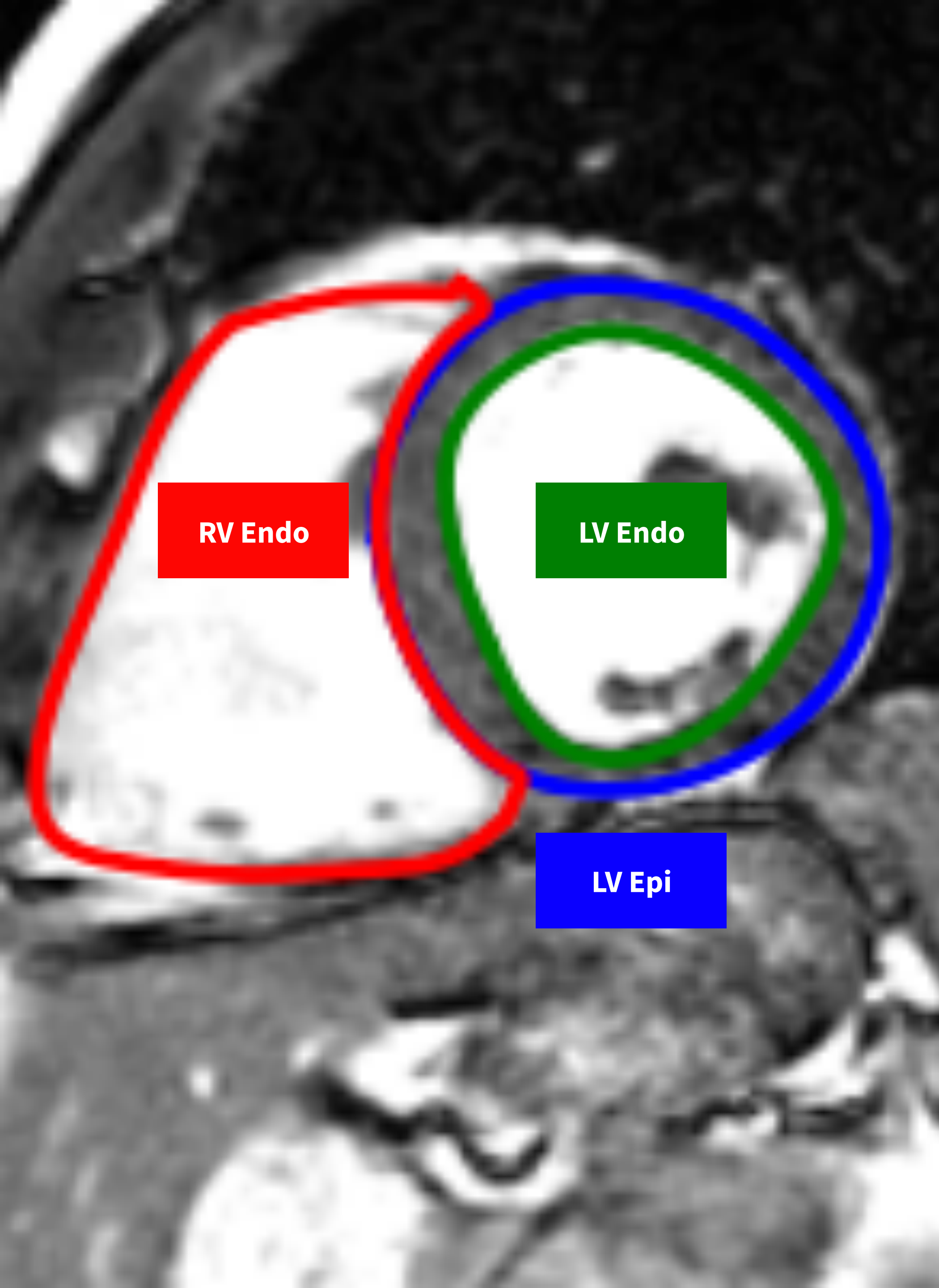
Healthy EF: 55–70%

Goal: help clinicians make **timely and accurate** diagnosis of heart failure

From Area to **Volume**

Manual EF measurements take ~30+ minutes. Goal: **automate contouring**





Dataset

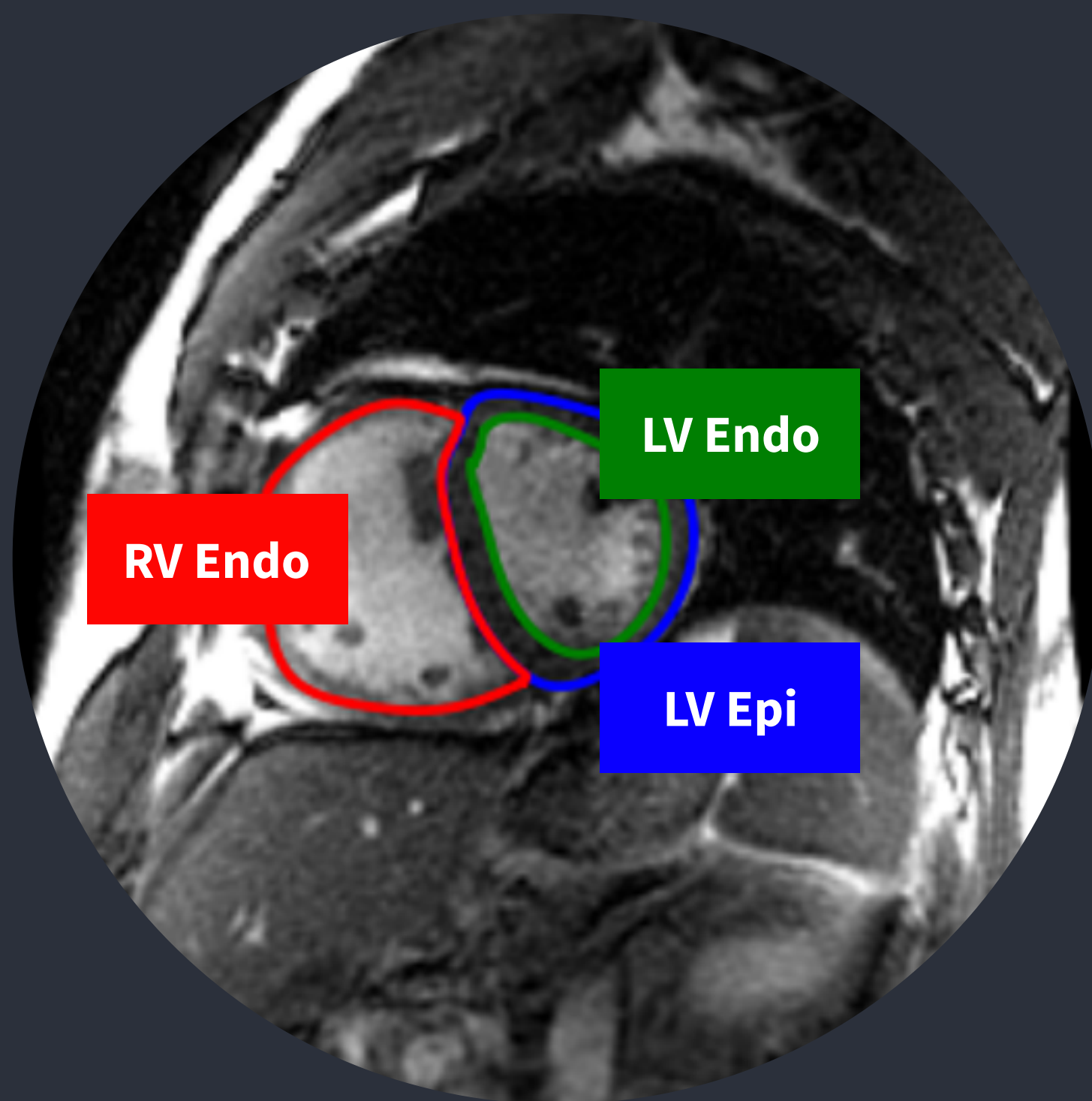
Steady-state free precession imaging (SSFP)

~1000 de-identified studies

3 types of ground truth contours:

- Left ventricle endocardium (blood pool)
- Left ventricle epicardium (blood pool + myocardium muscle)
- Right ventricle endocardium (blood pool)

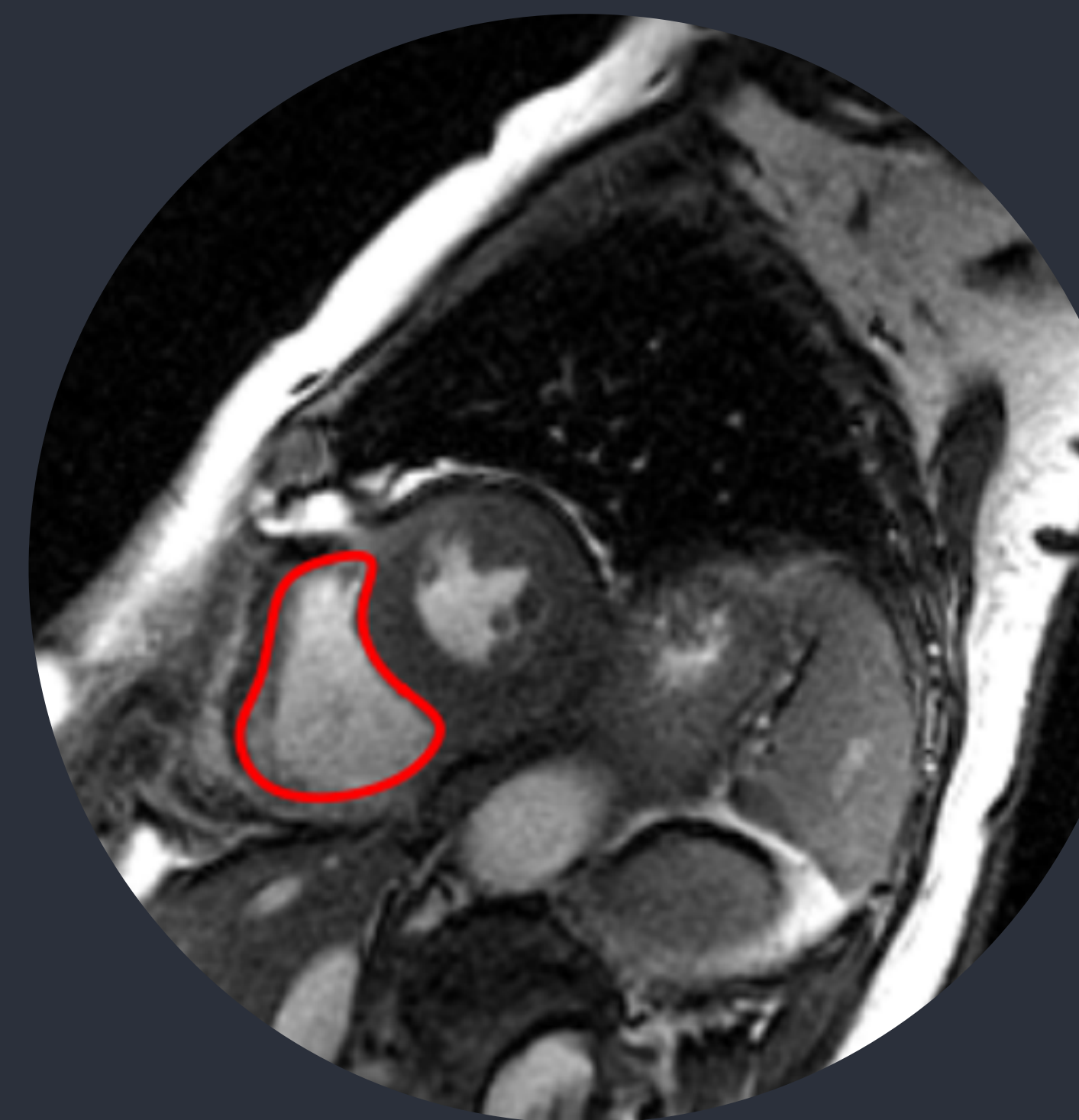
Missing Data



All contours present



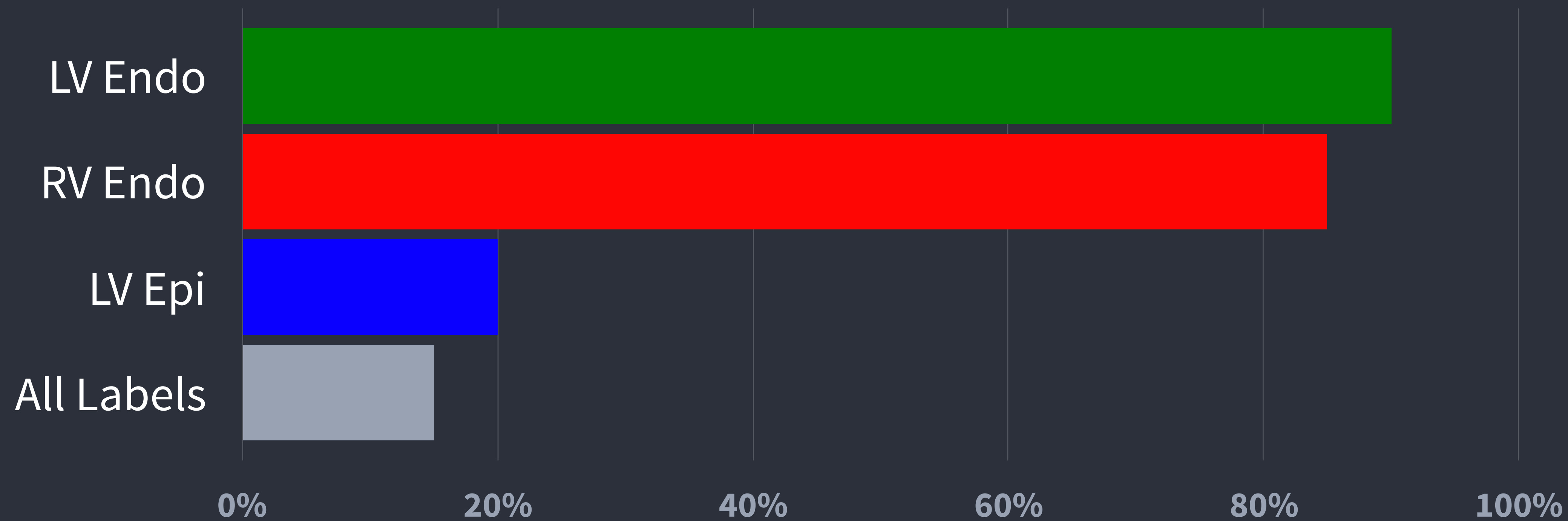
Missing LV epi



Missing LV endo and LV epi

Missing Data

Percentage of all images with label



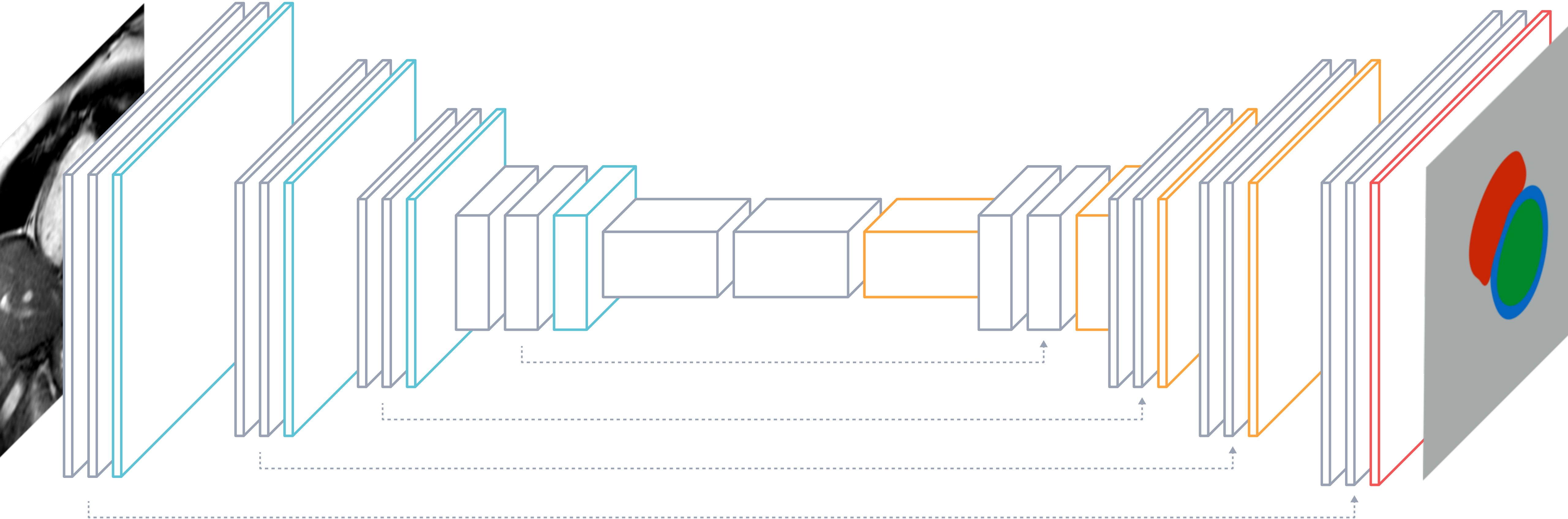
DeepVentricle Network Architecture

● 3x3 Convolution

● Max Pooling

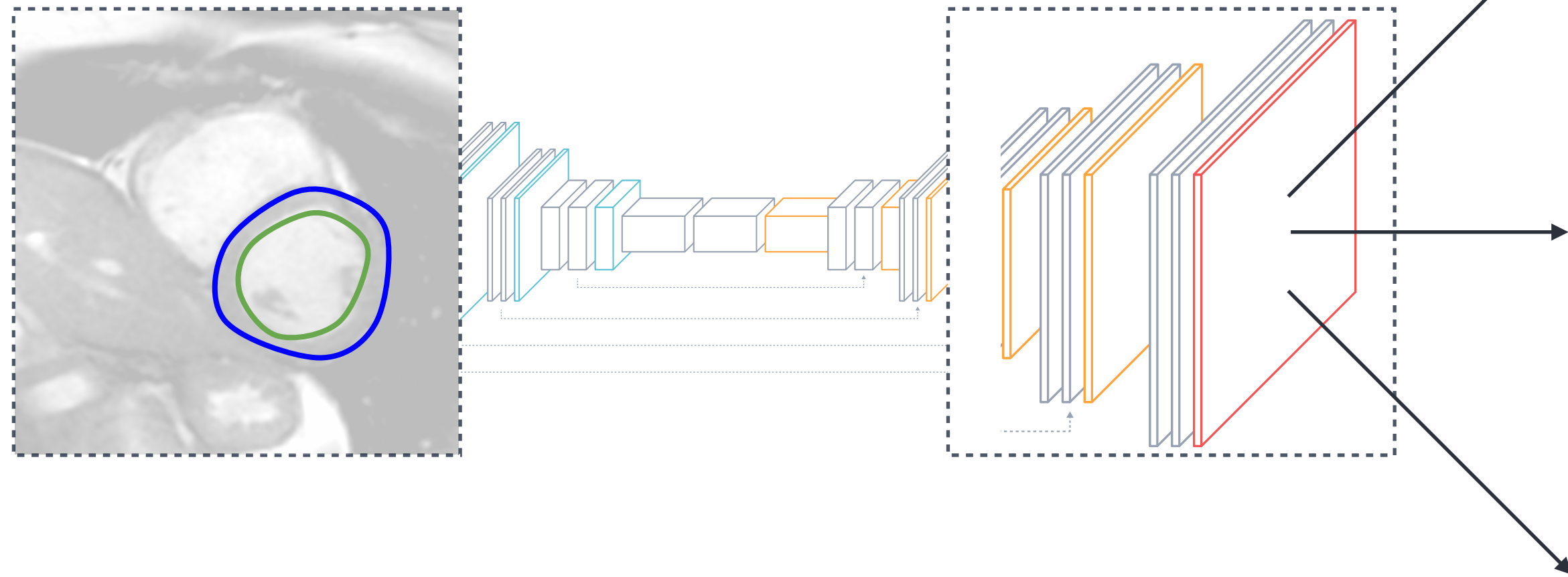
● Usample + Convolution

● 1x1 Convolution

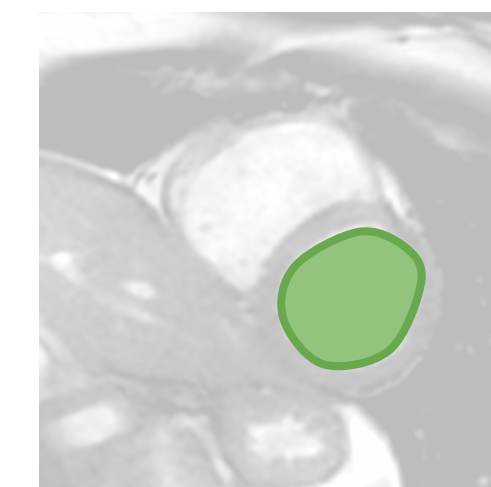
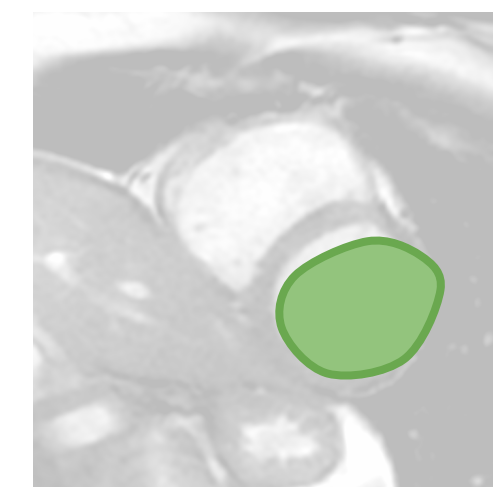
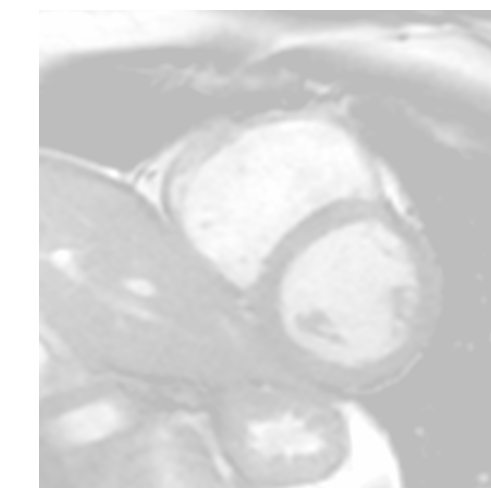
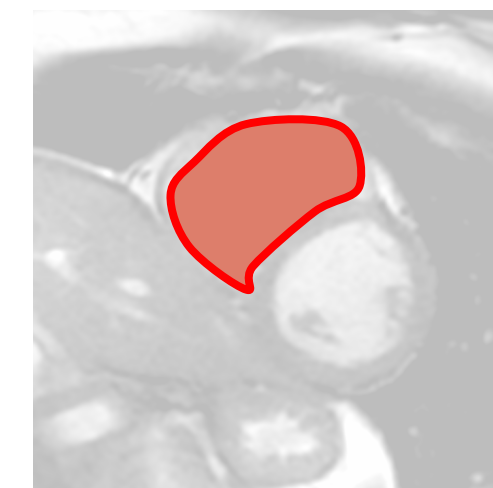


Incorporating Missing Data

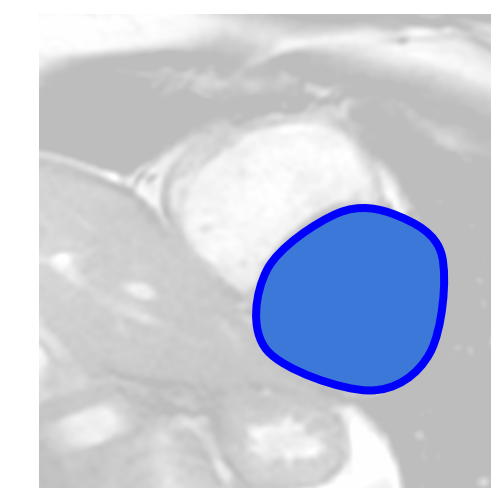
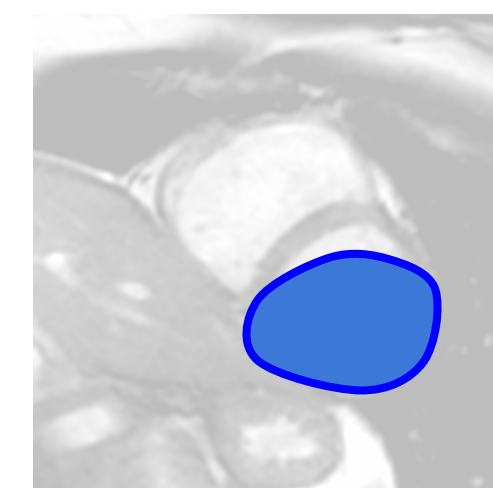
Ground truth



Prediction Ground truth Cross-entropy



0.2



0.4

Final = 0.3

Effect of missing data

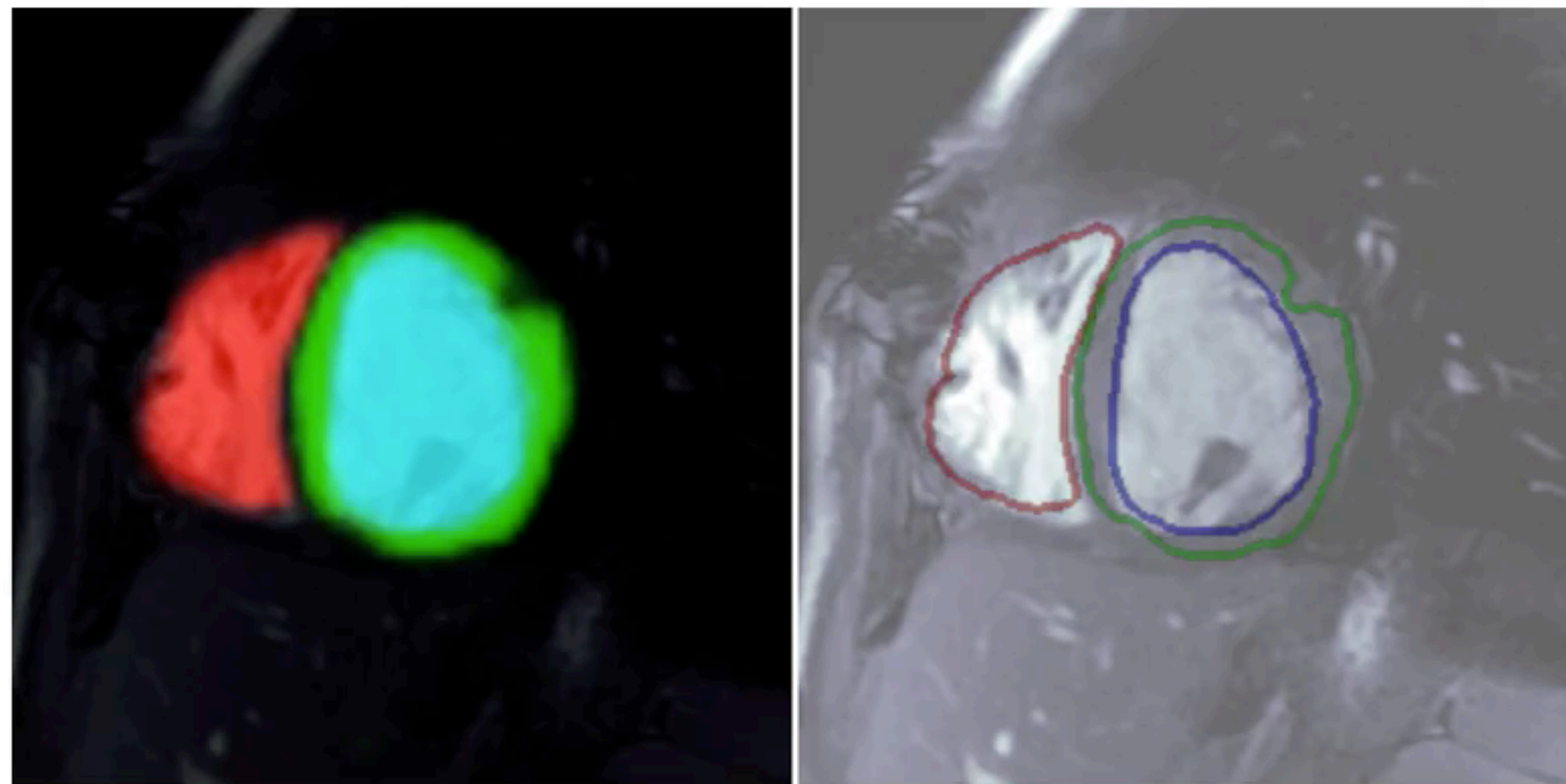
Before

(without missing data, 20% of data)

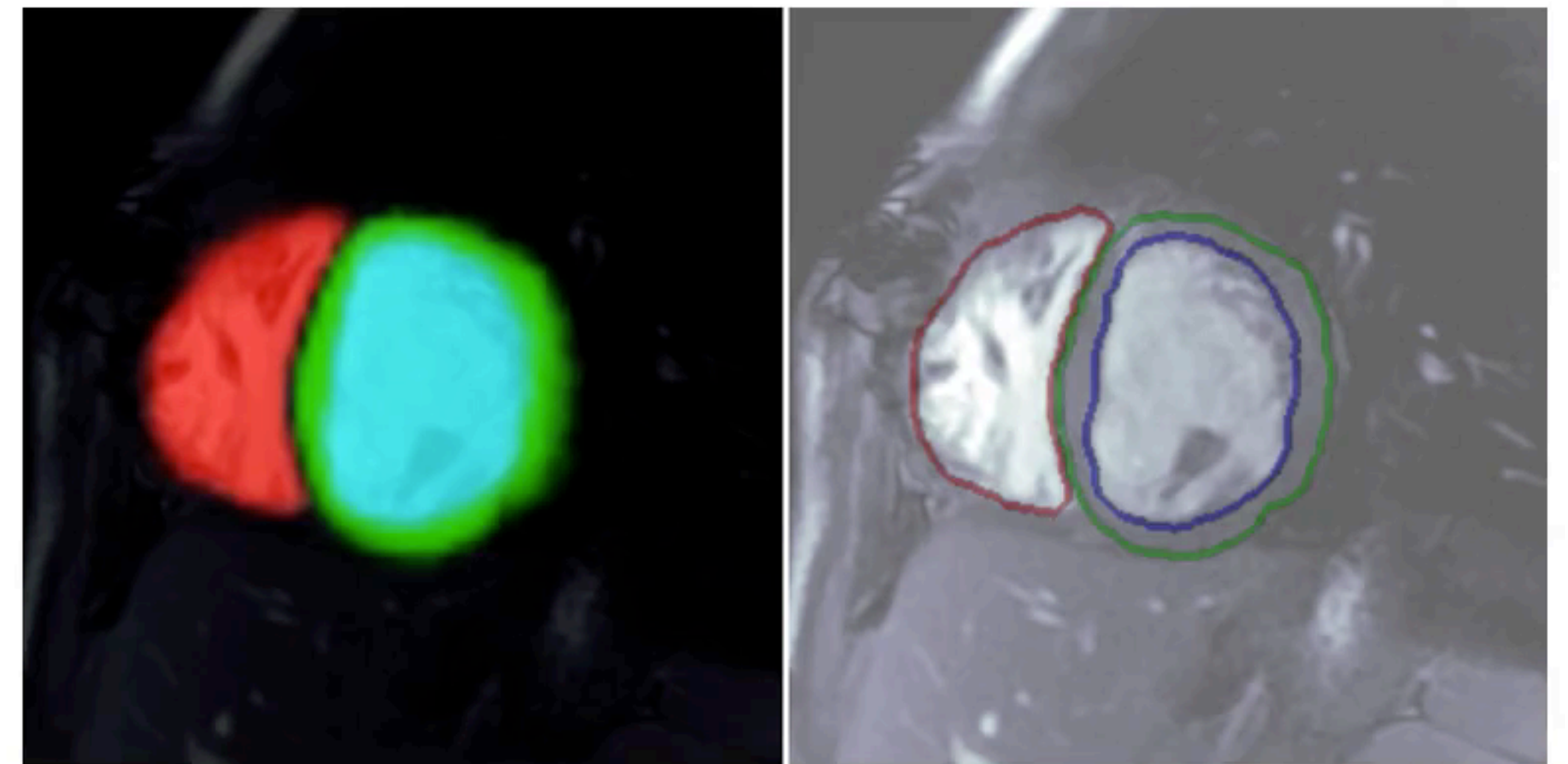
After

(with missing data, all data)

rv=red lvepi=green lvendo=blue



rv=red lvepi=green lvendo=blue



Evaluation on **100-study** test set

Data

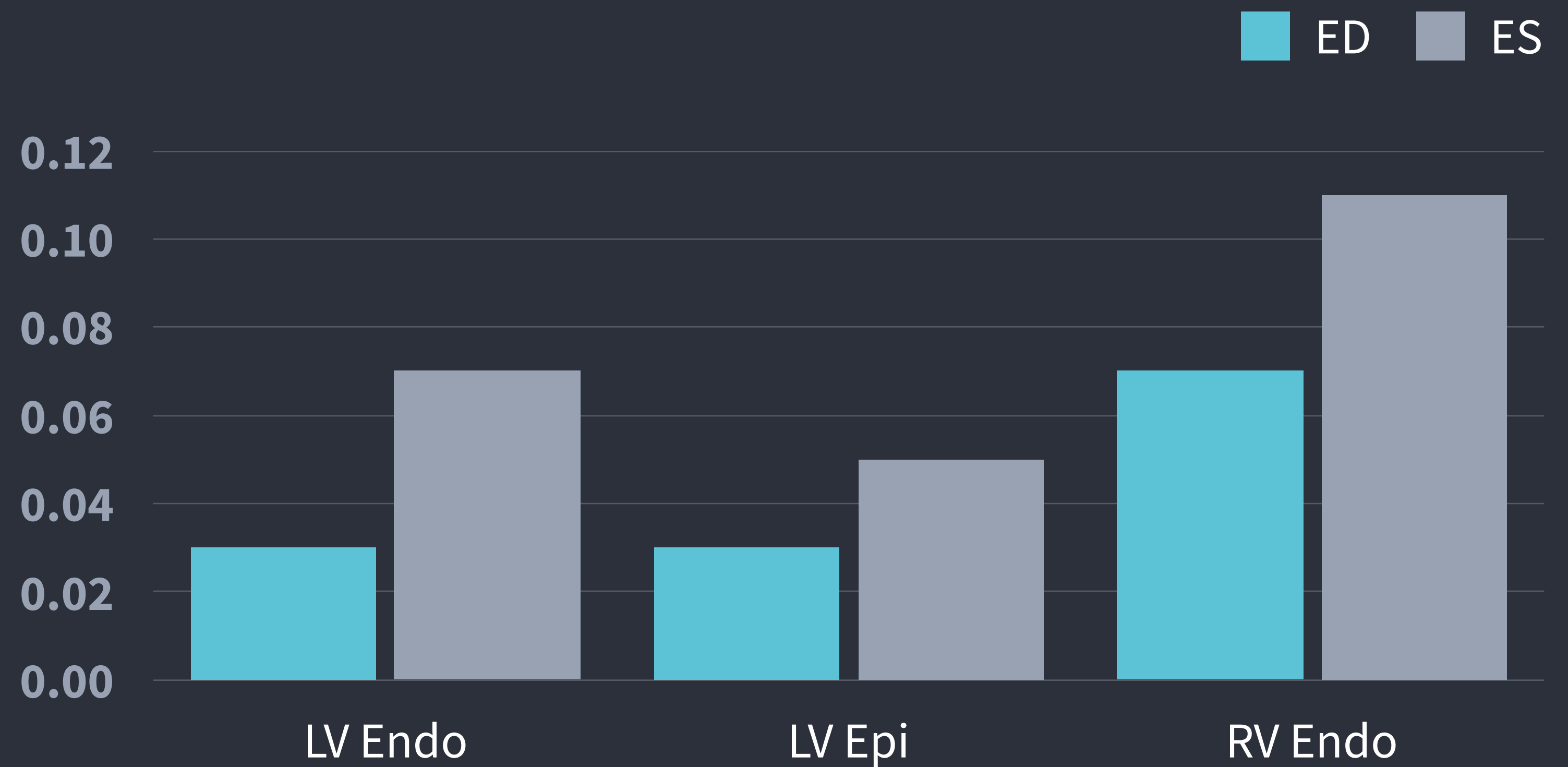
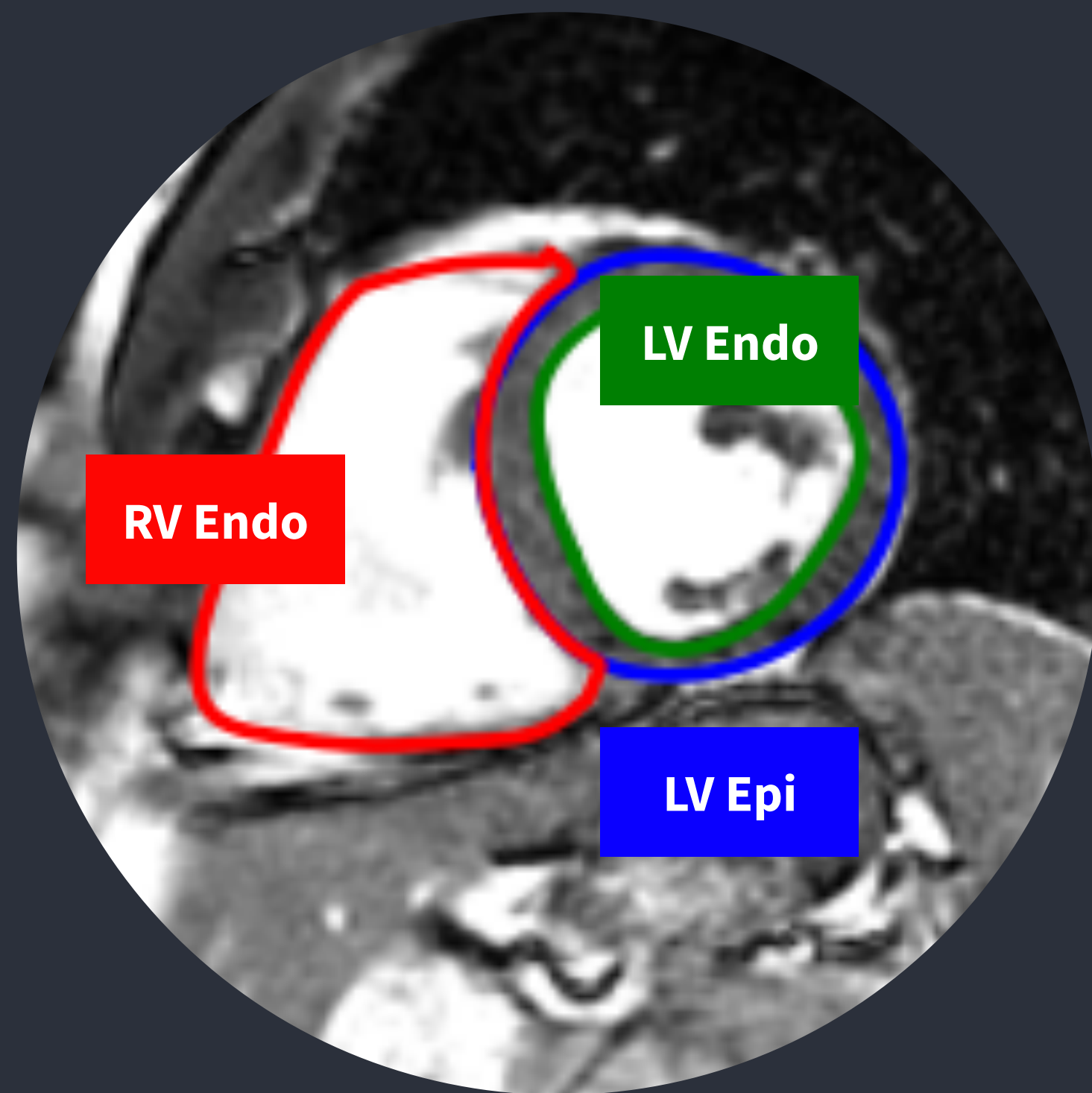
- 100 studies, each with a single clinician's annotation

Procedure

- Perform inference on each study
- Calculate Relative Absolute Volume Error (RAVE)
- E.g., if true volume is 100 mL, and we calculate 110 mL, RAVE is $\text{abs}(110 - 100)/100 = \mathbf{0.1}$

Evaluation on **100-study** test set

Relative Absolute Volume Error (RAVE)



Evaluation on **15-study** multi-annotator set

Data

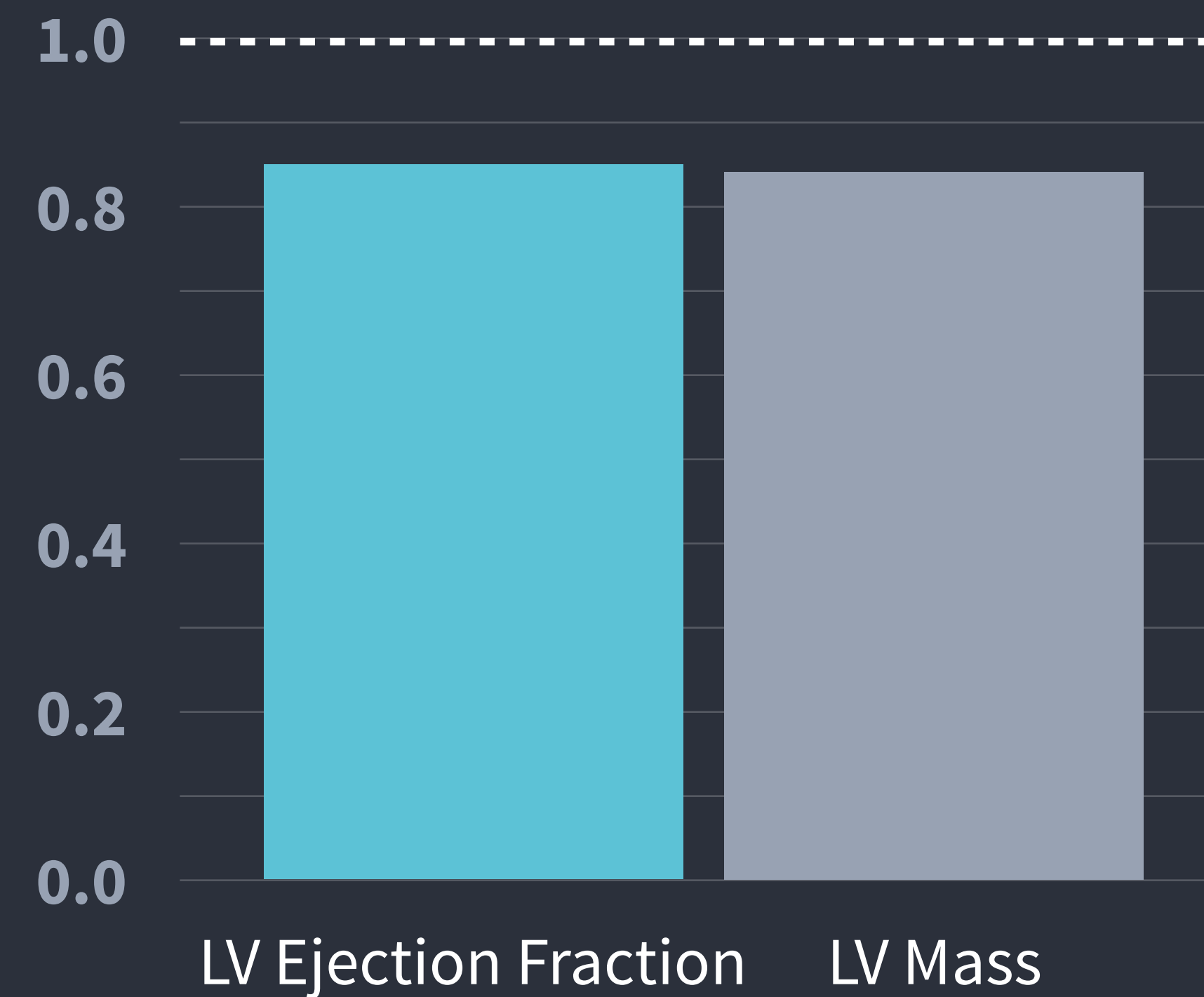
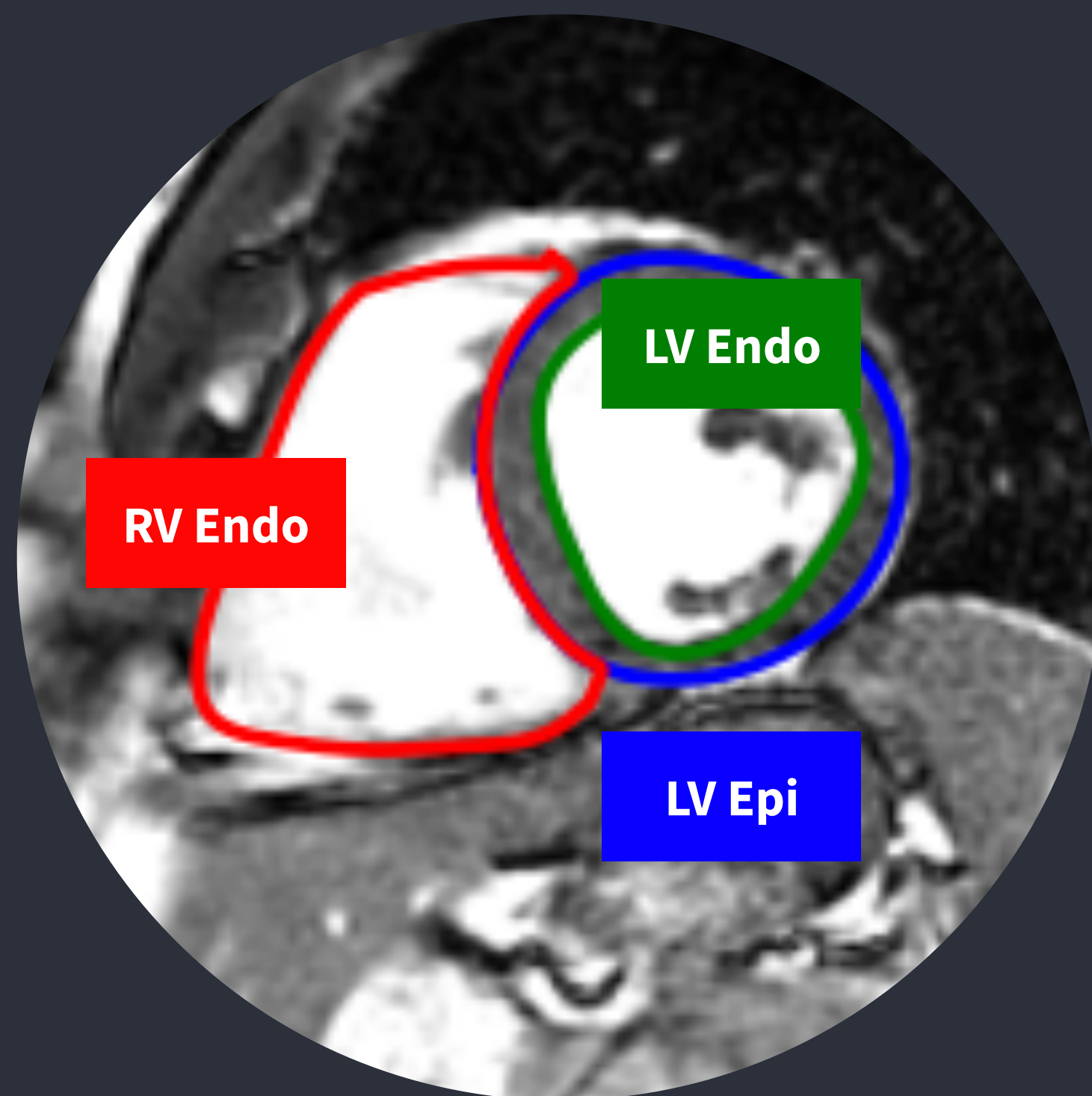
- 15 studies, each with 7 blinded readers' annotations

Procedure

- Metrics: Ejection Fraction, Myocardial Mass
- Calculate consensus volumes
- Calculate standard deviation of readers' measurements
- Perform inference on each study
- Calculate error in units of inter-reader standard deviation

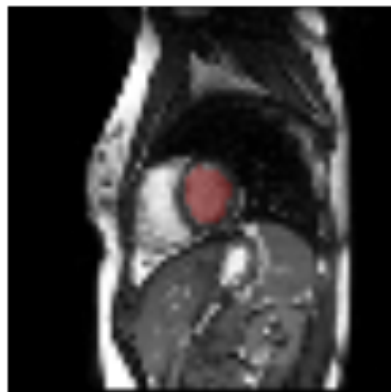
Evaluation on **15-study** multi-annotator set

Relative Error (Inter-reader Standard Deviations)

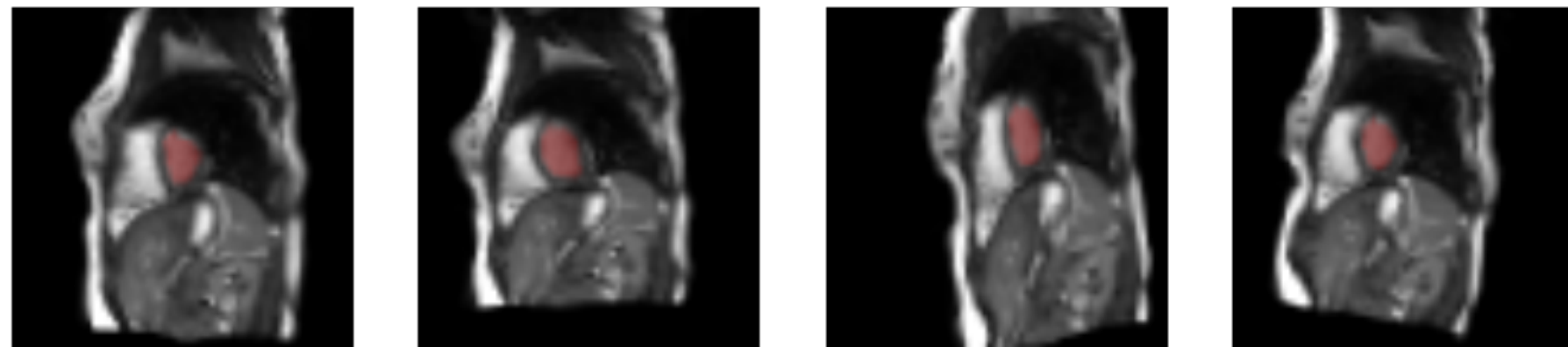




Original



Augmented images



Training Procedure

Keras, TensorFlow, AMD GPUs (LOL J/K 🤔)

Dev Boxes with Titan X and Google Compute Engine with K80s

Real-time data augmentation (cropping, rotation, flipping, elastic distortion, shifting and scaling)

Hyperparameter optimization with random search

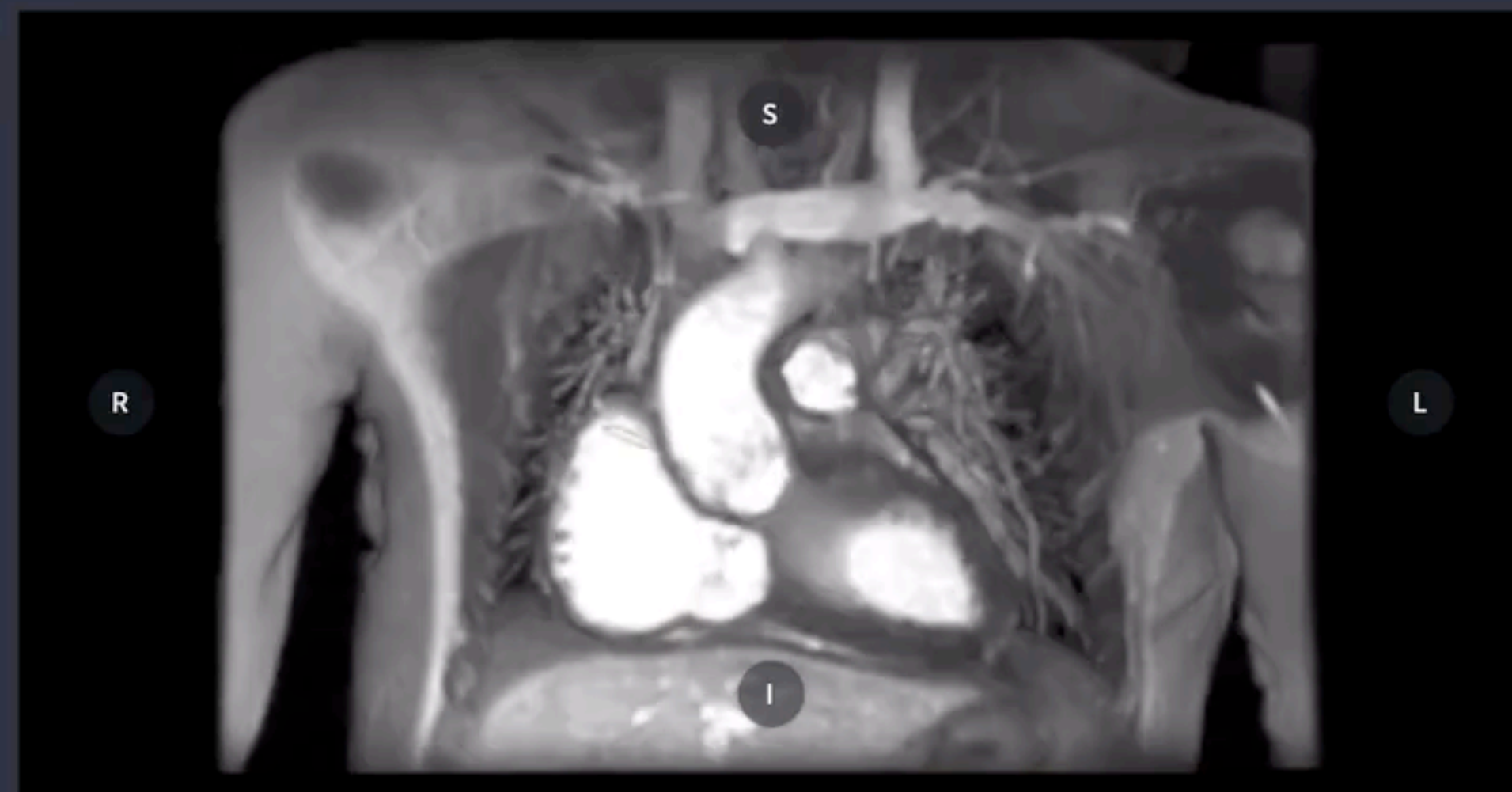
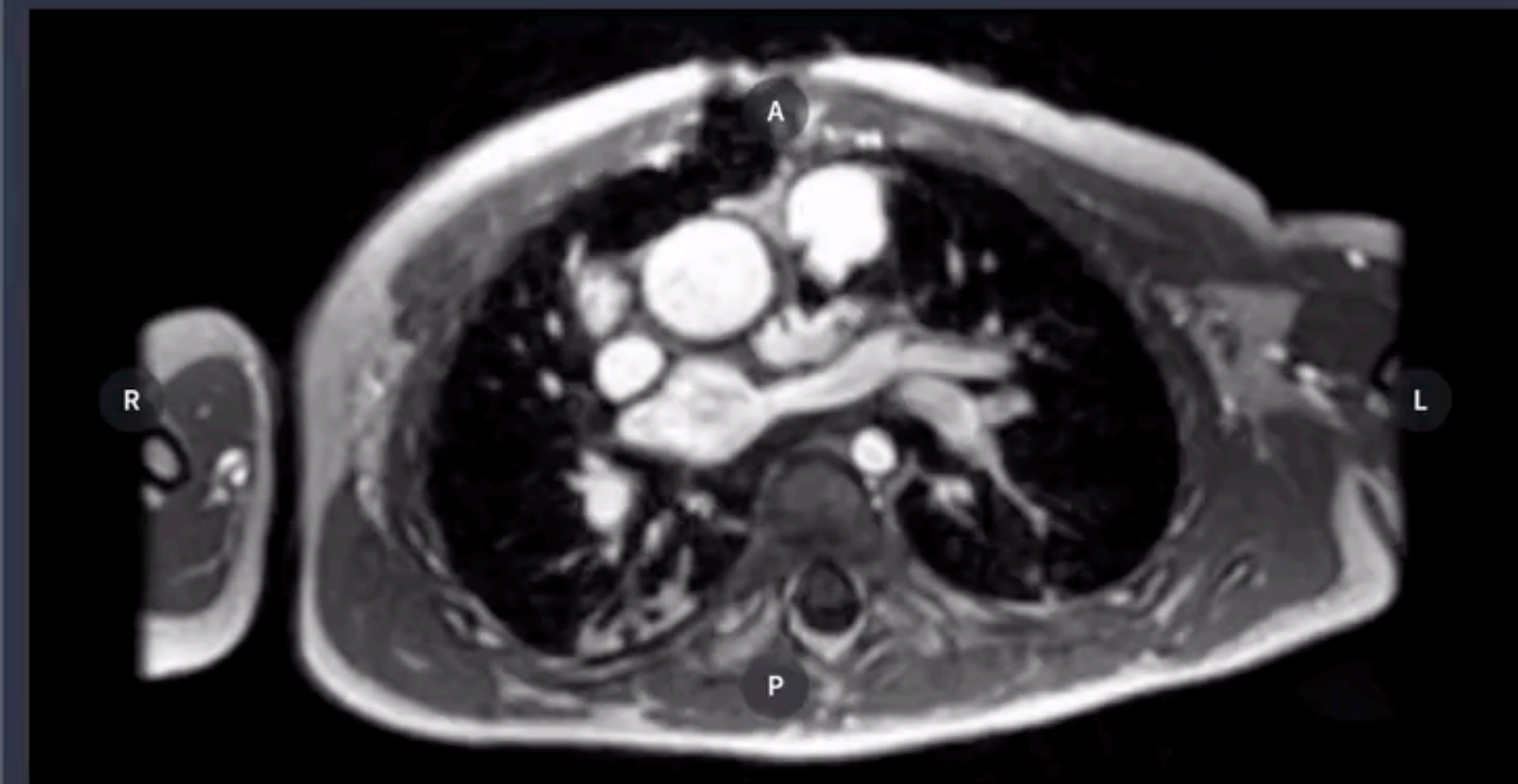
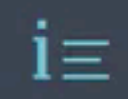
Cardio DL

Cardio DL: first ever clinical, cloud-based deep learning software with FDA clearance (Jan 2017)

Full cardiac suite

Fully cloud based on AWS, enables **continuous learning**

Inference takes around **~15 seconds** for a 300-image study parallelized across four P2 instances



SCENES

+ ×

- Sagittal 3D
- Streamlines
- Vectors
- Flow Measur...
- 4-up
- Function
- Cardiac Views

⏪ || ⏩

ES ED

94 bpm

0.5x

● Correction ON

REPORT

FastVentricle: Cardiac Segmentation with ENet

FastVentricle: Cardiac Segmentation with ENet

Jesse Lieman-Sifry[✉], Matthieu Le, Felix Lau, Sean Sall, and Daniel Golden

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Abstract. Cardiac Magnetic Resonance (CMR) imaging is commonly used to assess cardiac structure and function. One disadvantage of CMR is that post-processing of exams is tedious. Without automation, precise assessment of cardiac function via CMR typically requires an annotator to spend tens of minutes per case manually contouring ventricular structures. Automatic contouring can lower the required time per patient by generating contour suggestions that can be lightly modified by the annotator. Fully convolutional networks (FCNs), a variant of convolutional neural networks, have been used to rapidly advance the state-of-the-art in automated segmentation, which makes FCNs a natural choice for ventricular segmentation. However, FCNs are limited by their computational cost, which increases the monetary cost and degrades the user experience of production systems. To combat this shortcoming, we have developed the FastVentricle architecture, an FCN architecture for ventricular segmentation based on the recently developed ENet architecture. FastVentricle is 4× faster and runs with 6× less memory than the previous state-of-the-art ventricular segmentation architecture while still maintaining excellent clinical accuracy.

1 Introduction

Patients with known or suspected cardiovascular disease often receive a cardiac MRI to evaluate cardiac function. These scans are annotated with ventricular contours in order to calculate cardiac volumes at end systole (ES) and end diastole (ED); from the cardiac volumes, relevant diagnostic quantities such as ejection fraction and myocardial mass can be calculated. Manual contouring can take upwards of 30 minutes per case, so radiologists often use automation tools to help speed up the process.

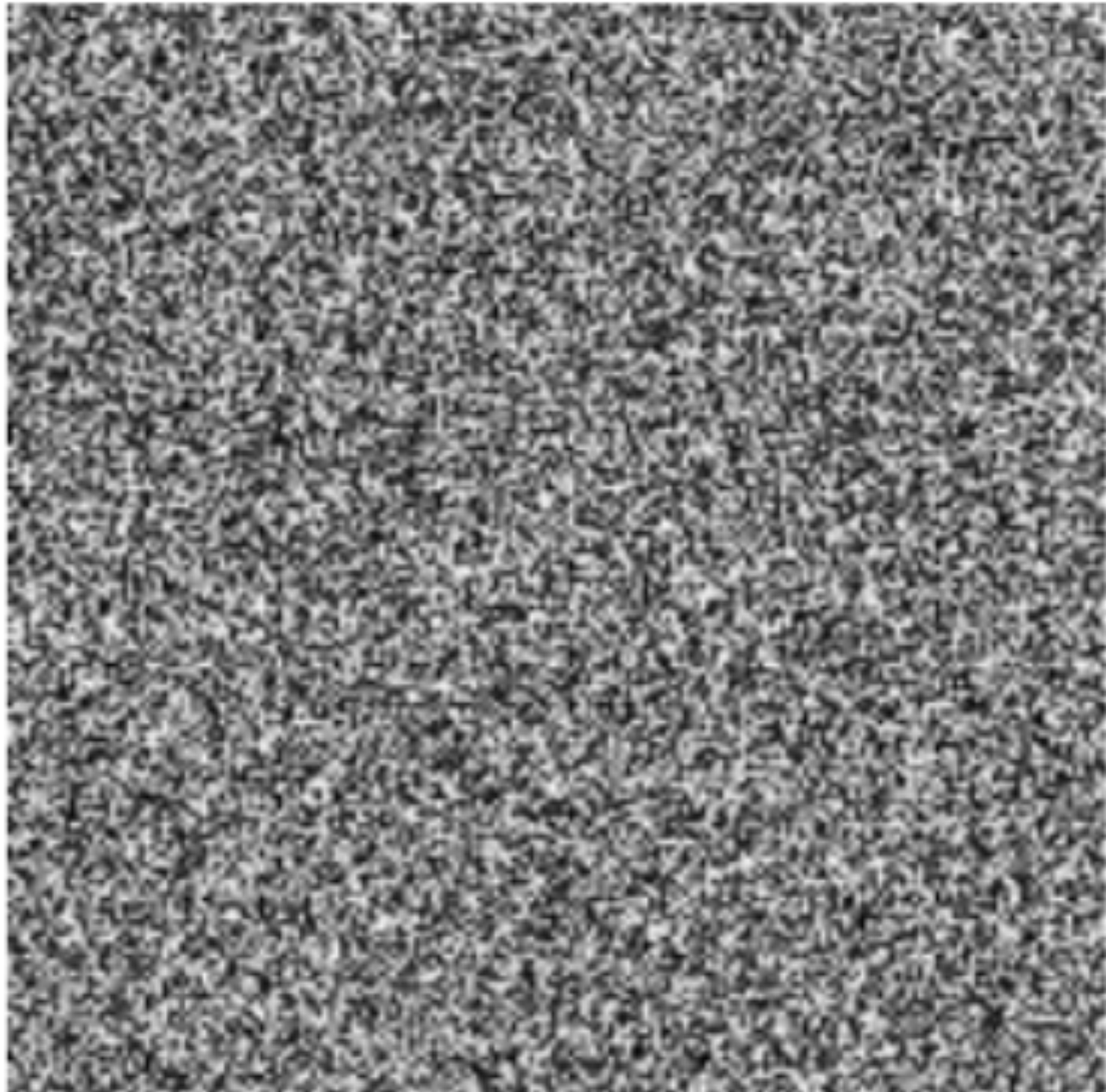
Active contour models [1] are a heuristic-based approach to segmentation that have been utilized previously for segmentation of the ventricles [2, 3] with optional use of a ventricle shape prior [4, 5]. However, active contour-based methods not only perform poorly on images with low contrast, they are also sensitive to initialization and hyperparameter values. We encourage the interested reader to refer to recent review papers [6, 7] as a jumping-off point for further insight on the usage of these (and many other) non-deep learning approaches for cardiac segmentation.

arXiv:1704.04296v1 [cs.CV] 13 Apr 2017

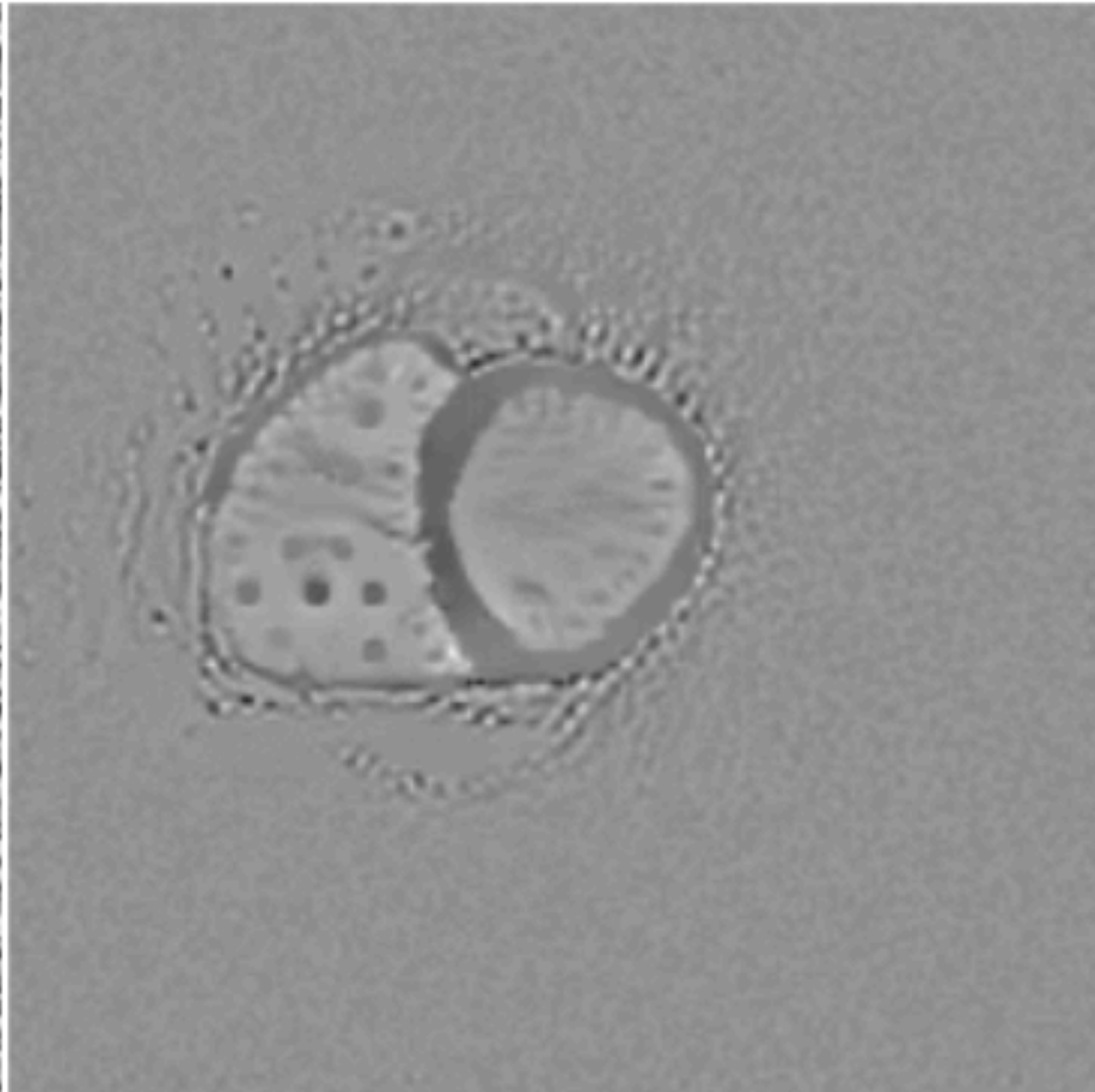
<https://arxiv.org/abs/1704.04296>

DeepDream-style Model Introspection

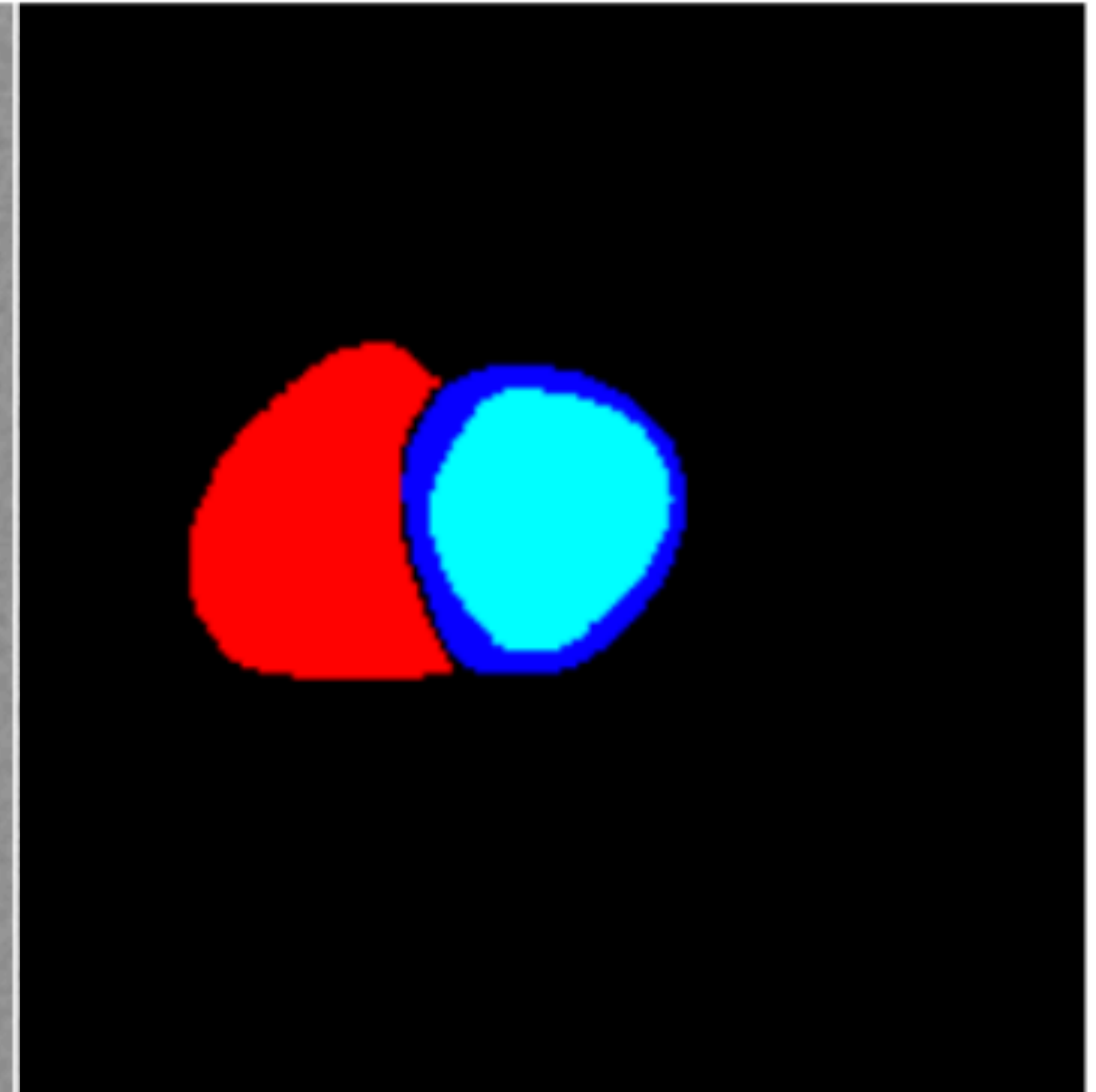
Input Noise



DeepVentricle



Label Map



Arterys **Machine Learning** Team



Felix Lau



Matthieu Le



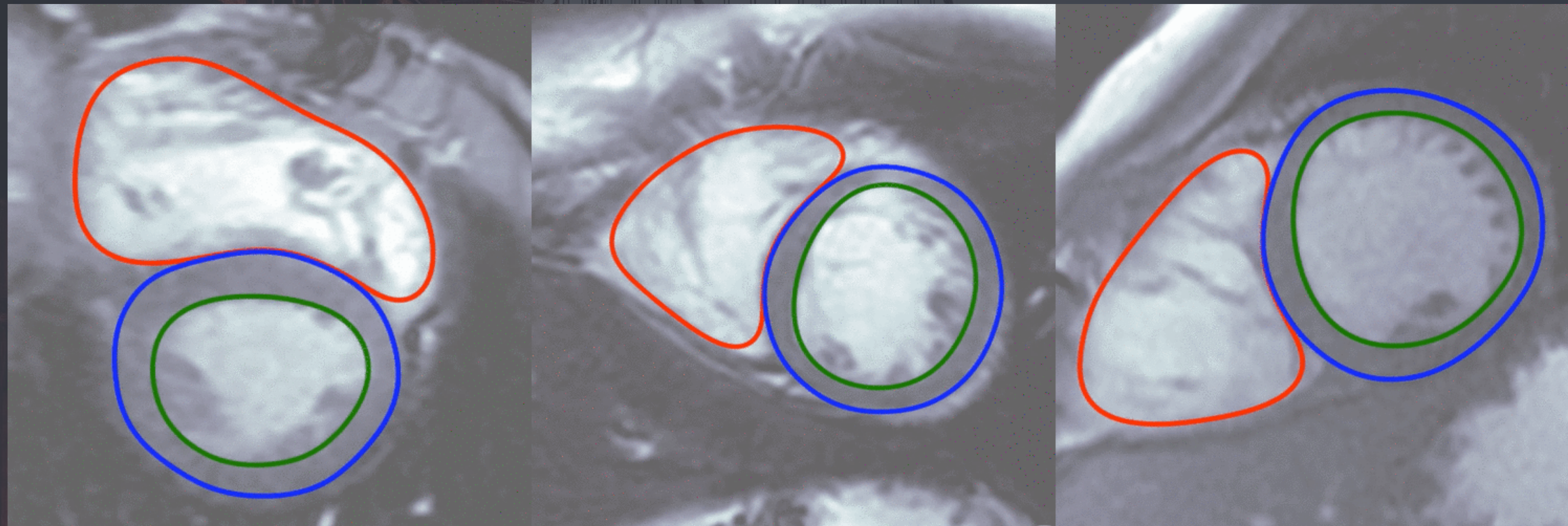
Jesse Lieman-Sifry



Sean Sall

With support from John Axerio-Cilies (CTO) and Albert Hsiao (Clinical Co-Founder)

Daniel Golden
Director of Machine Learning, Arterys
dan@arterys.com

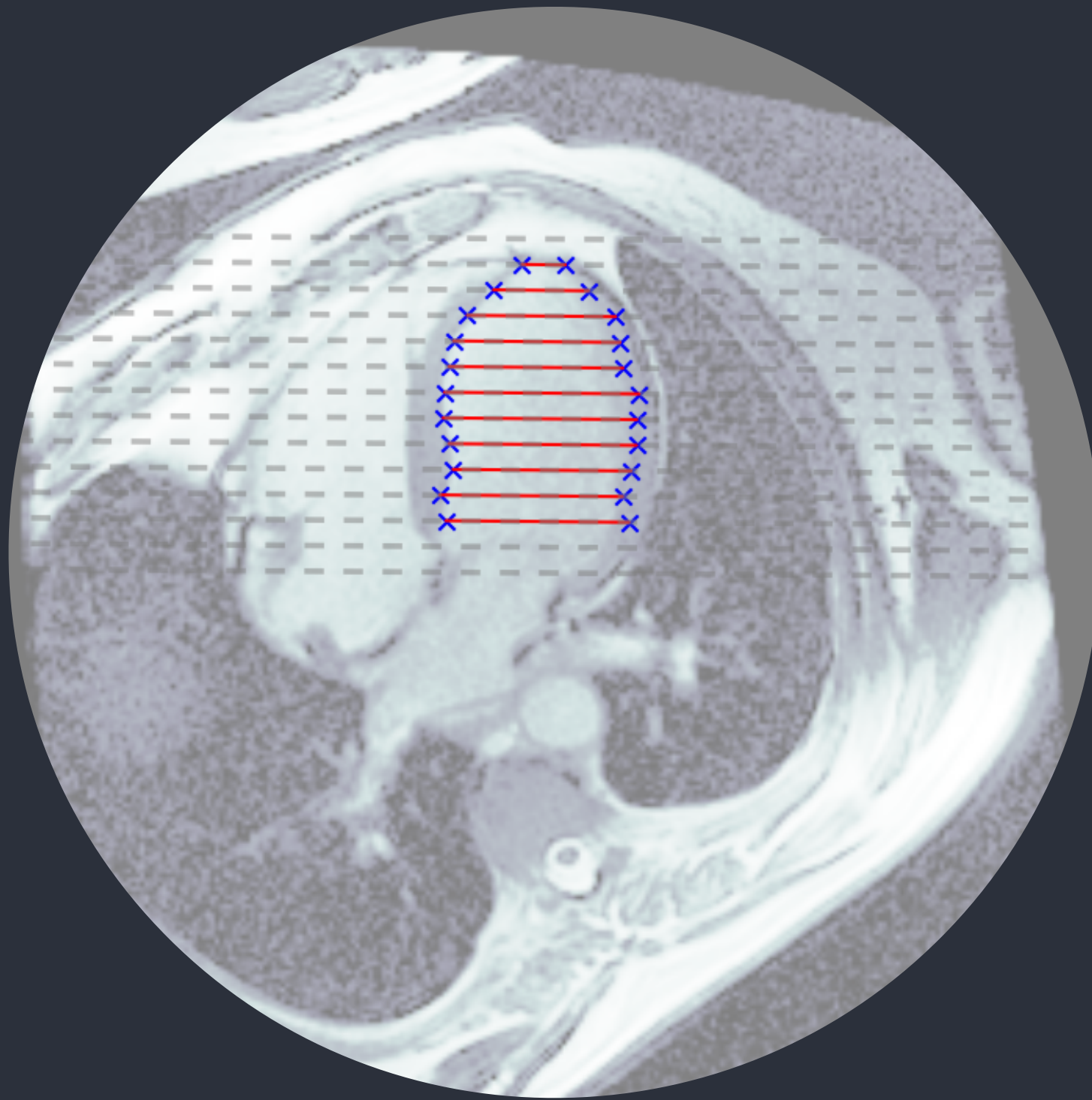


15-study set inter-rater variation

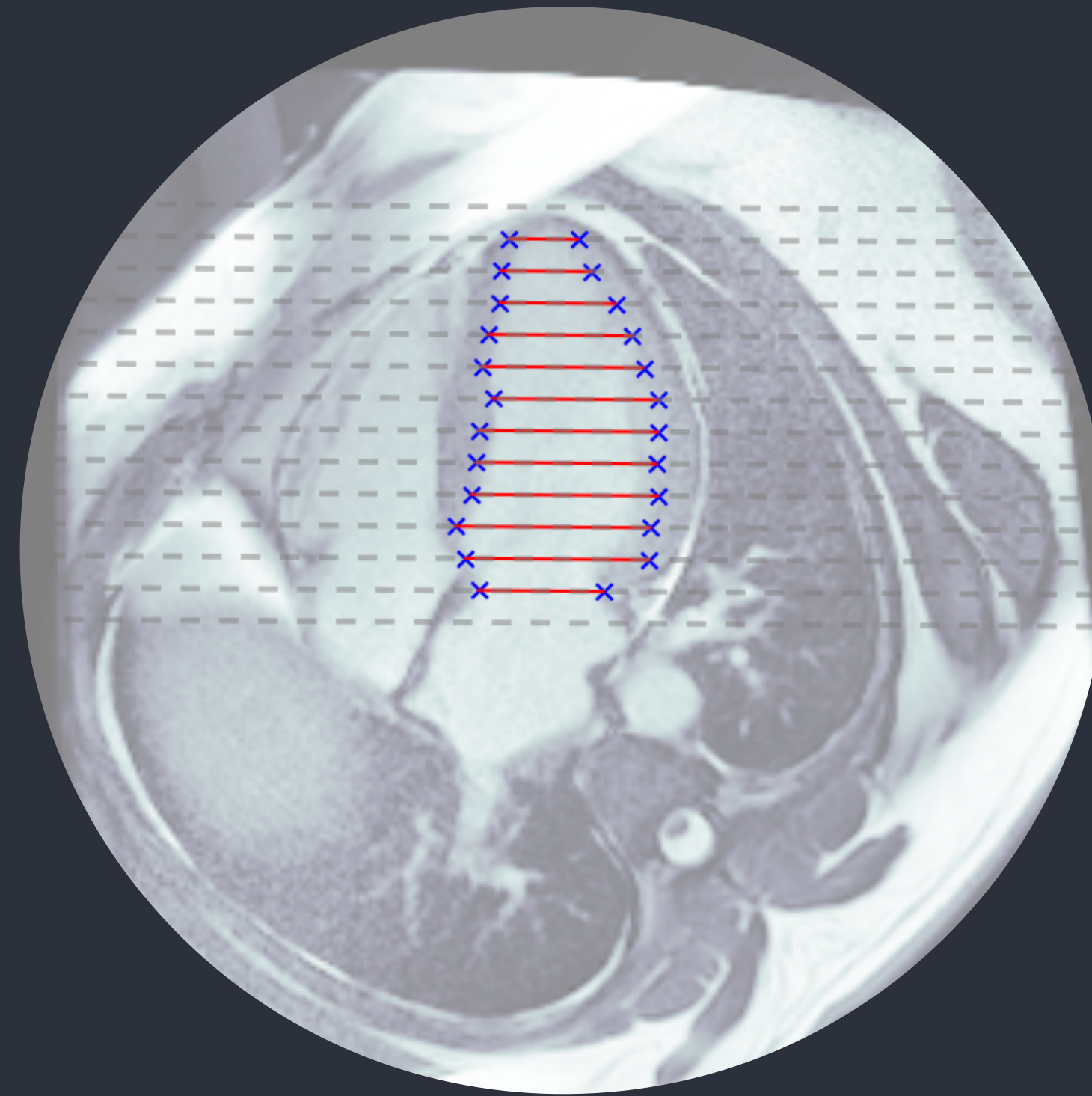
Avg. st. dev. of ground truth EF: 4.4% (rel: 0.11)

Avg. st. dev. of ground truth mass: 18 g (rel: 0.14)

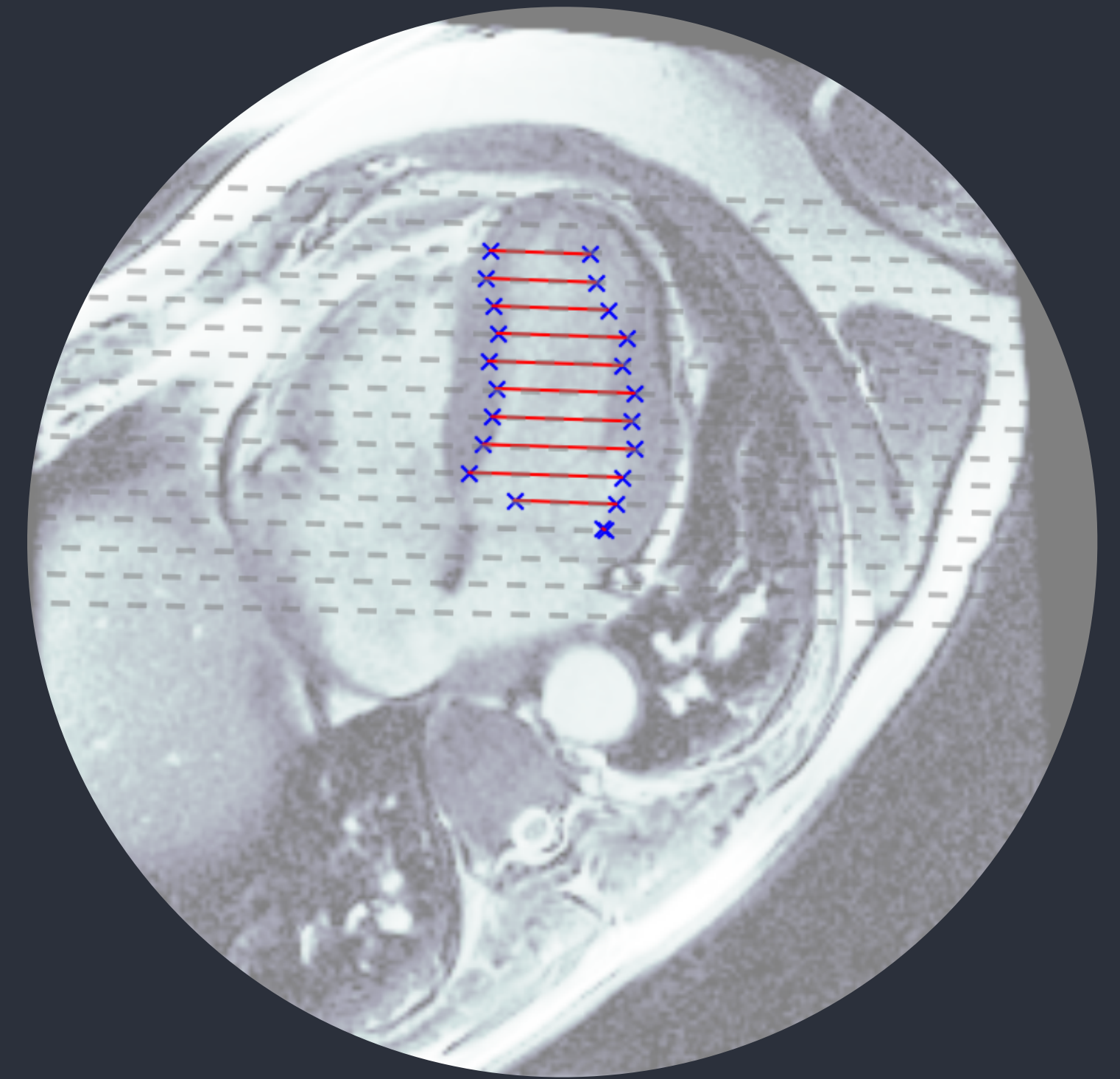
Inter-rater **variability**



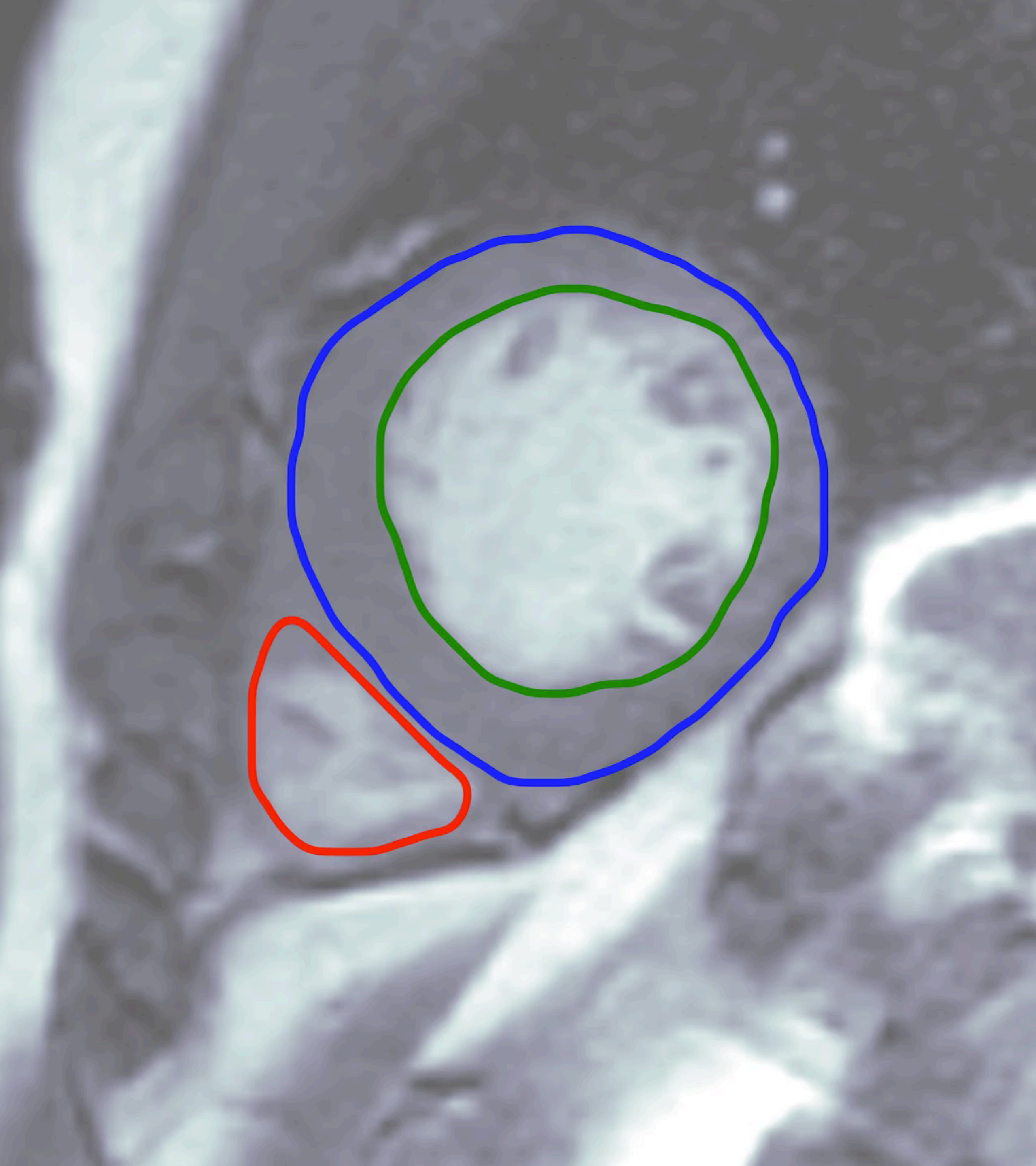
Below valve plane



Above valve plane

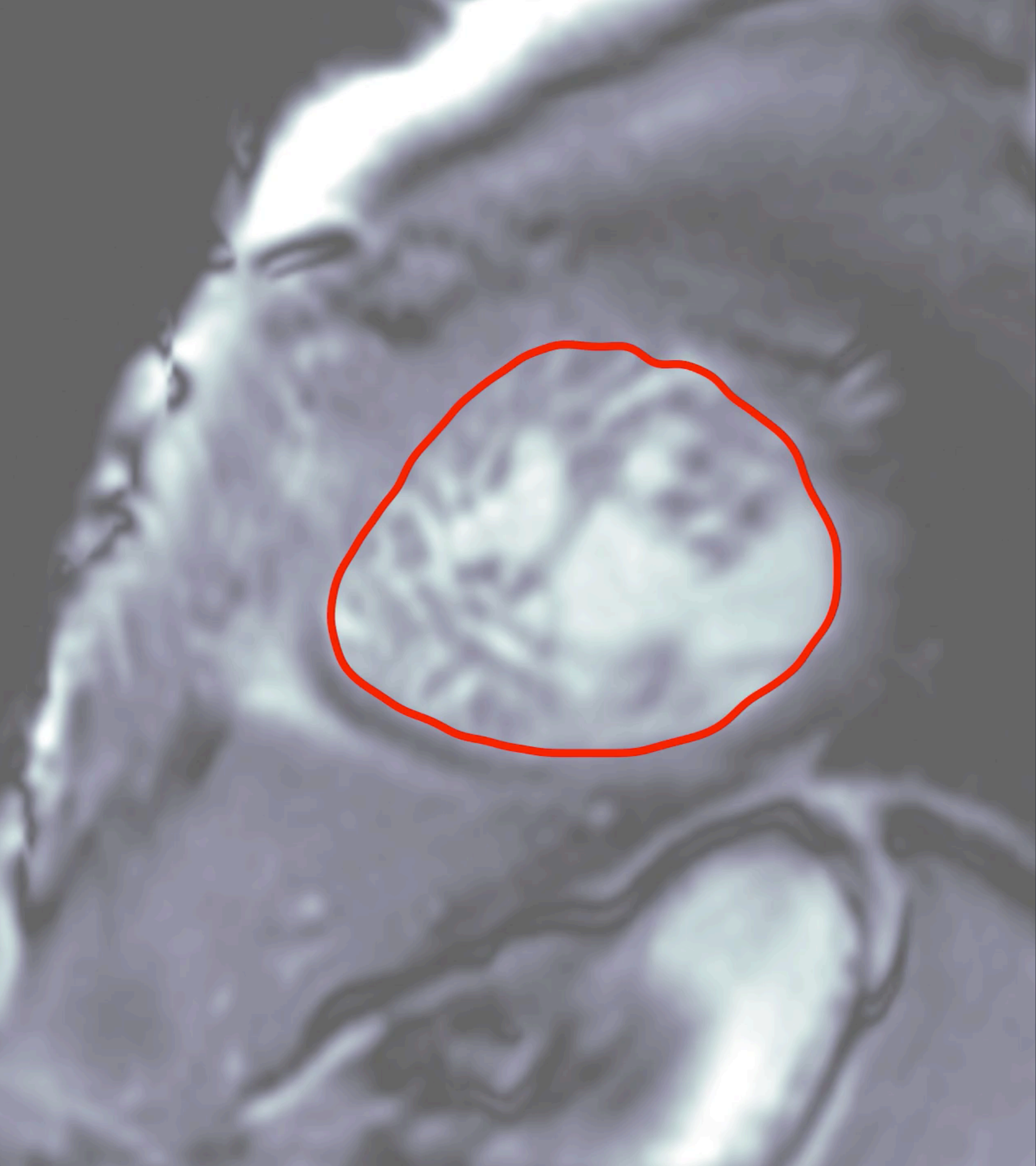


Partial segmentation



Hypertrophic
cardiomyopathy

(Enlargement of heart muscle)



Single ventricle defect