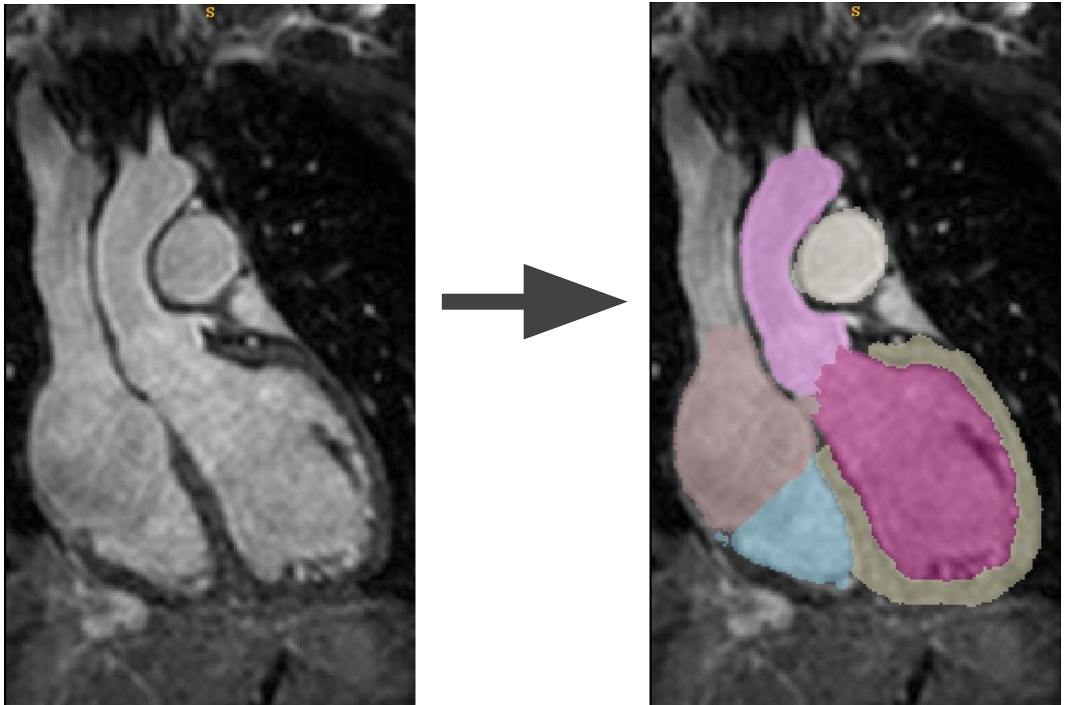
Automating cardiac image segmentation using deep learning

Team 9
U-Hack Med
11-10-18

Objective: increase the degree of automation in cardiac image segmentation



Segmentation is the assignment of one tissue label to each pixel (Rt Ventricle, Left Atria, etc...)

Why segment cardiac images?

- To quantify the structure of the heart, great vessels, and its function:
    - Extent of damage from a heart attack
    - Heart failure
    - Coronary artery disease (CAD)
    - Congenital heart defects
    - Heart valve and membrane defects
    - Ejection fraction

Segmentation is currently suboptimal:

Segmentation is performed **manually** by cardiologists

- Time consuming
- Variable accuracy based on physician expertise
- Error-prone

Why is this bad?

- Less time for physicians to spend with patients
- Errors and inaccuracies affect patient outcomes
- Low reproducibility
- Not amenable to large scale studies

Therefore automation is a key step forward

Approach: start with planning

Together we conducted scientific literature review of 6 papers, got a sense for strengths and weaknesses of methods

Decision to use deep learning UNets due to their ability to yield high seg accuracy and generalize to unseen data. Ideally we build a model, trained on subset of diseased and healthy subjects that can adapt to other disorders (e.g. congenital heart defects).

We designed overall pipeline and volunteered for team roles on major steps:

1. Data pre-processing: 70% of time is typically spent here, so we allocated accordingly.
2. Deep learning model implementation and evaluation: 30%

1. Pre-processing

1. **Normalize data to reduce intersubject variability** [Nick Acevedo and Paul Acosta]

   a) Resample images to uniform voxel size, image size
   b) Reduce scan variability: isolate heart region
   c) Reduce variability in location, orientation, scale of hearts through coregistration

      (1) Identify reference subject for coregistration with clearly presenting 4 chamber view

      (2) Identify 2D images with clinical relevance .... Now we can tackle 2D or 3D
      [Paige McKenzie, Navina Mohan, Albert Montillo]

2. **Augment data to increase training set 50x** : 20subj-> 1,000 subjects [Vishal Rajesh and Cooper Mellema]

   Affine transform including: translation, rotation, scaling

3. **Downsample images to reduce potentially long training time** [Luke Ge]

   provides multiple options for training given unknown training time and limited hackathon duration.

Data Preprocessing

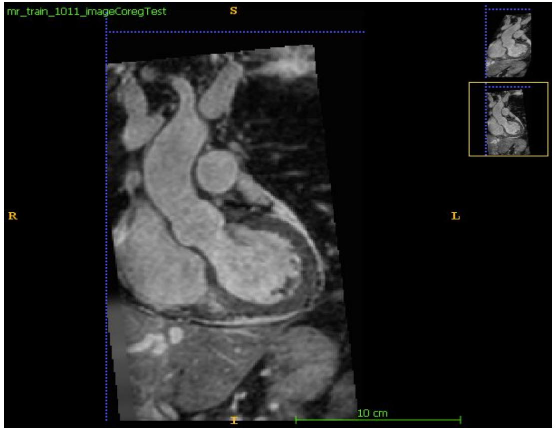
Voxel Spacing

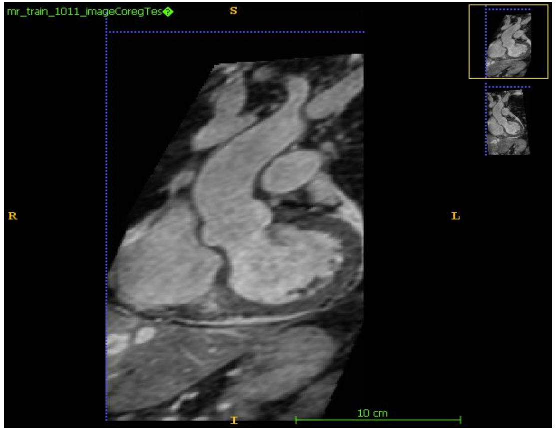
x: 0.7813 y: 0.7813 z: 1.6

Isometric

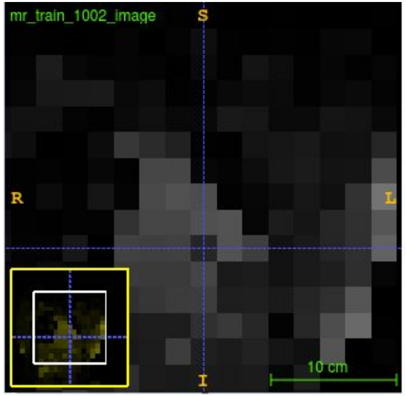
Voxel Spacing

x: 1 y: 1 z: 1





Downsampled Images



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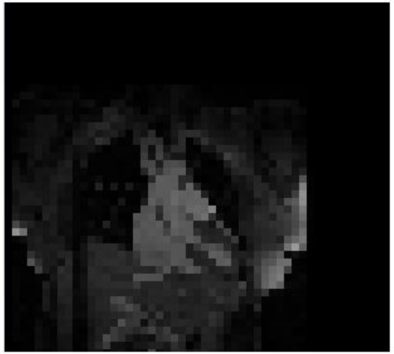

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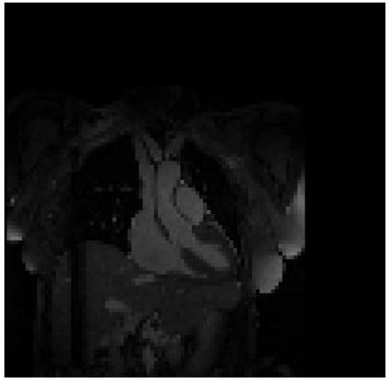

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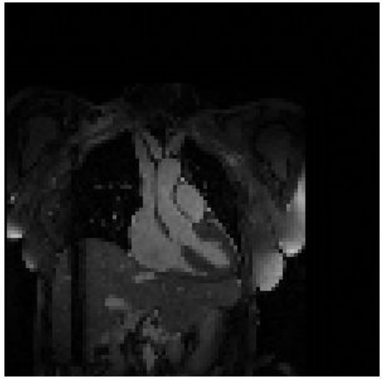


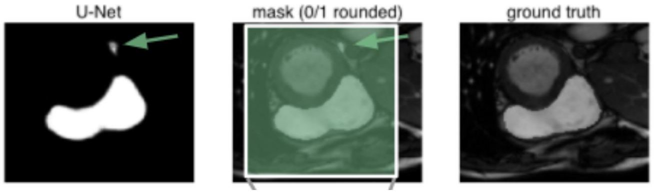
50%

2. Deep learning: implementation & testing

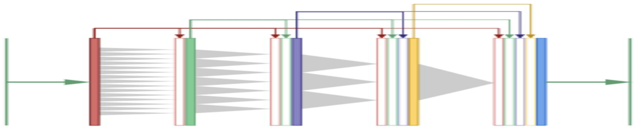
1. **Evaluated UNet, Dilated UNets, Dilated DenseNets on the most clinically relevant subset task**: 2D RV segmentation [Akhila Perabe, Albert Montillo]

Result: Dilated DenseNets gave superior performance

Dilation greater context seen by deep neurons so they learn more: e.g. heart has only 1 RV



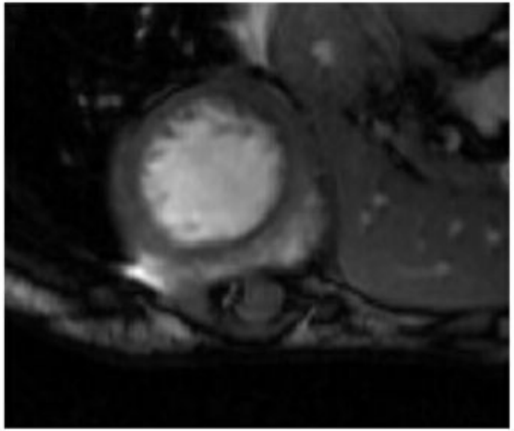
DenseNets fuse information from >1 previous levels which increases accuracy compared to UNets

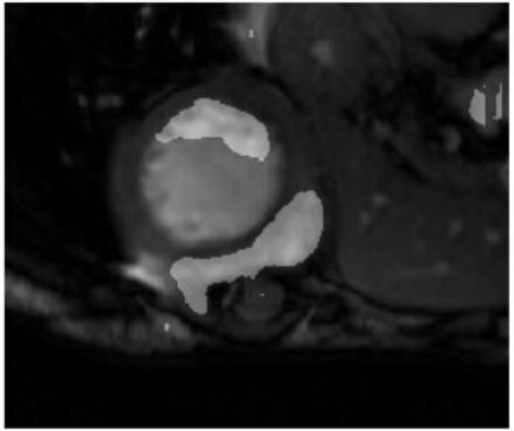


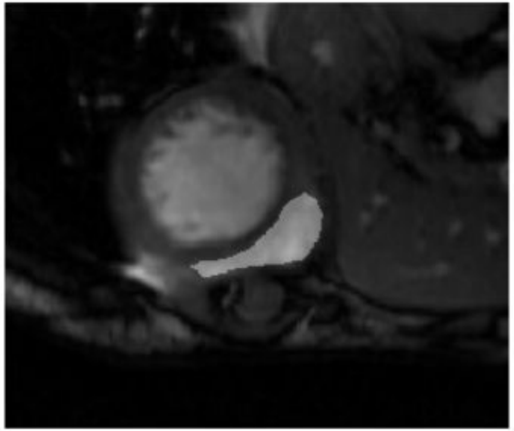
2. **Eight hyperparameters explored**: 1) loss function: {dice, pixel-wise cross-entropy}, 2) class weighted loss, 3) # layers, 4) # conv filters/layer, 5) learning rate, 6) class weighted loss, 7) batch size, 8) optimizer

Results: Considerable improvements found: Dice: 0.05 → 0.1 → 0.25 → 0.46 [with additional time we would increase data augmentation, levels and continue training.]

Dilated Densenet - Nadam Optimizer

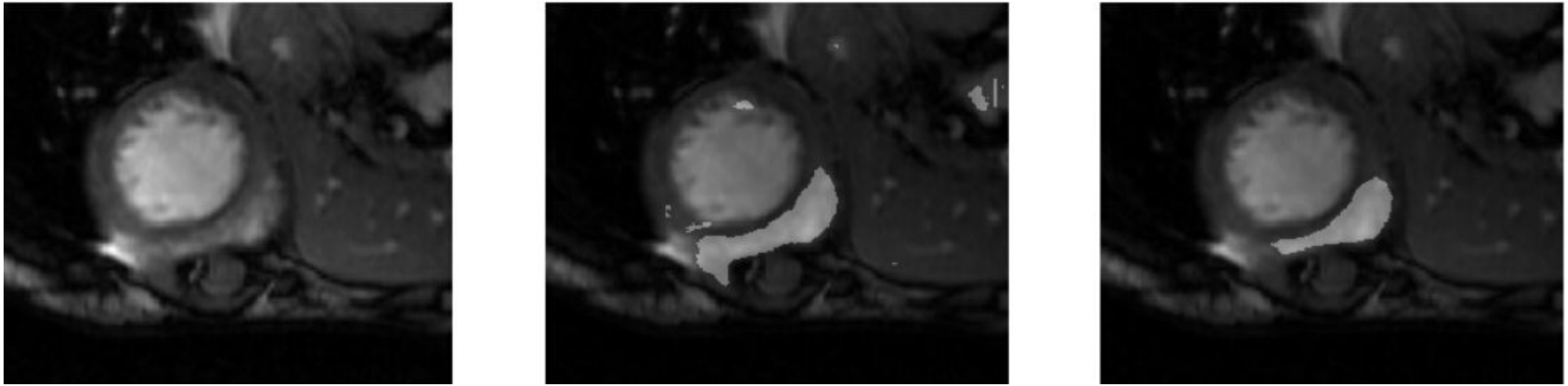






- NADAM essentially adds Nesterov momentum to the ADAM optimizer.

Dilated Densenet - Learning Rate Tuning



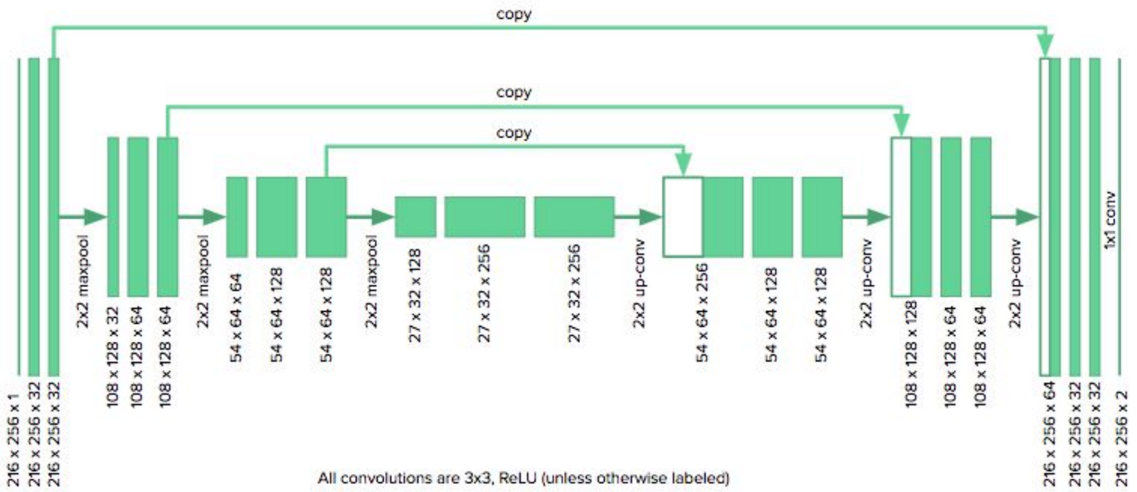
Clinical Applications

- Consolidation of tools developed during this hackathon will allow for the segmentation of the hearts of patients with more complicated congenital anatomies such as:
    - Tetralogy of Fallot (TOF)
    - Transposition of Great Arteries (TGA)
    - Double-Outlet Right Ventricle (DORV)
    - Atrial Septal Defect (ASD)
- Can help give insight on prognoses of these patients as well as predict optimum timings for valve replacement procedures

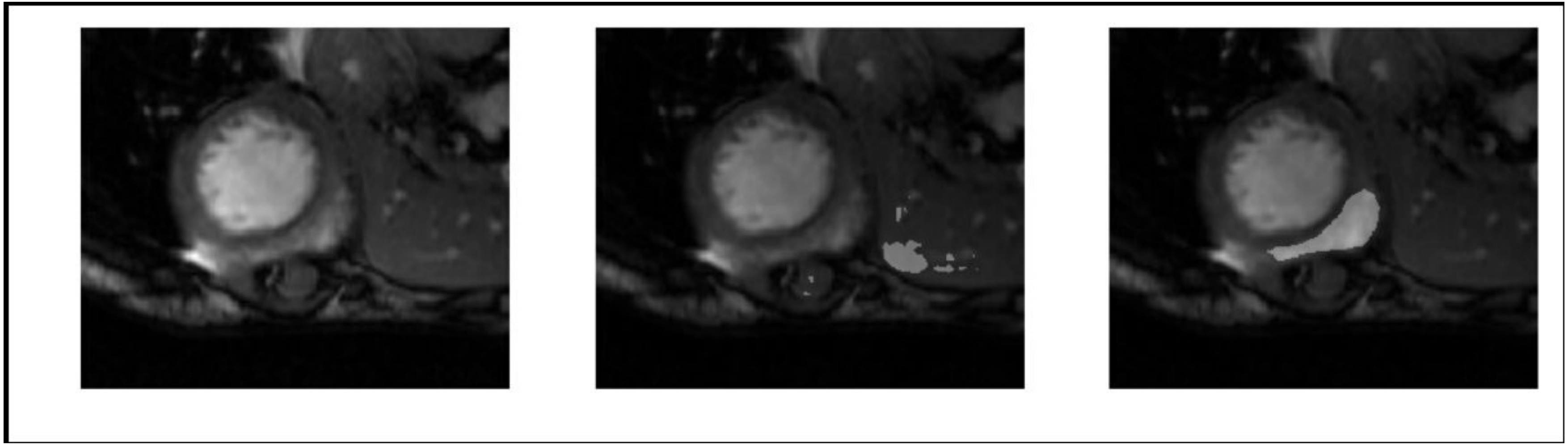
Many thanks!! from the hackathon team 9 : Akhila Perabe, Nick Acevedo, Paul Acosta, Vishal Rajesh, Cooper Mellema, Luke Ge, Paige McKenzie and Navina Mohan, Albert Montillo

2D U-net Implementation

- Contracting path downwards collapses an image down into a set of high level features
- Expanding path uses the feature information to construct a pixel-wise segmentation mask
- “Copy and Concatenate” connections to pass information from early layers to later layers



Dilated Densenet - Adam Optimizer

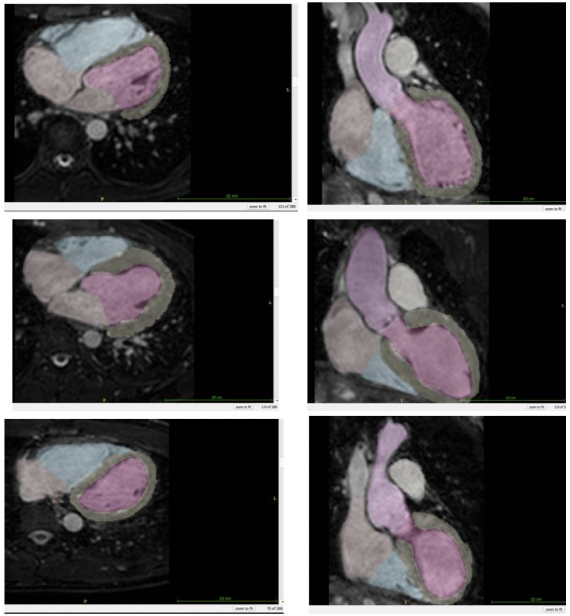


Selecting a Suitable Reference Subject

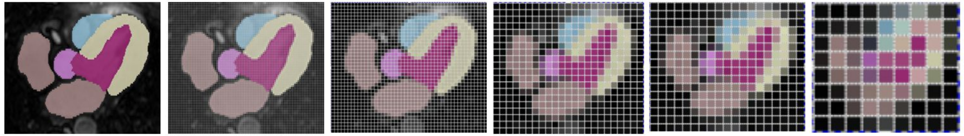
18

10

03



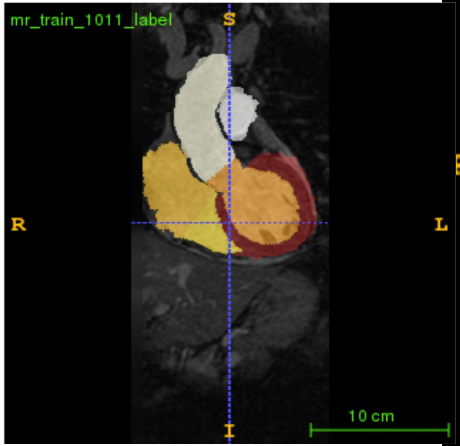
Full 100% | 20% | 10% | 5% | 4% | 2%



450x400 | 90x80 | 47x39 | 23x20 | 19x16 | 9x8

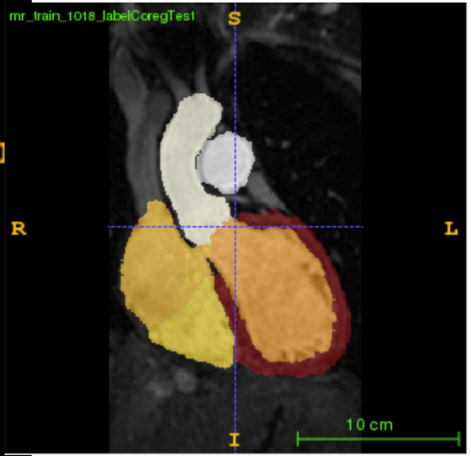
Much detail in the segmentation mask is retained up to about 5%

Coregistering to subject 18



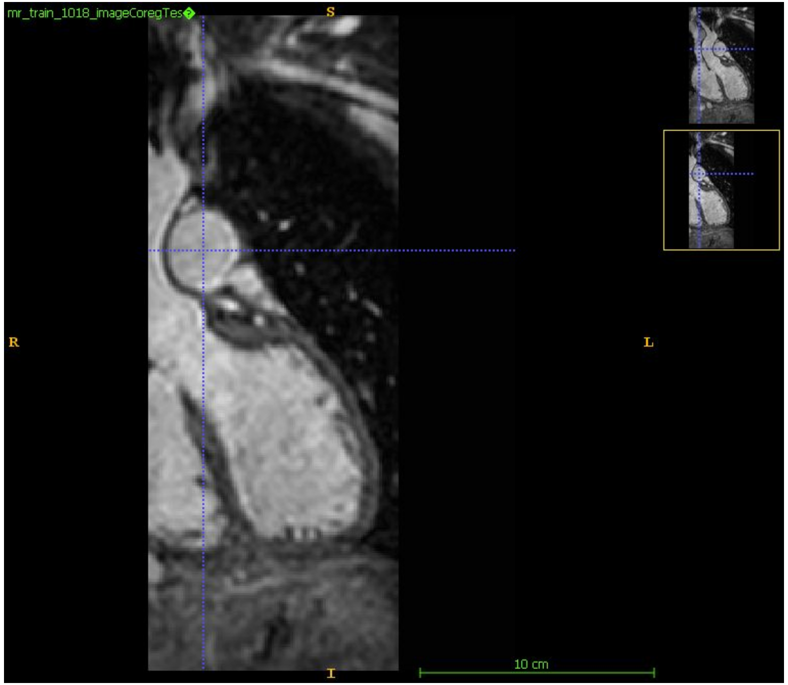
Subject 11 cropped
(Coronal Slice)

Subject 11 Coreg
(Coronal Slice)

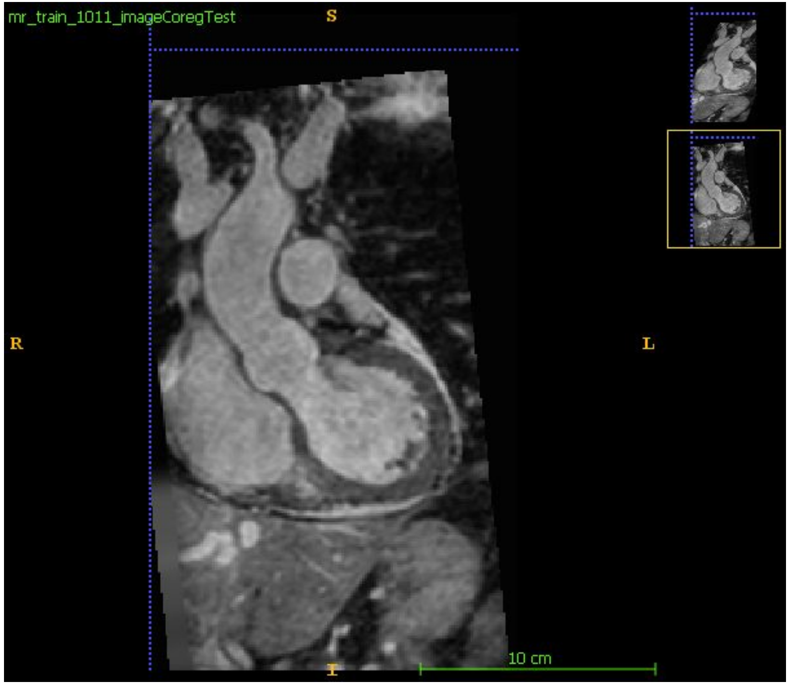


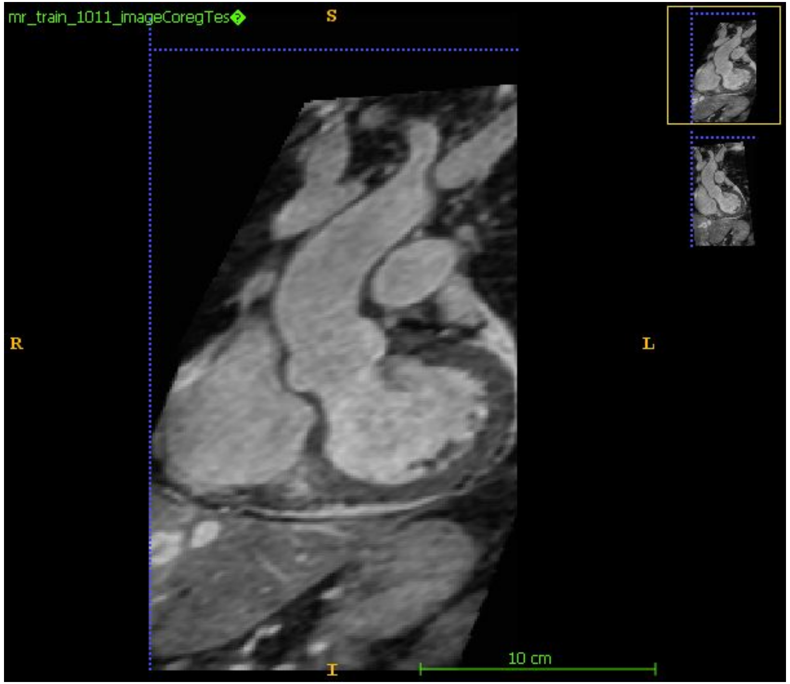
Subject 18 Coreg
(Coronal Slice)

Data Augmentation- Jitter



Data Augmentation- Rotation





Data Augmentation- Scaling