Deep Learning for Cardiac Segmentation:

SEMI-AUTOMATIC METHOD TO BUILD LEFT VENTRICLE MESH

Politecnico di Milano
A.A. 2020/21

ADVANCED NUMERICAL METHODS FOR COUPLED PROBLEMS WITH APPLICATION TO LIVING SYSTEMS

Daniele Ceccarelli

Project Outline

[https://github.com/danielececcarelli/DL_cardiac_segmentation]

1. **First model:** 2D automatic segmentation for Short Axis MRI **Endocardium**

2. **Ring model:** 2D automatic segmentation for S-A MRI **Myocardium**

3. 3D Mesh building and **shape refining**

4. 4D segmentation during a complete **cardiac cycle**

- 3D-UNet automatic segmentation [Future work]

- Transfer Learning from other medical images segmentation task [Future work]

Short Axis MRI Datasets

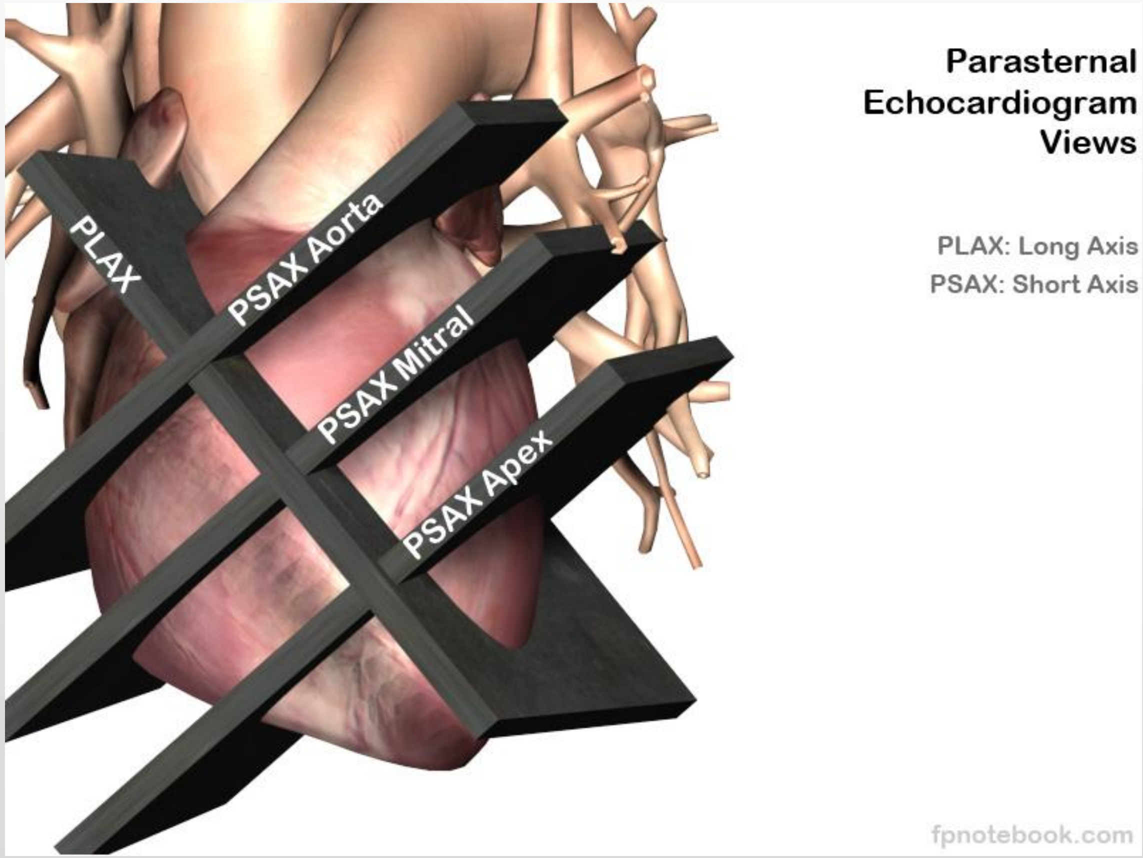
SUNNYBROOK AND ACDC DATA

Short Axis MRI Cardiac images

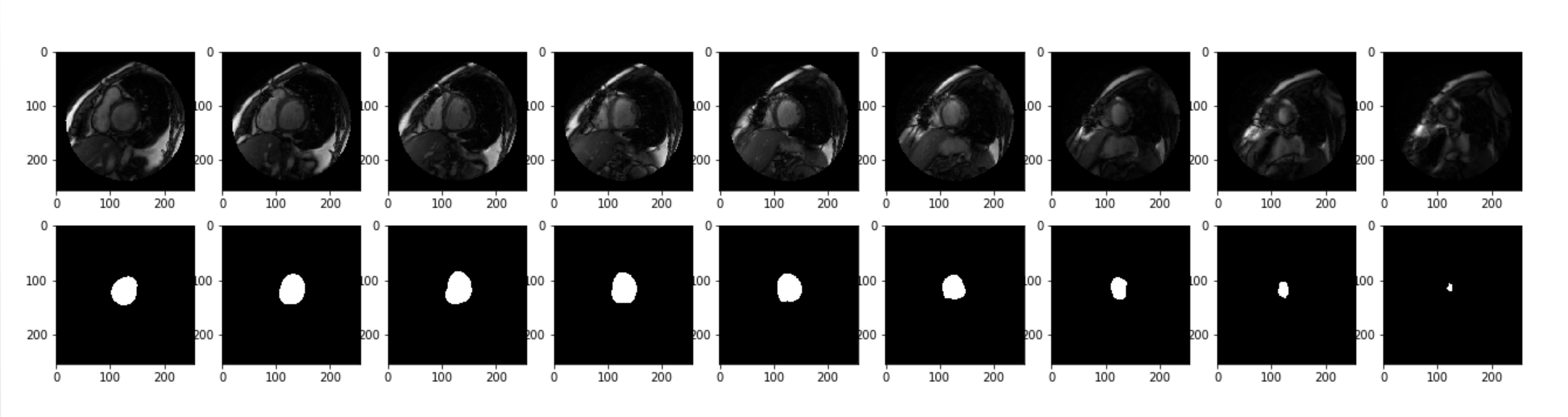
4D images of shape (n_x, n_y, n_z, t)

Where:
- n_x and n_y are around 200/300
- n_z is very small, from 5 to 15/20
- t goes from 10 to 30, but we have manual contour only for ED and ES

For every patient we have manual contours of Left Ventricle (and RV) at two different moment:
- End-Systolic (ES)
- End-Diastolic (ED)

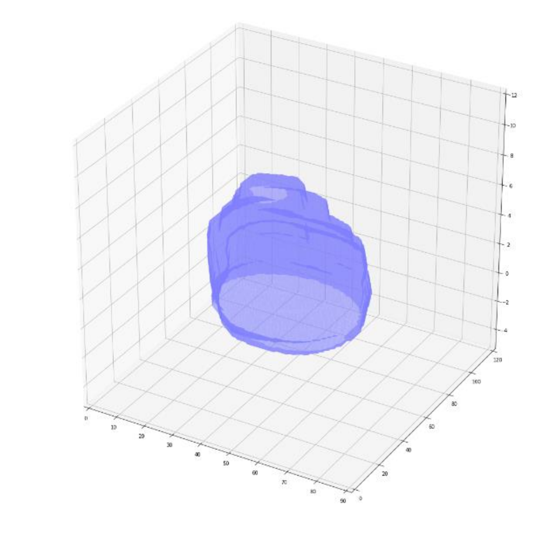


Short Axis example



Above, an example of a Short Axis MRI for a patient: 9 images along the short axis and the relative segmentation of the inner endocardium of Left Ventricle.

On the right, an example of the possible 3D segmentation we can get from these images.
(made by me using mpl_toolkits.mplot3d.art3d **Poly3DCollection** python function to build the volume starting from the slices)



Short Axis MRI Datasets: Sunnybrook

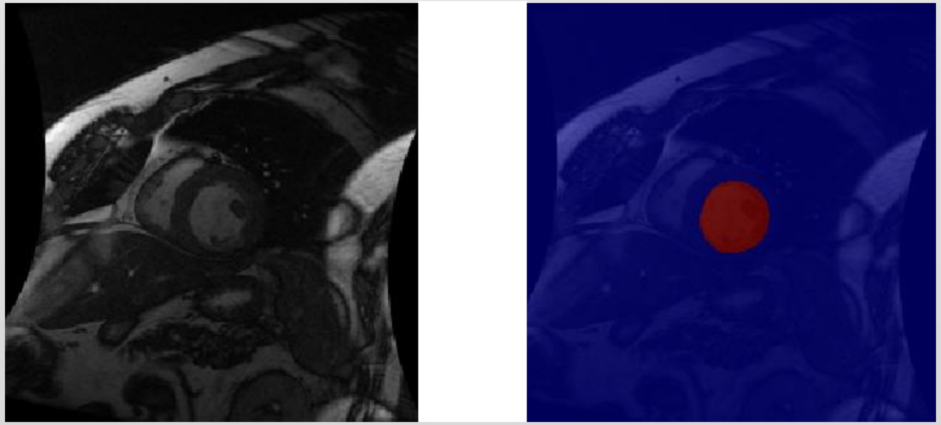
Sunnybrook data (already preprocessed here:

https://github.com/mshunshin/SegNetCMR/tree/master/Data)

100 patients, 2 different time (ED and ES) for each

→ 200 3D patients images (x,y,z) → trasformed in 1000 2D images

Contour: Inner endocardium of Left Ventricle



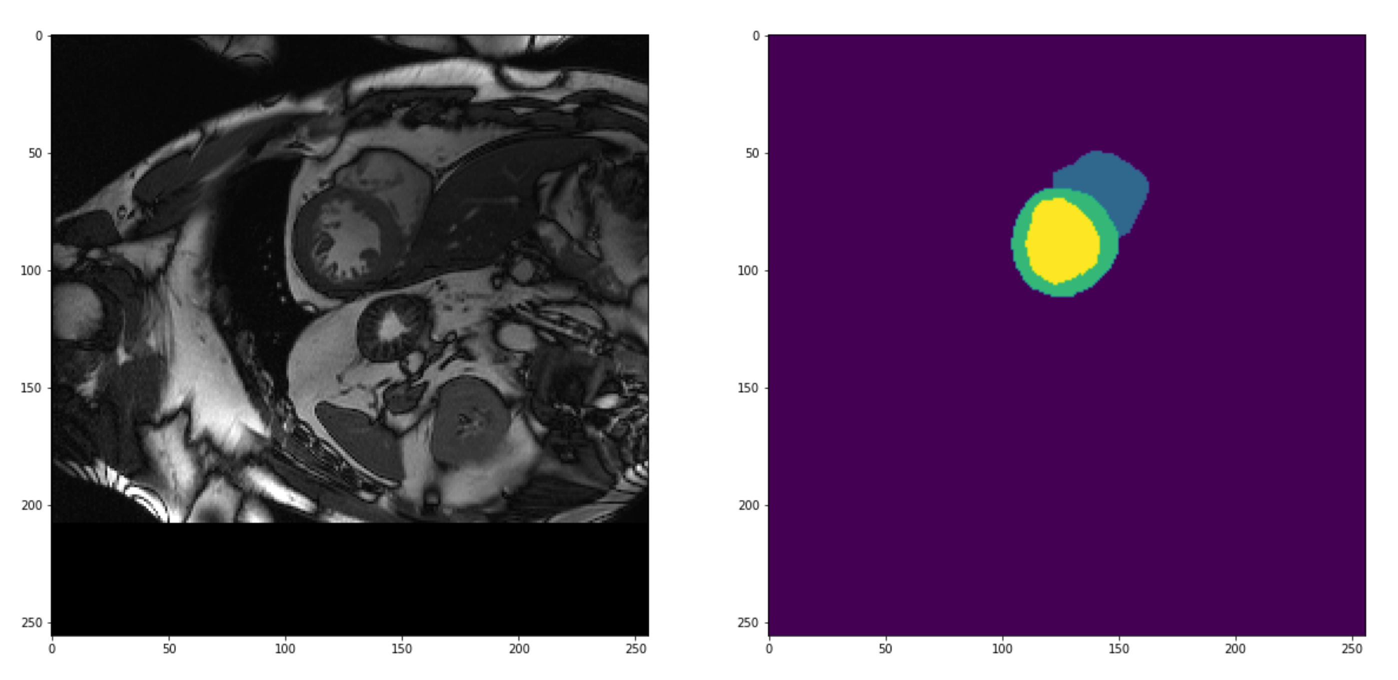
Short Axis MRI Datasets: ACDC dataset

ACDC dataset: https://www.creatis.insa-lyon.fr/Challenge/acdc/databases.html

95 patient at ED and ES → 190 3D images (n_X x n_Y x n_Z) (where n_Z is 8-11 more or less)

→ 1812 2D images, reshaped by me to 256x256 with padding to zeros around the images

Contour:
Inner LV(yellow),
Outer LV(bluemarine)
and RV(blue)



First models: 2D UNet

MODEL WITH SUNNYBROOK AND ACDC DATA SEPARATELY

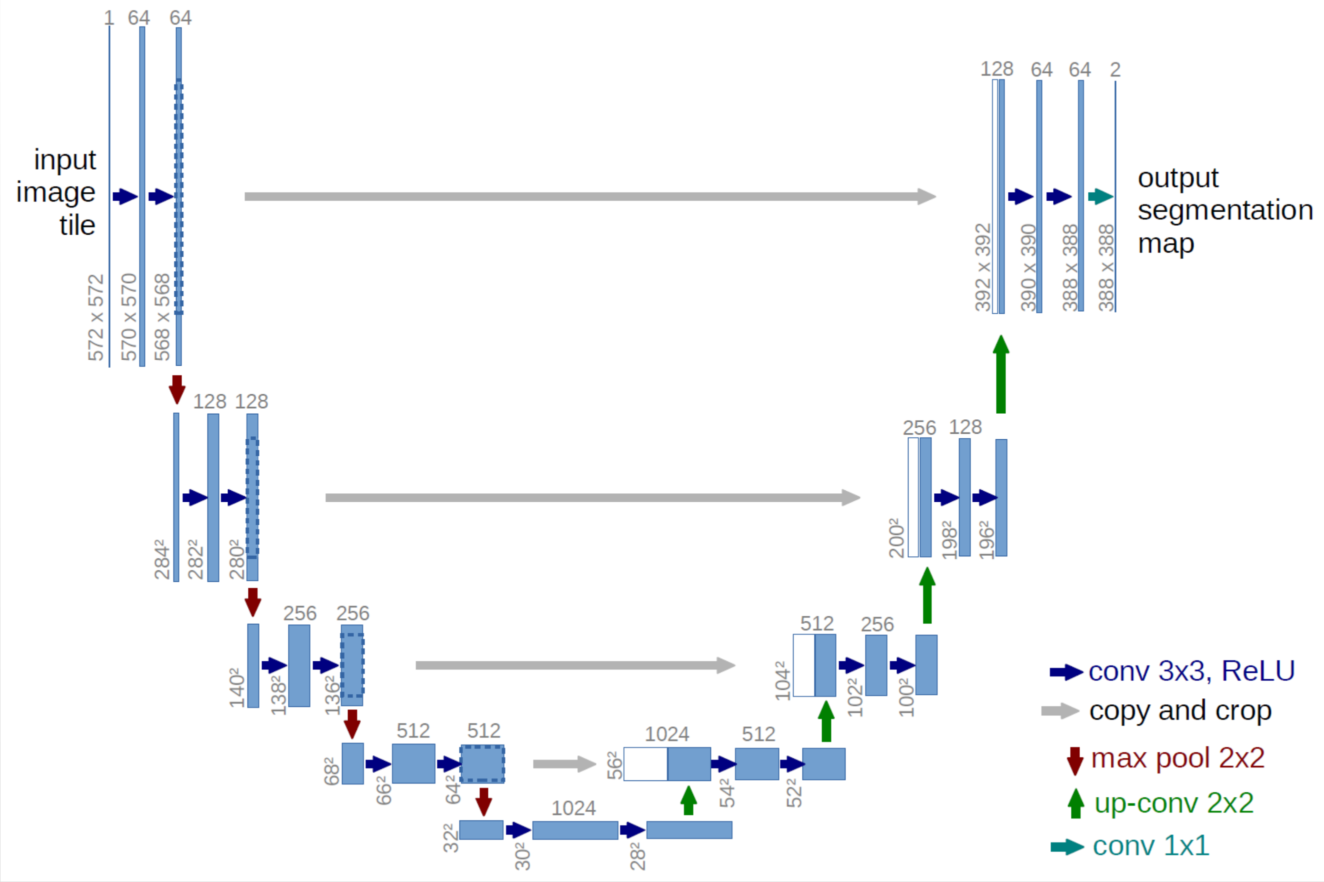
First Model: Unet VGG16 for Sunnybrook

Net: Unet with VGG16 architecture
Input: (256,256,1)
Output: (256,256,1), binary 0/1 classification
Initial weights: ImageNet

Model build with Tensorflow & segmentation_models library [(https://github.com/qubvel/segmentation_models)](https://github.com/qubvel/segmentation_models)

Epochs: 100
Optimizer: Adam
Learning rate: 10^-3
Batch size: 8
Loss: DICE Loss
Metric: IOU Score

Train set: 450
Validation set: 76
Test set: 230



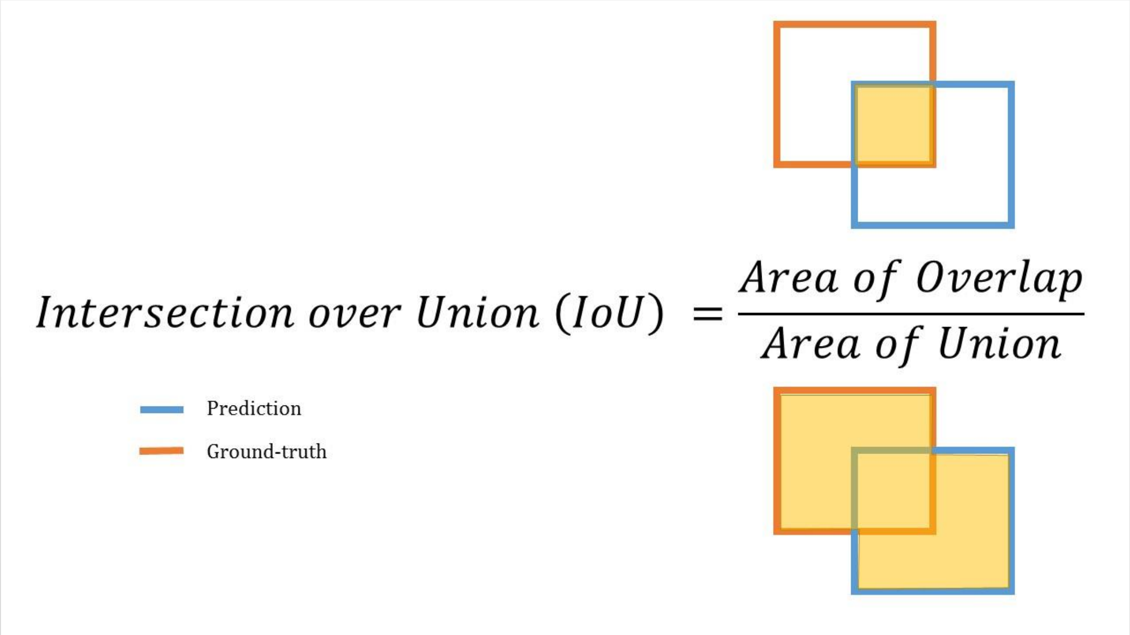
Source: https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/

Loss and Metric: Definition

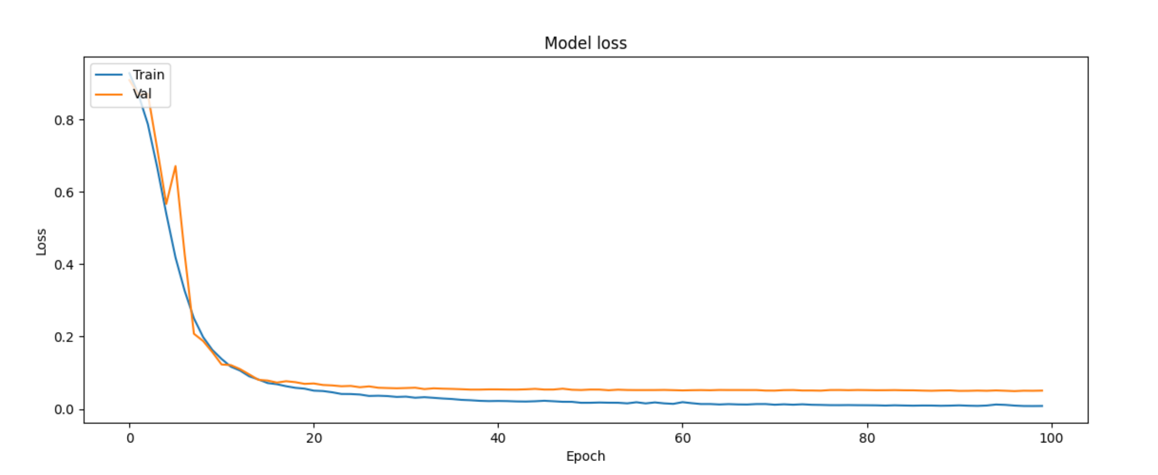
- **Loss: DiceLoss**

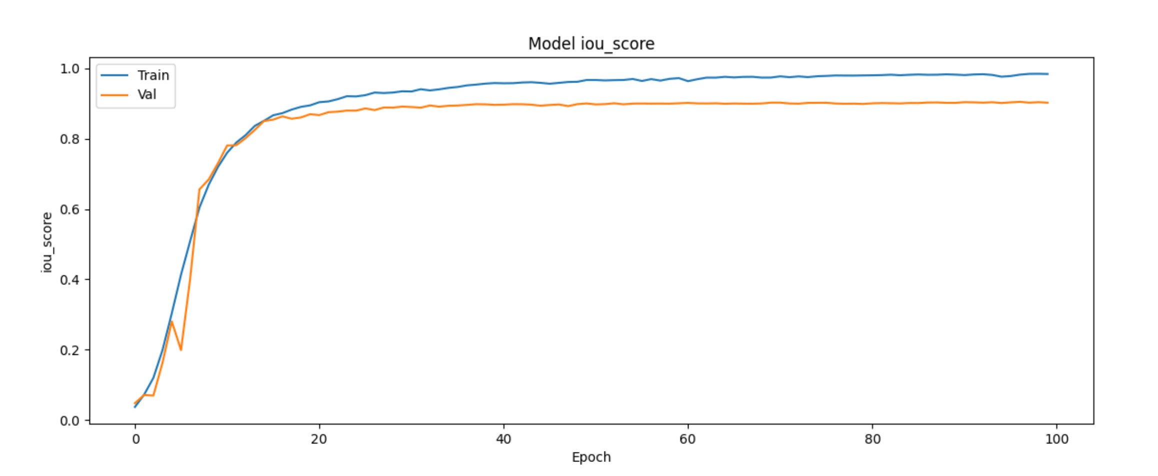
$$DiceLoss(y_{true}, y_{pred}) = 1 - \frac{\sum_{pixels} y_t * y_p}{\sum_{pixels} y_t^2 + \sum_{pixels} y_p^2}$$

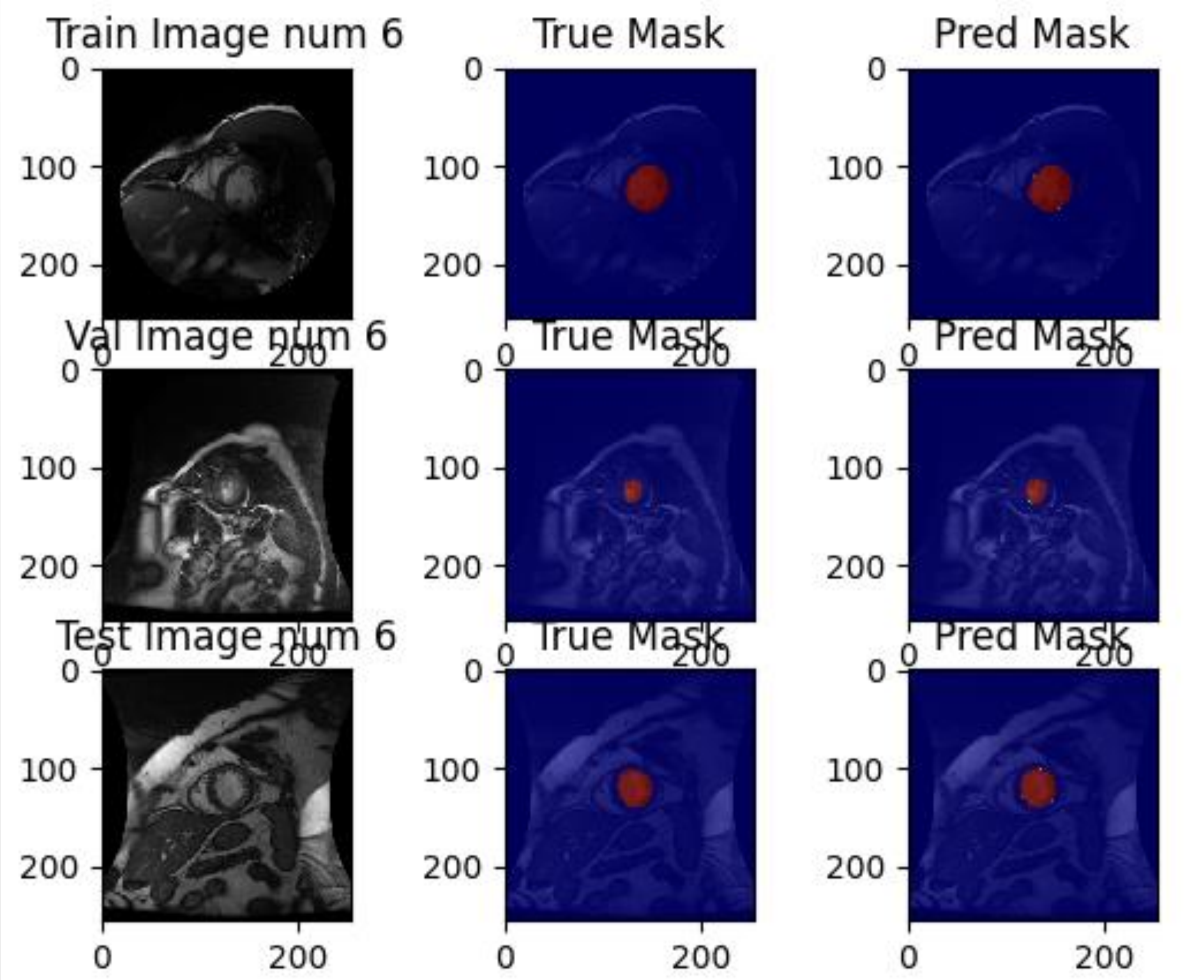
- **Metric: IoU Score**



Result: Loss and Metric & train/val/test example







Second Model: Unet VGG16 for Sunnybrook

Net: Unet with VGG16 architecture

Input: (256,256,1)

Output: (256,256,4) now it is a multiclass classification
(4 classes: Inner LV, Outer LV, RV and background)

Initial weights: **ImageNet**

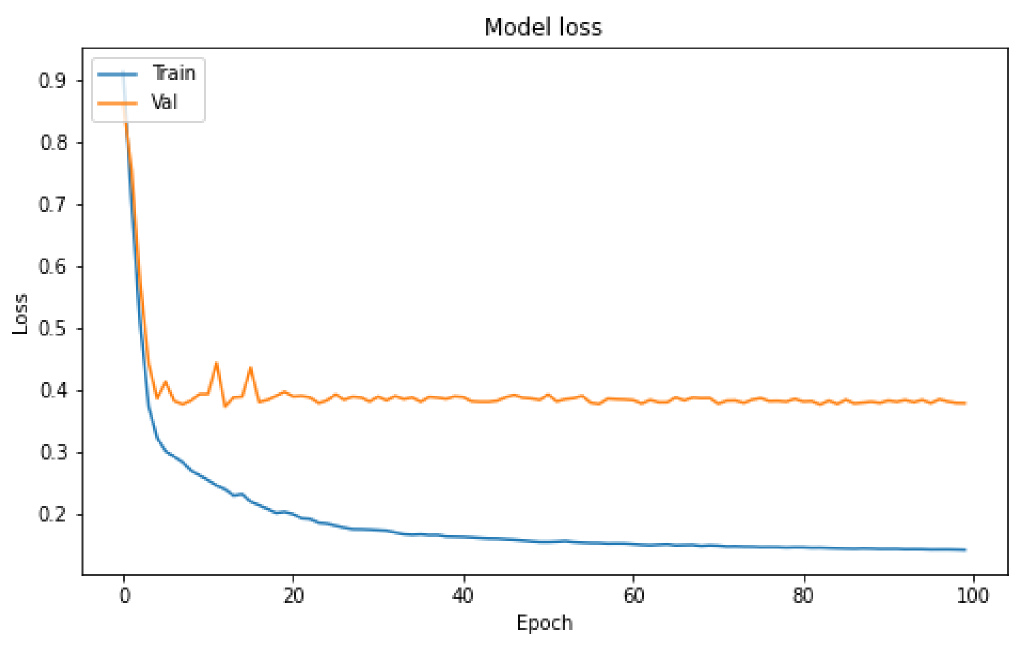
Loss: Soft DICE (with weights 0.5 for background)
+ Categorical Focal Loss

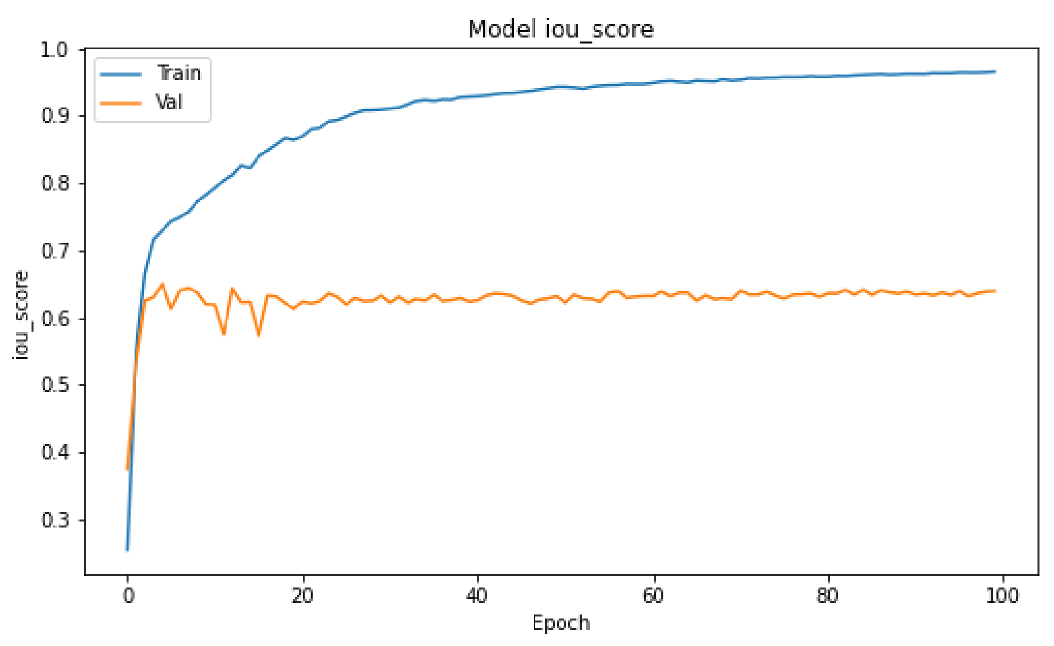
Metric: IOU Score

Train set: 1200
Validation set: 200
Test set: 412

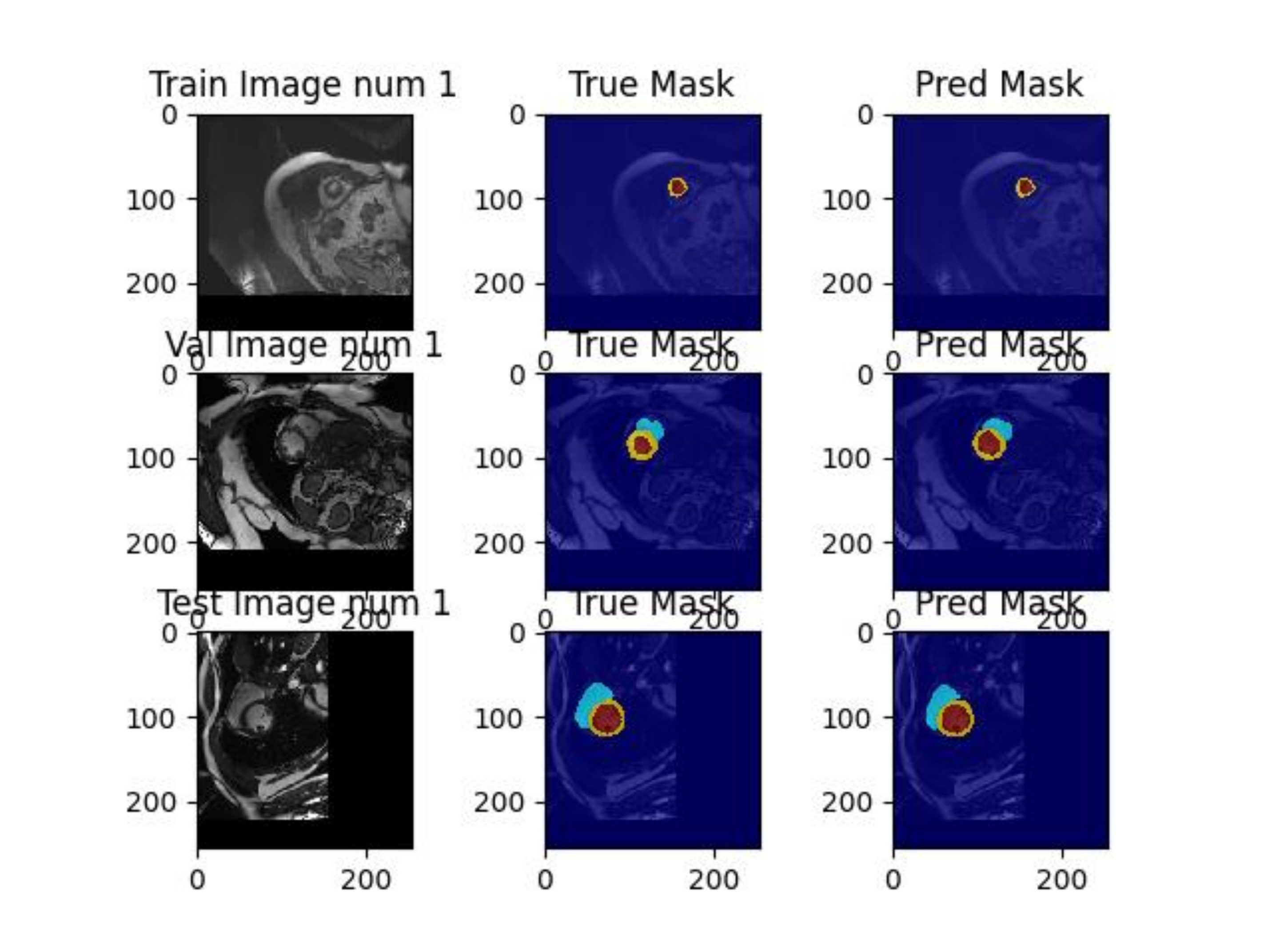
Results: Loss and Metrics

Here the results of loss and metrics are very different from train set to validation set: this is a symptom of **overfitting.** To overcome this problem we need more data (augmentation) or using a smaller net with less parameters



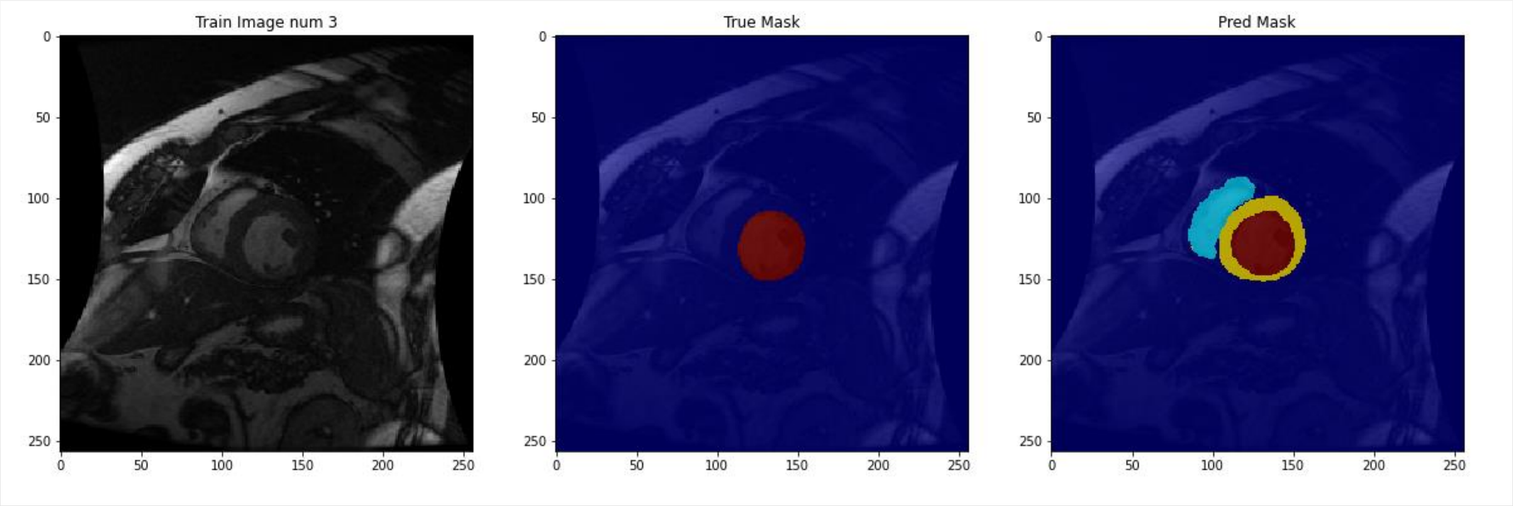


Prediction: train/val/test example



Predict classes of sunnybrook data using the Net trained with ACDC

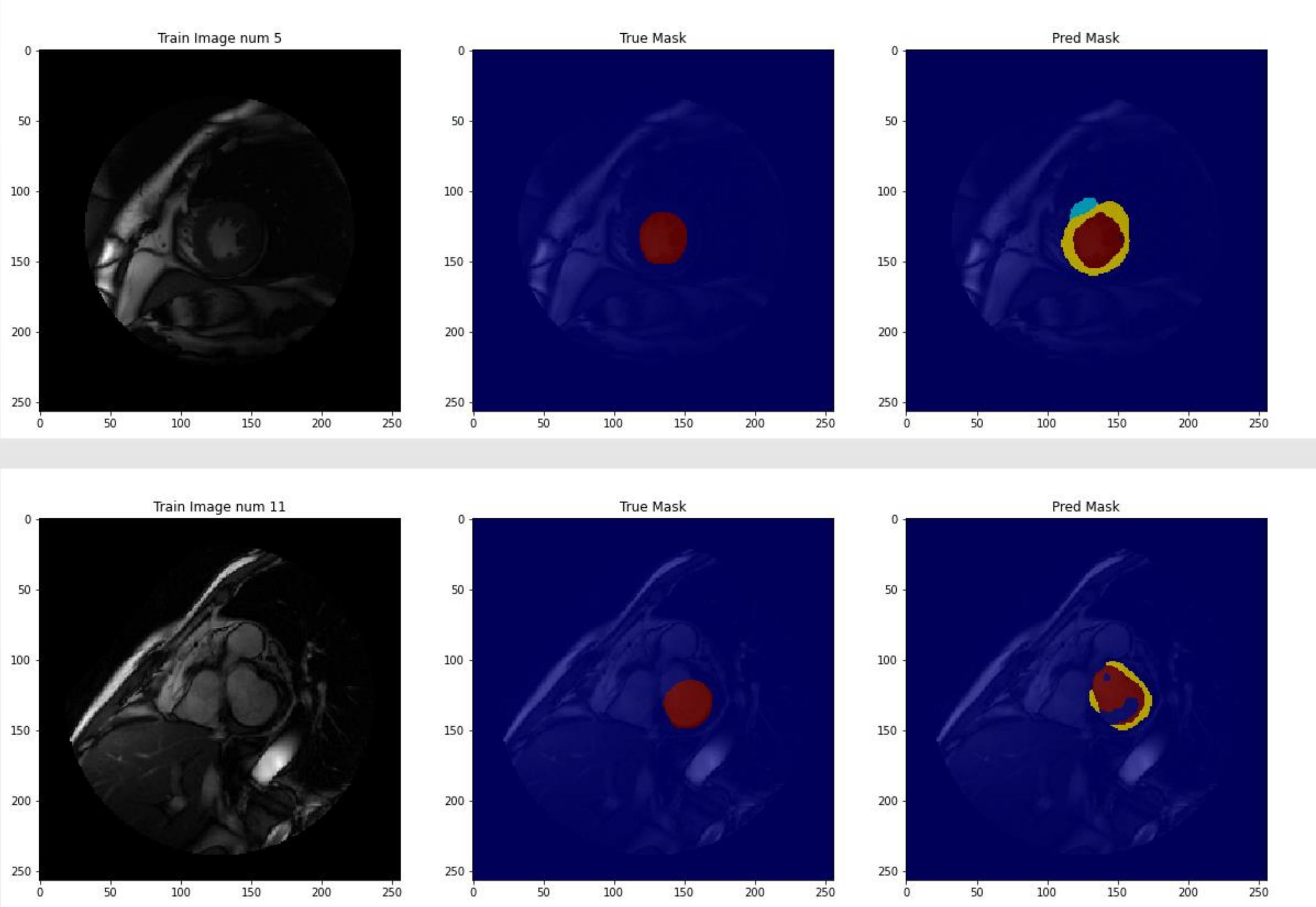
We can use the net trained with acdc data to segment all the three classes (Inner LV, outer LV and RV) on Sunnybrook data, where we have manual contour only for Inner LV



Of course in True Mask we have only the Inner LV (since in Sunnybrook this is the only manual contour we have) while in the prediction we can segment all the three classes (and compared to the real image it seems quite good)

Predict classes of sunnybrook data using the Net trained with ACDC

Of course the results can be not perfect, both because we are using the net trained with Acdc dataset on a different dataset (Sunnybrook) and both because the we need a fine-tuning on this net (to improve prediction result on validation set for instance)



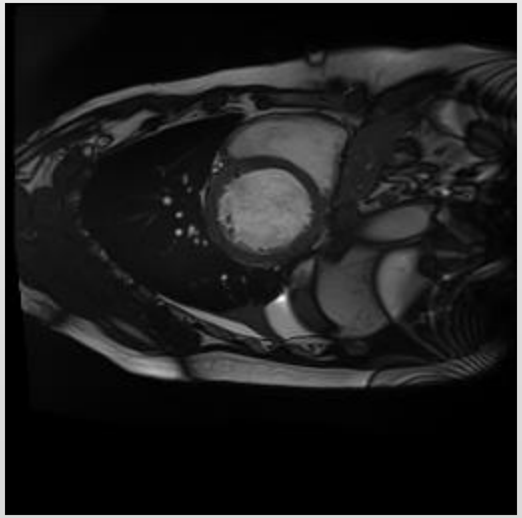
Ring model: 2D Unet for myocardium

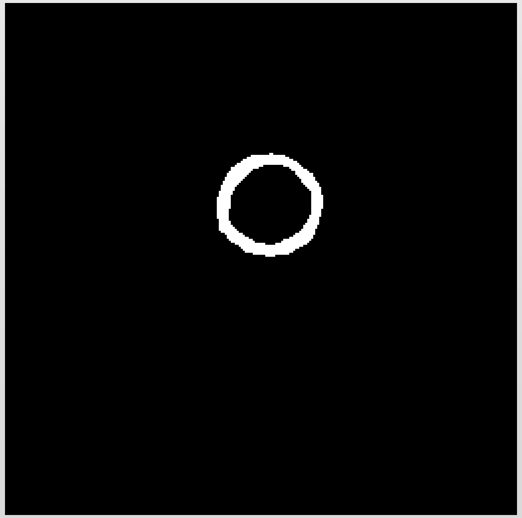
MODEL WITH SUNNYBROOK AND ACDC DATA TOGETHER

Merge the two datasets to segment Myocardium

Since our final aim is to build a mesh of Left Ventricle, we need to segment both inner endocardium and outer epicardium, or at least the ring between them, the Myocardium

To achieve this, we can merge the two datasets and preprocess the data in order to mask only the myocardium, like in the example below:





After merging the datasets, we come up with a total of 1812+420 = 2232 (2D-images)

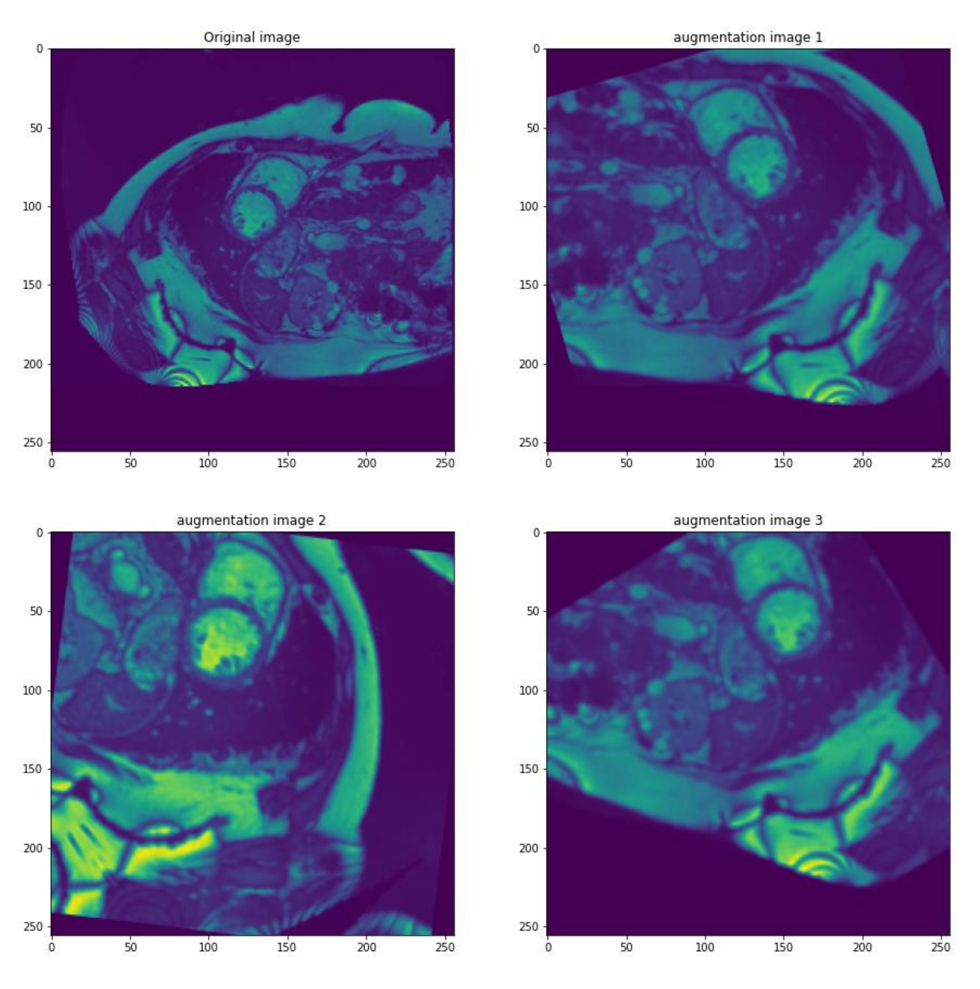
Augmentation

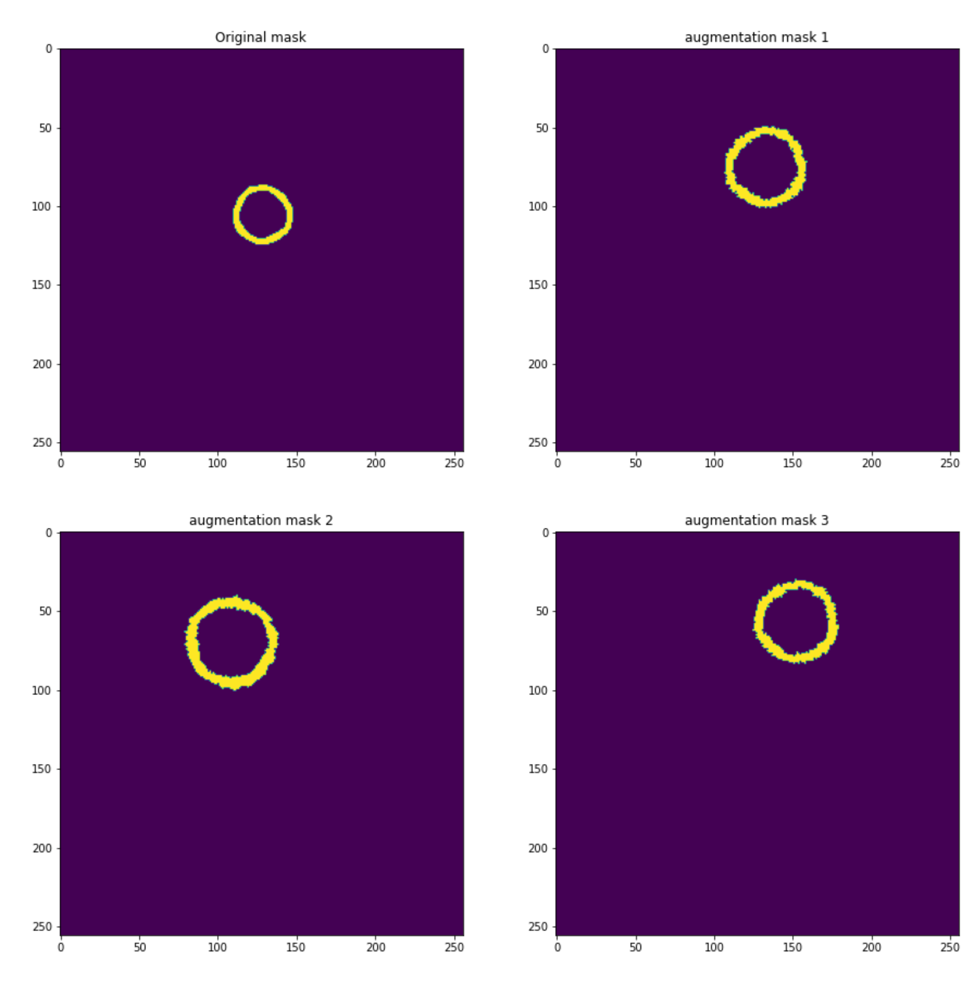
With data augmentation we can train on different images in every epochs, created from our training-set with a composition of transformation like:

- Random-sized crop
- Horizontal and Vertical flip
- Random rotation with an angle in [-90°,90°]
- Blur the image
- Random change of brightness

Since we are going to segment these images, we have to apply the same transformations also to the mask

Augmentation: an example





Final model: Unet with VGG16

Net: Unet with VGG16 architecture + 2 additional layers of Dropout
(to help preventing overfitting)

Input: (256,256,1)

Output: (256,256,1)

Initial weights: **ImageNet**

First layer of Dropout before VGG16 with drop rate = 0.1

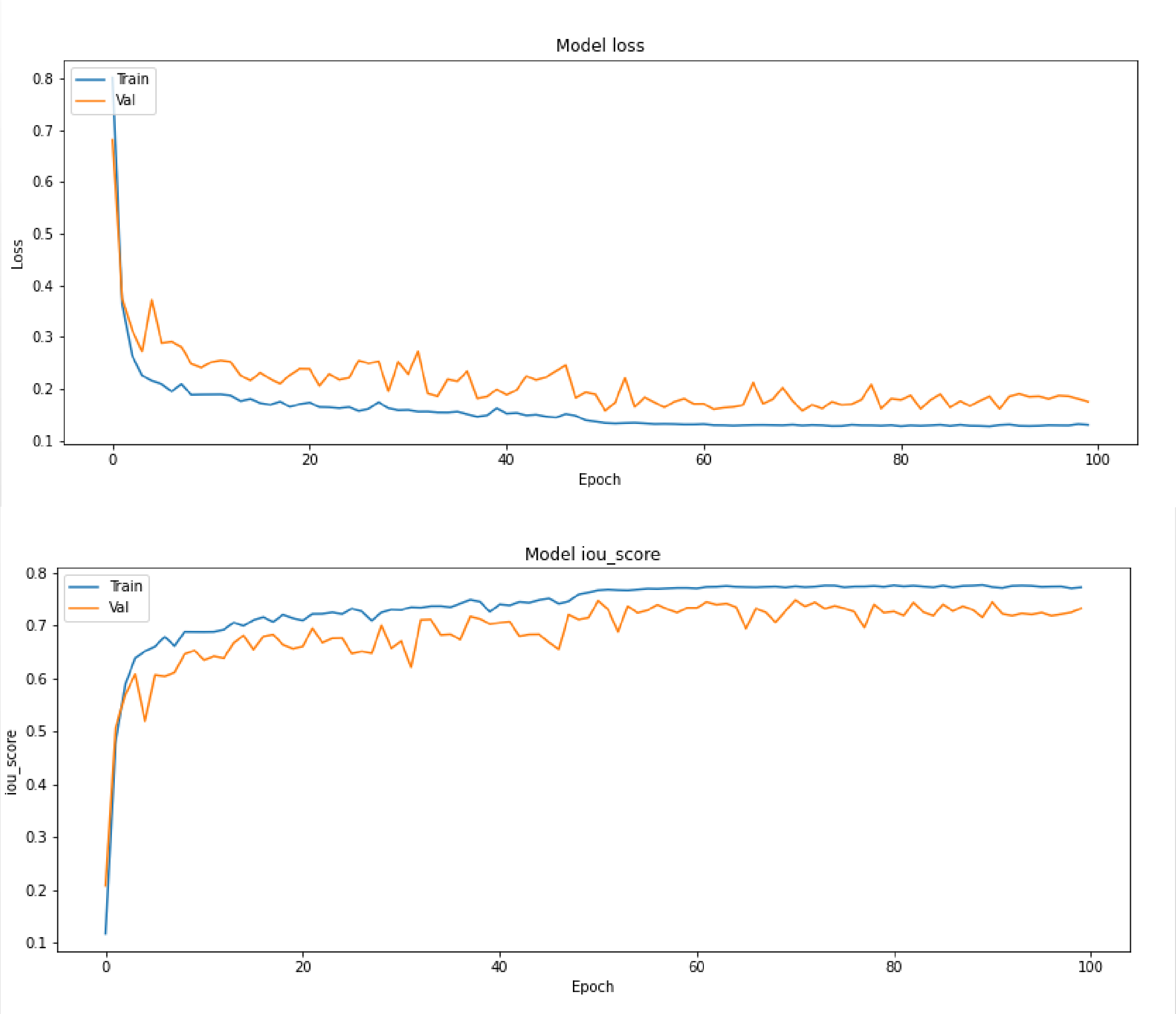
Second layer of Dropout after the last layer of Unet with drop rate = 0.05

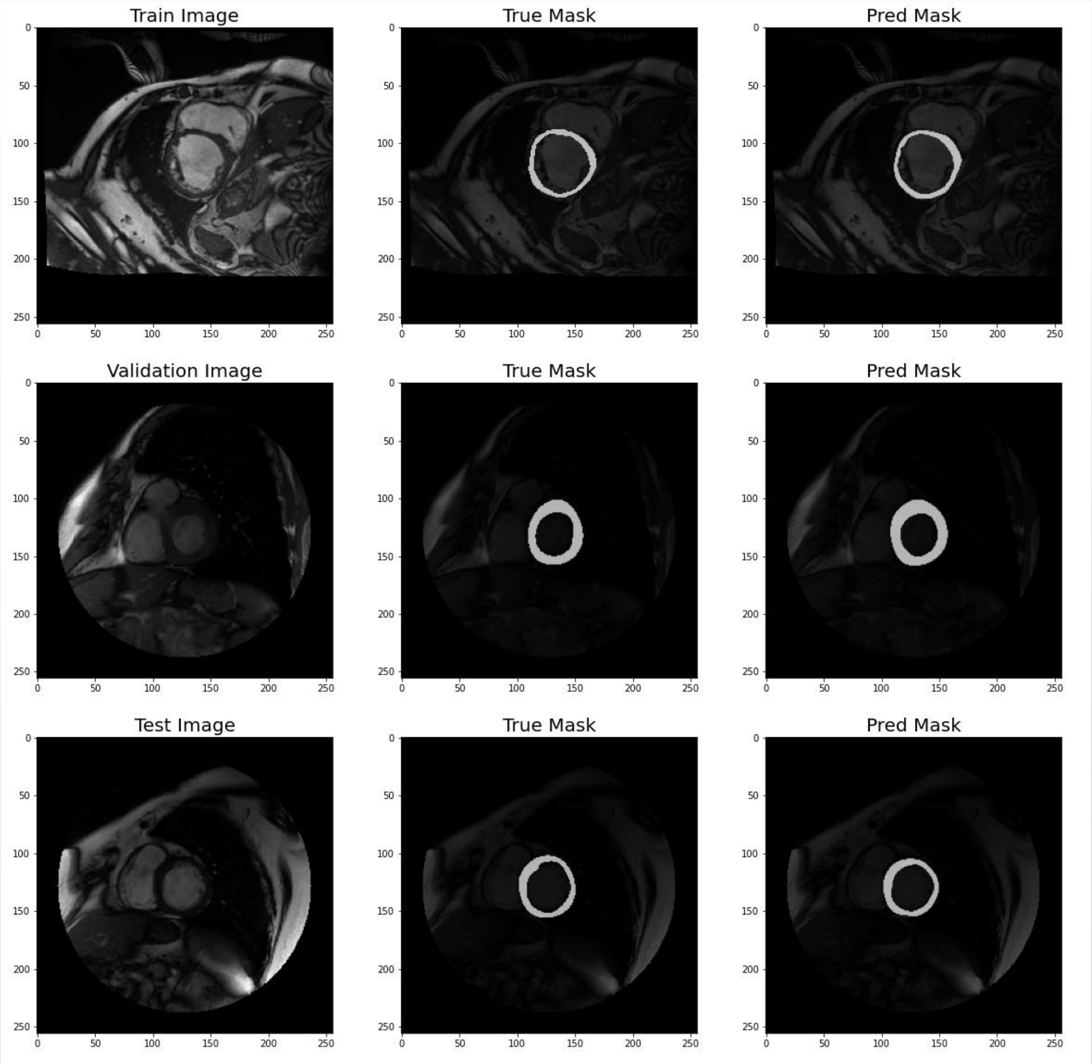
Loss: Soft DICE

Metric: IOU Score

Train set: 1887
Validation set: 104
Test set: 234

Result: Loss and Metric & an example of train/val/test

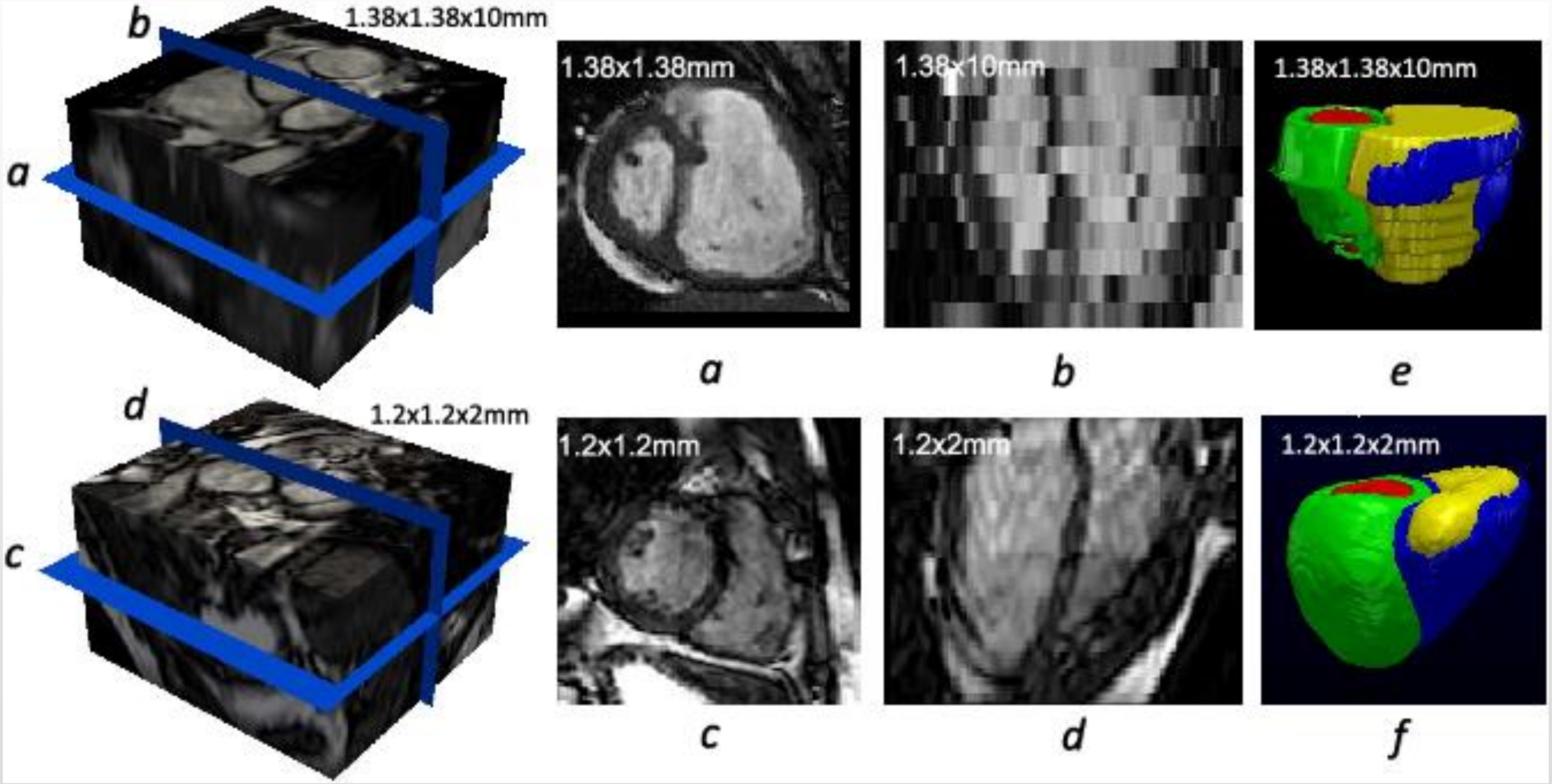




3D mesh building

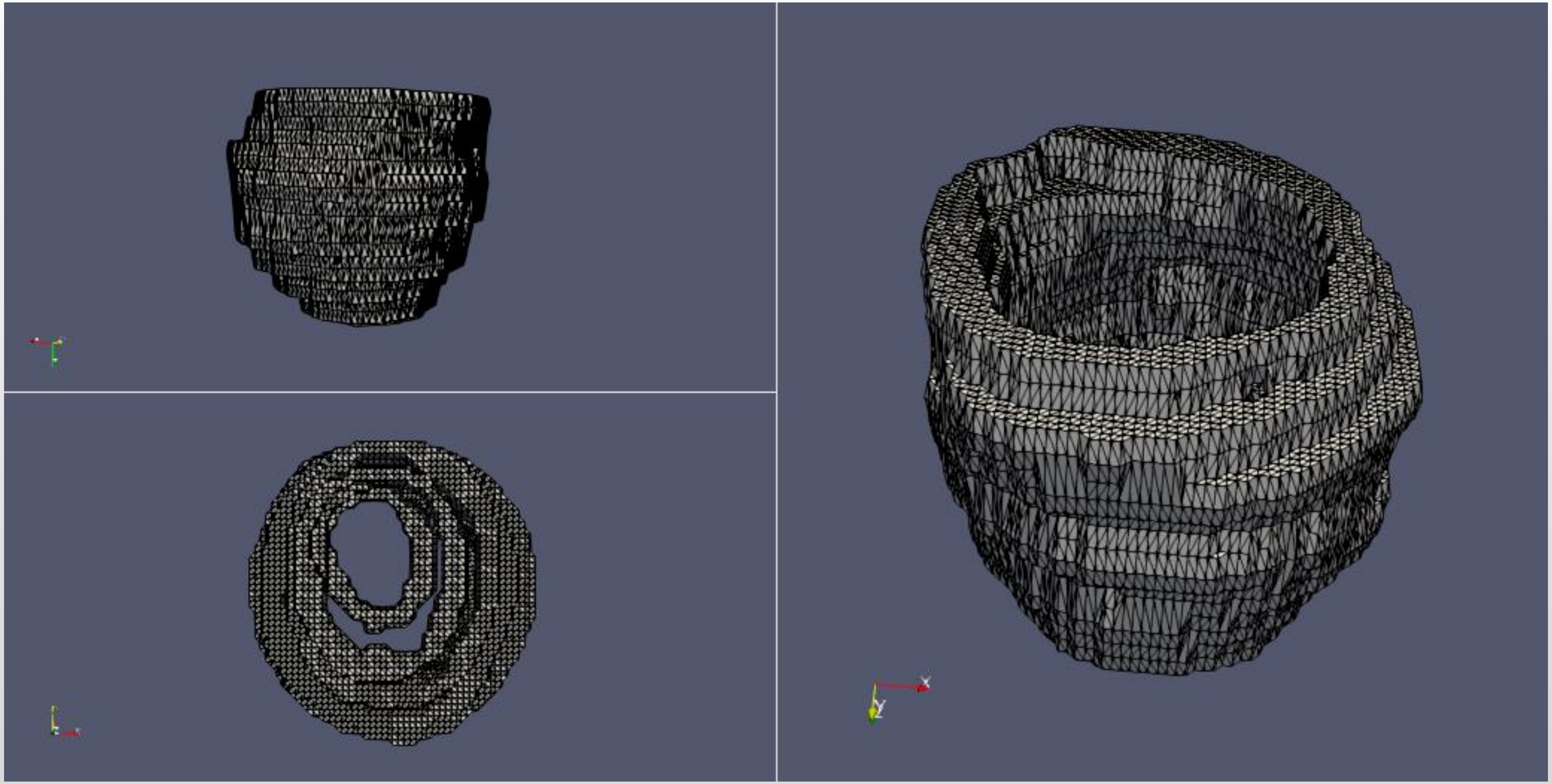
PROBLEM OF RESOLUTION AND SHAPE REFINEMENT

Volume building: problem of resolution



Source: Automatic 3D Bi-Ventricular Segmentation of Cardiac Images by a Shape-Refined Multi-Task Deep Learning Approach; https://arxiv.org/abs/1808.08578

Volume building: problem of resolution



Shape refinement: algorithm (OpenCV)

Pipeline for shape refinement and building volume:

1)Extract the endo and epi from ring images using OpenCV

2)Extract contours of both endo and epi from the slices

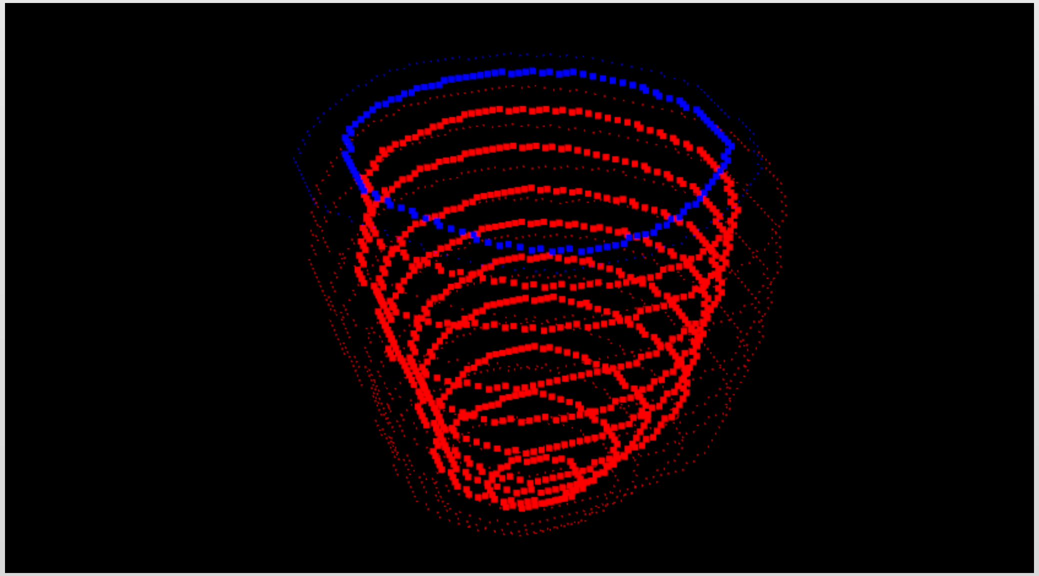
3)(Optionally) Shift correction for the contours

4)Create the volume

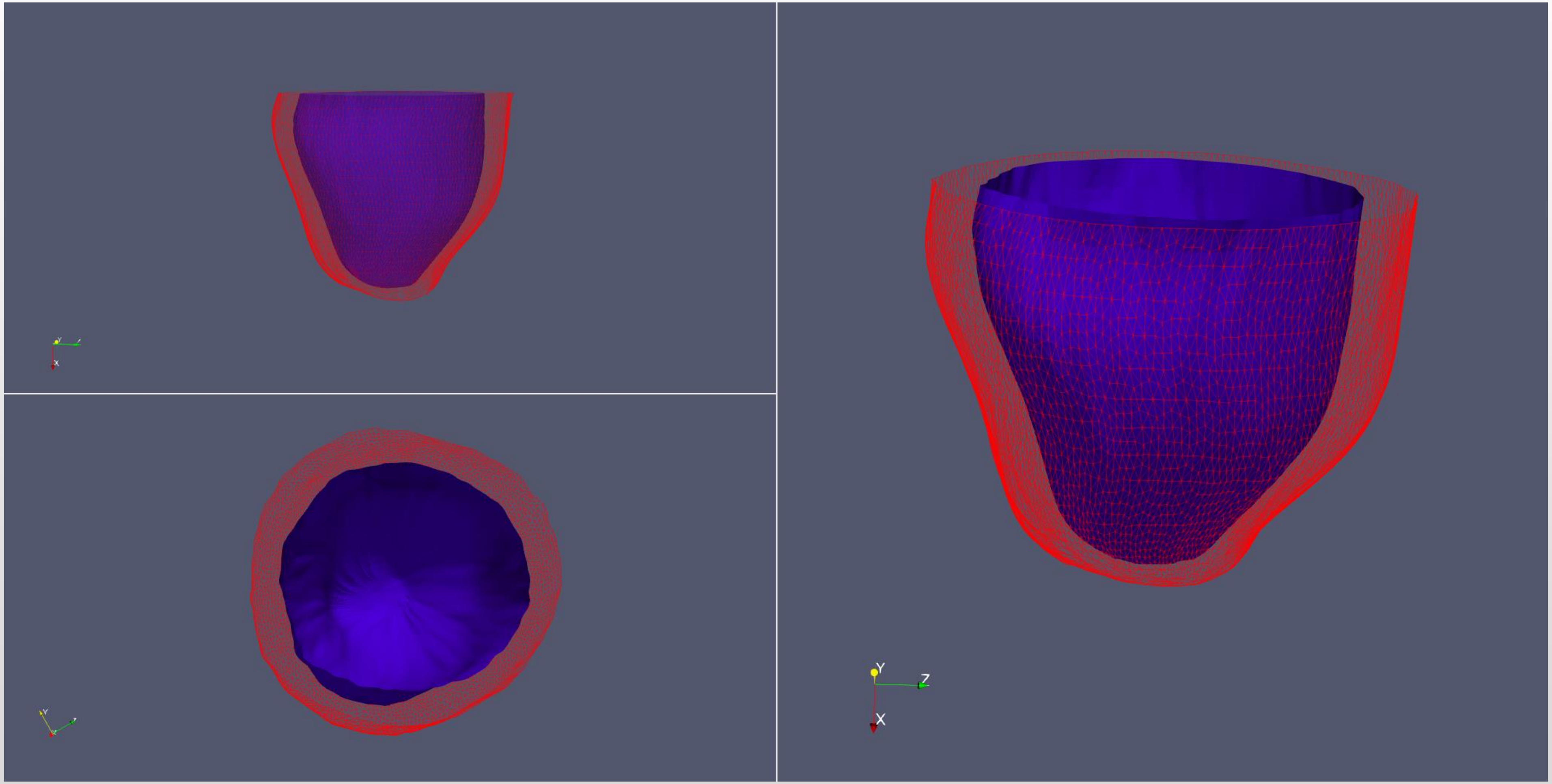
5)Add the apex if required

(Points from 2 to 5 taken from

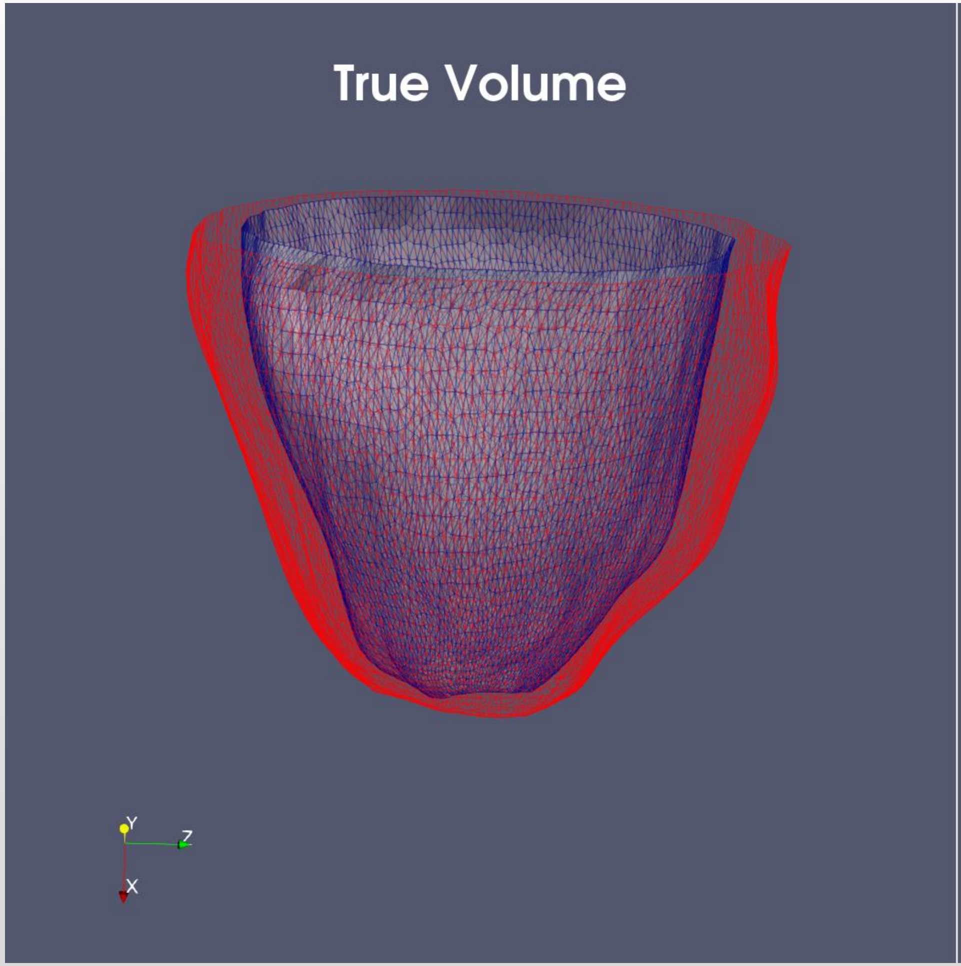
https://github.com/cbutakoff/tools/)

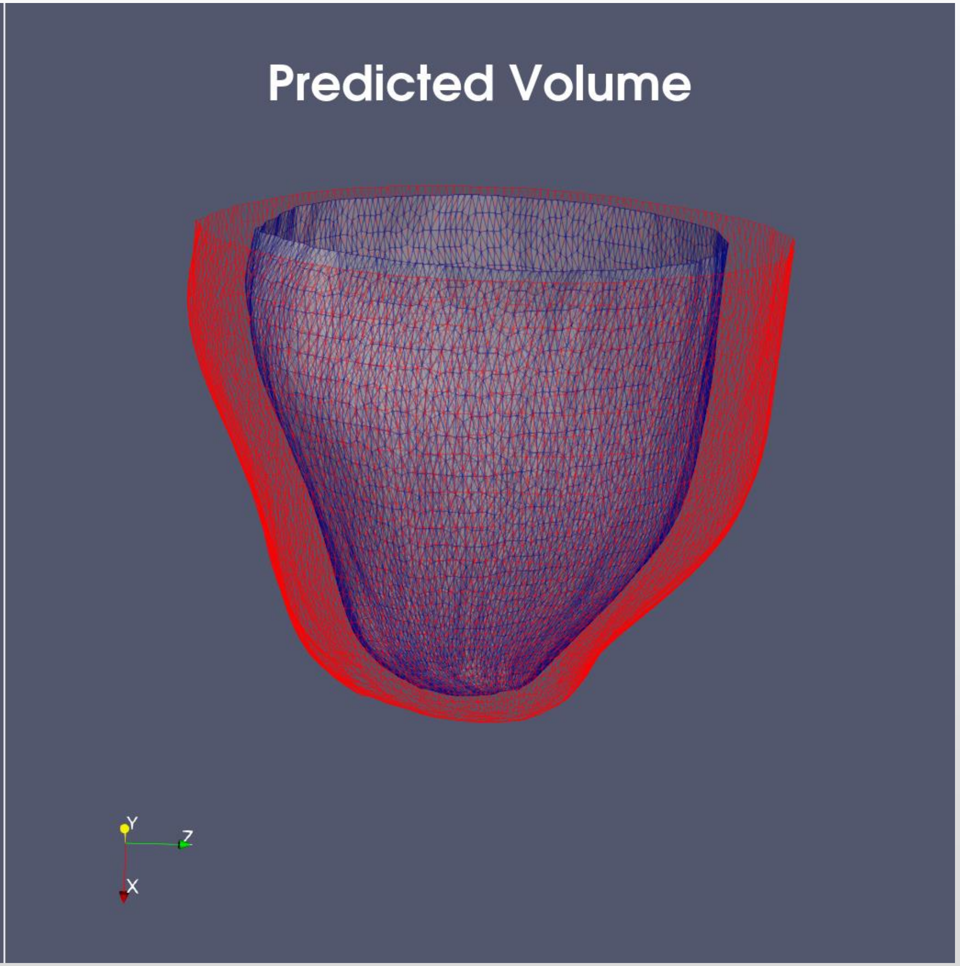


Shape refinement: an example



Shape refinement: True vs Pred on test patient





4D Segmentation

SEGMENTATION DURING A WHOLE CARDIAC CYCLE

4D segmentation of ACDC Dataset

In the ACDC Dataset we are provided with 4D MRI images $\longrightarrow$ (256, 256, N. Slices, N. Frames)

We have the 3D images of LV during a complete cardiac cycle; we can use our algorithm for a 4D segmentation of the LV volume

Unfortunately we have manual contours only for ED and ES, so we can't compute errors for every time frames

4D segmentation: an example