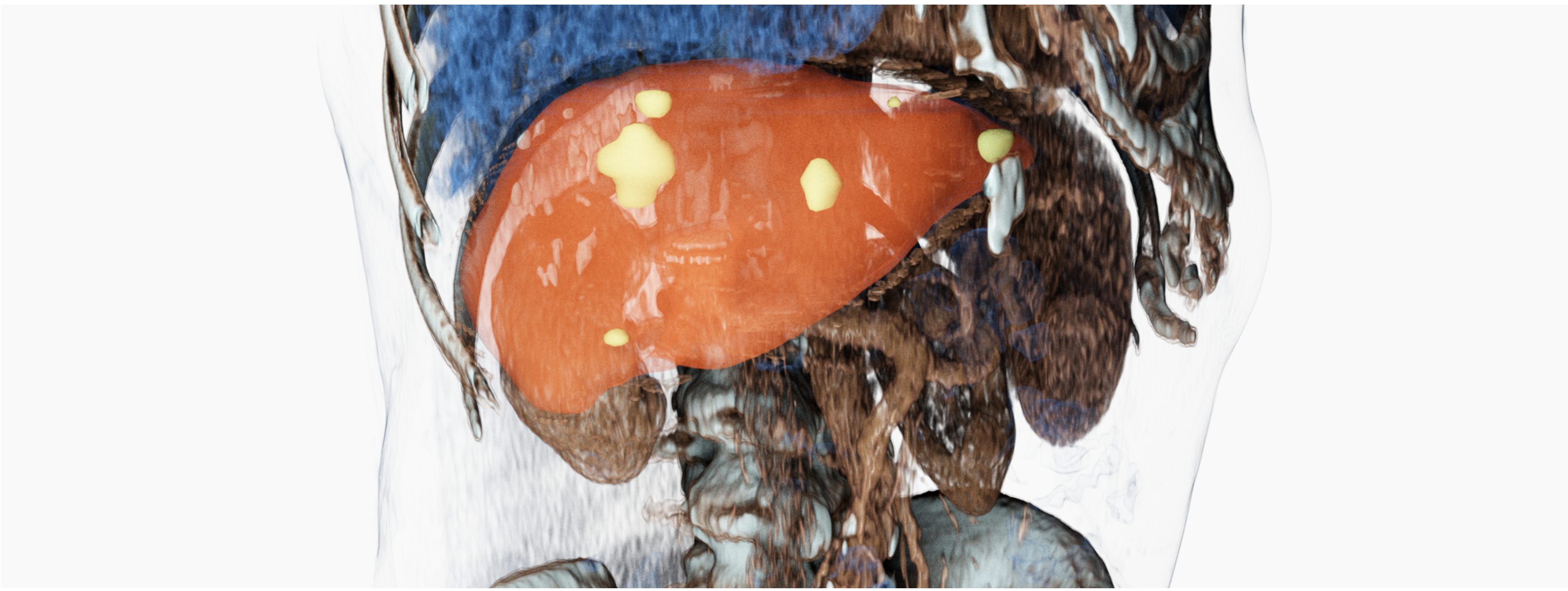
NEURAL NETWORK BASED AUTOMATIC LIVER AND LIVER TUMOR SEGMENTATION

Grzegorz Chlebus, Hans Meine, Jan Hendrik Moltz, Andrea Schenk



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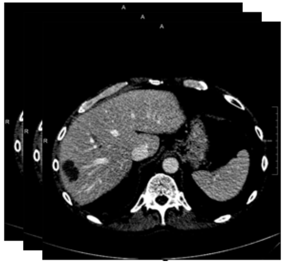
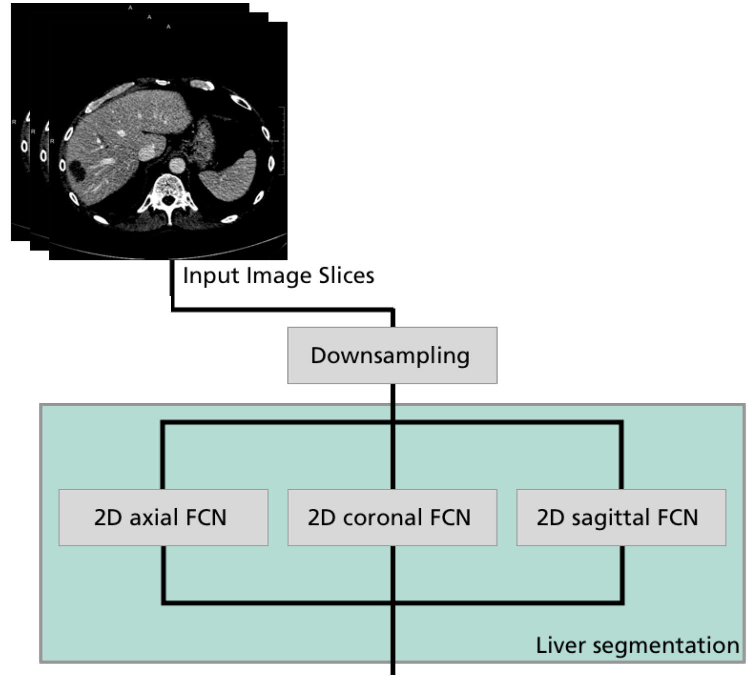
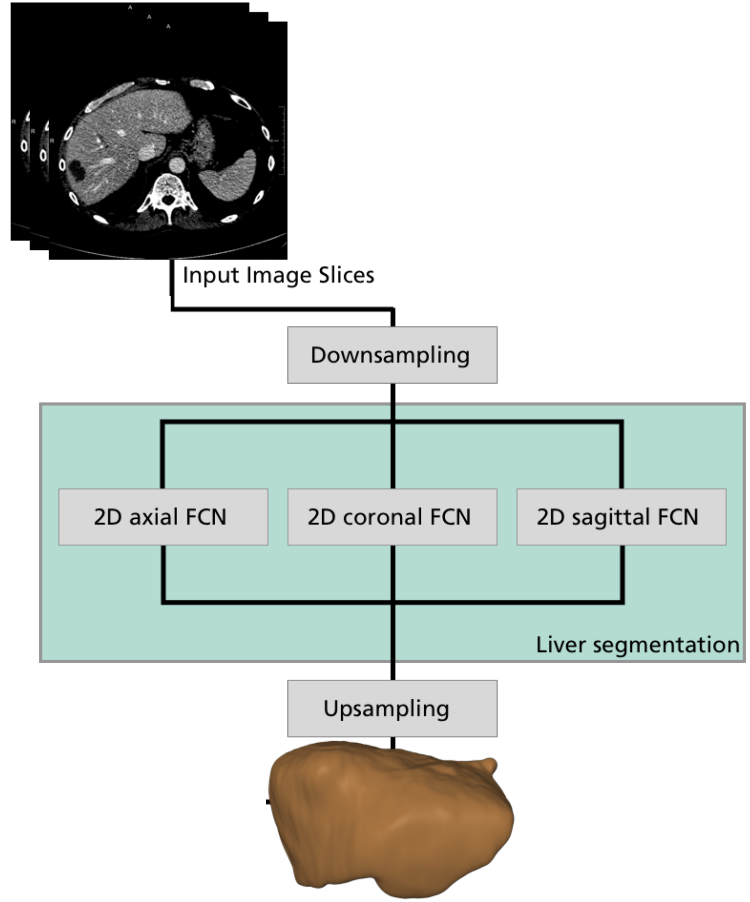


Input Image Slices


Input Image Slices
Downsampling
2D axial FCN
2D coronal FCN
2D sagittal FCN
Liver segmentation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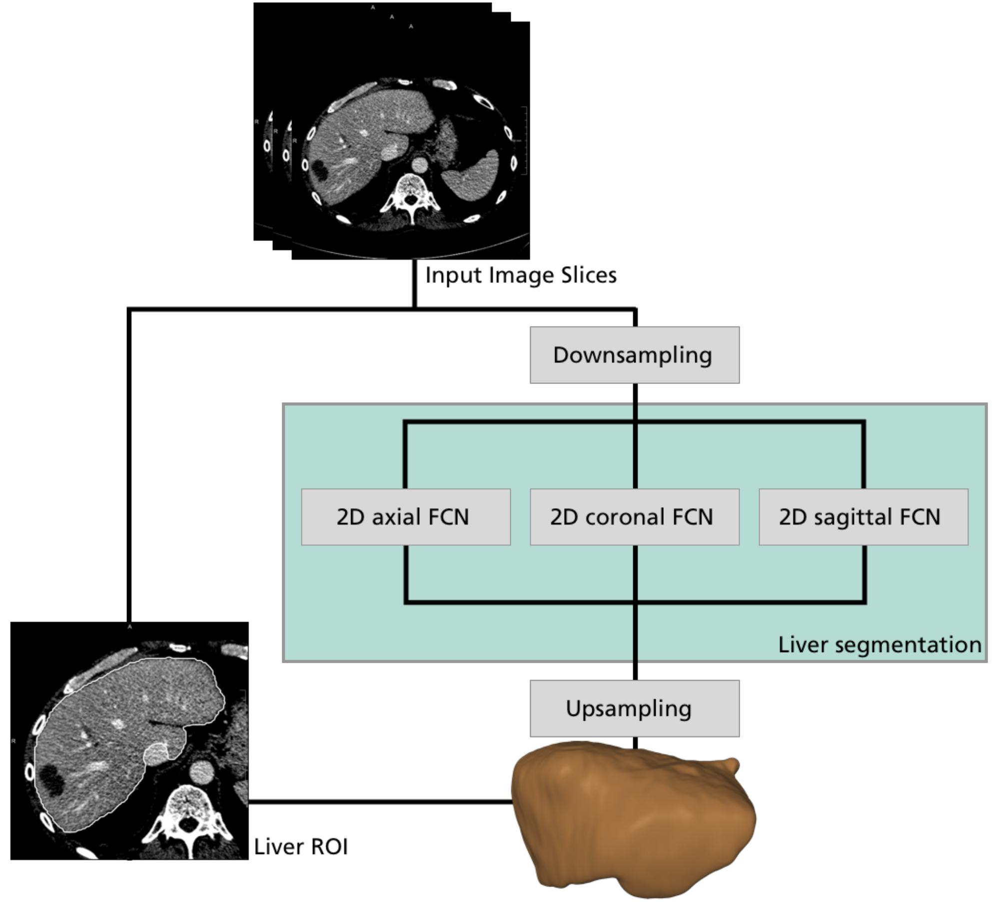
Liver segmentation
Upsampling



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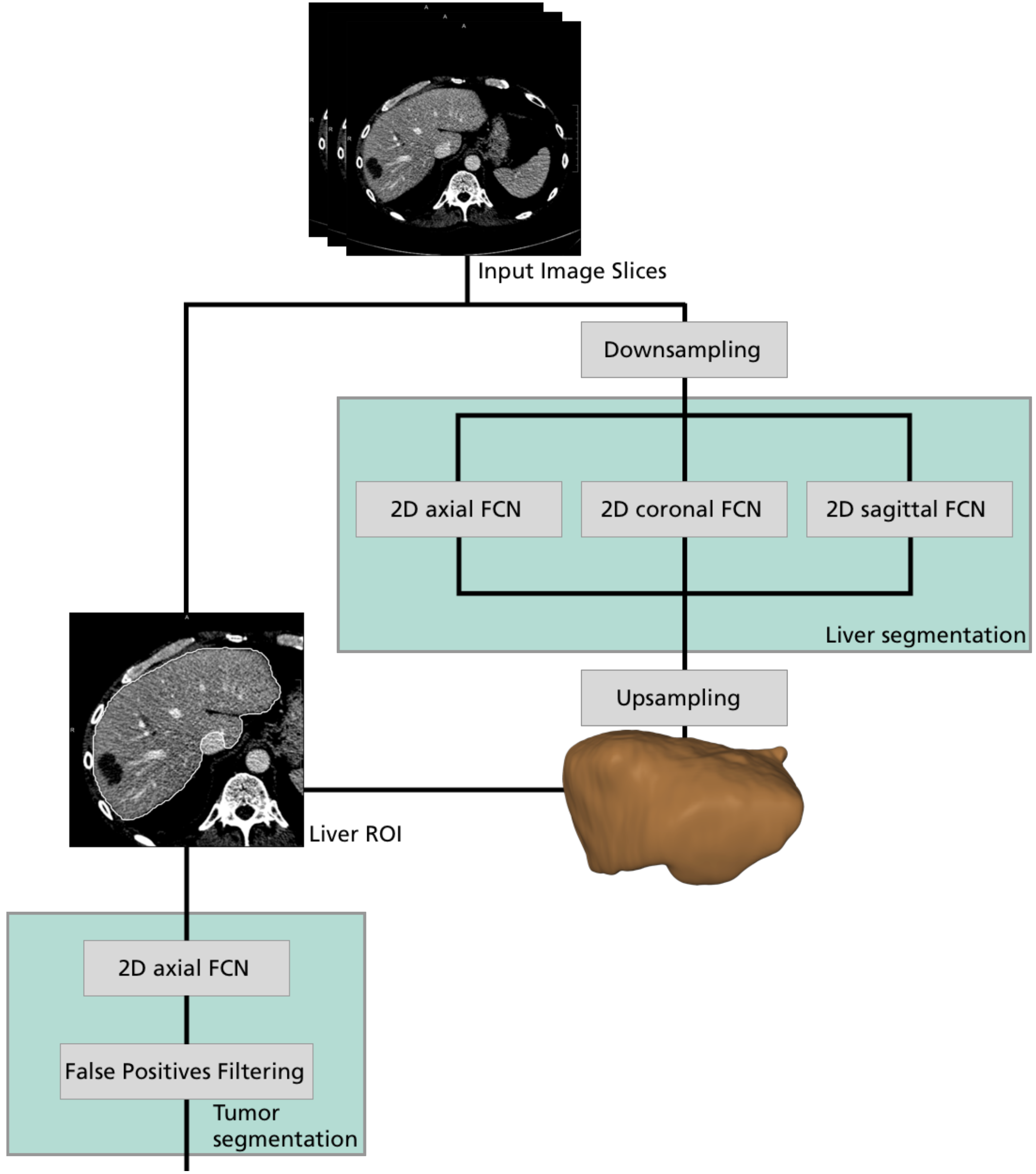
Upsampling
Liver ROI



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Liver segmentation
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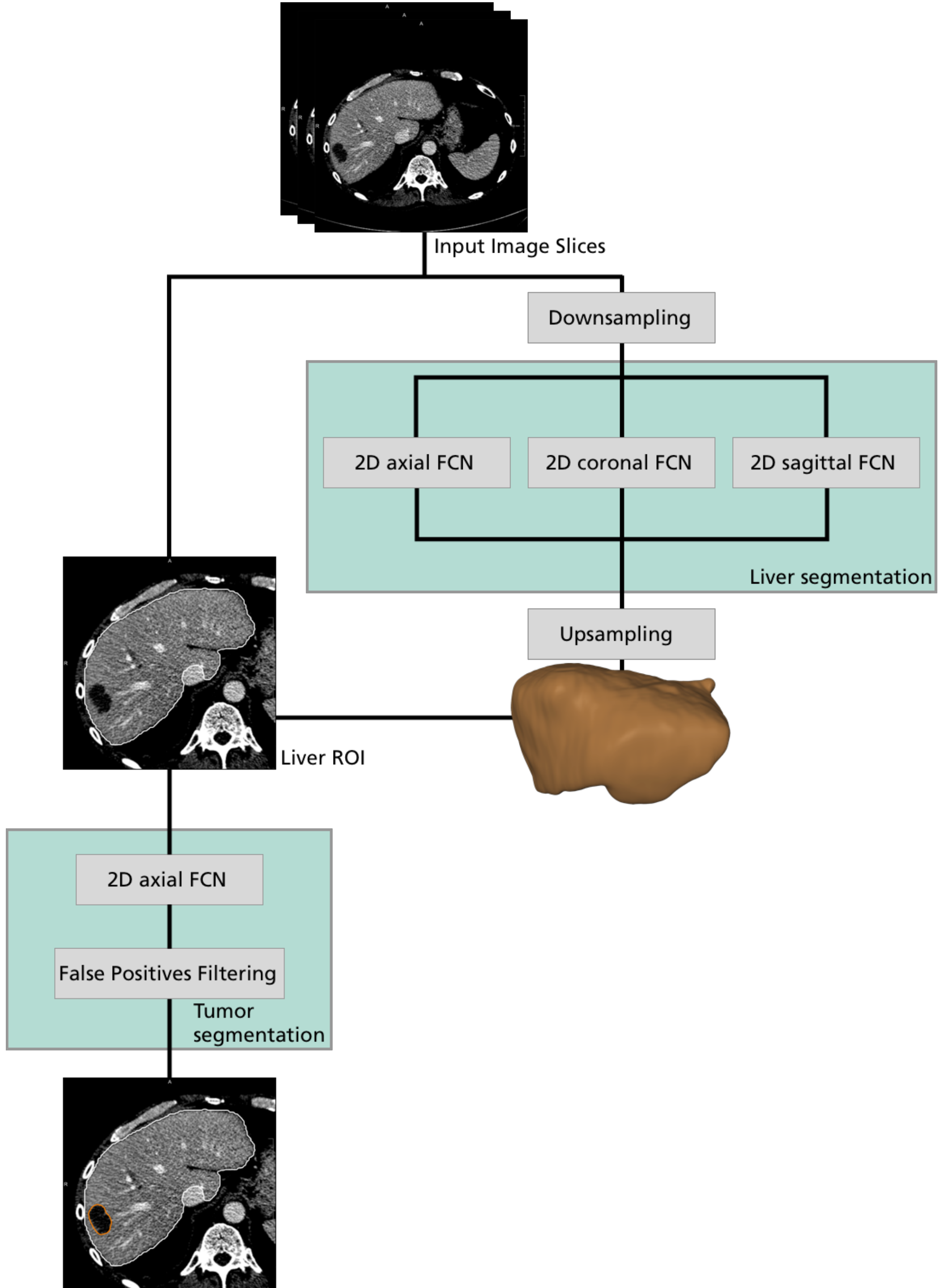
2D axial FCN
False Positives Filtering
Tumor segmentation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Datasets

- LiTS
  - 131 CTs:
    - 105 - training
    - 15 - validation
    - 11 - testing
  - ~0.8 mm in-plane resolution
  - ~1.5 mm slice thickness
- Liver surgery planning
  - 179 CTs all used for training
  - ~0.6 mm in plane-resolution
  - ~0.8 mm slice thickness
  - Livers segmented by radiological experts

Liver Segmentation
Data and Preprocessing

- Two training datasets
  - LiTS
  - Liver surgery planning

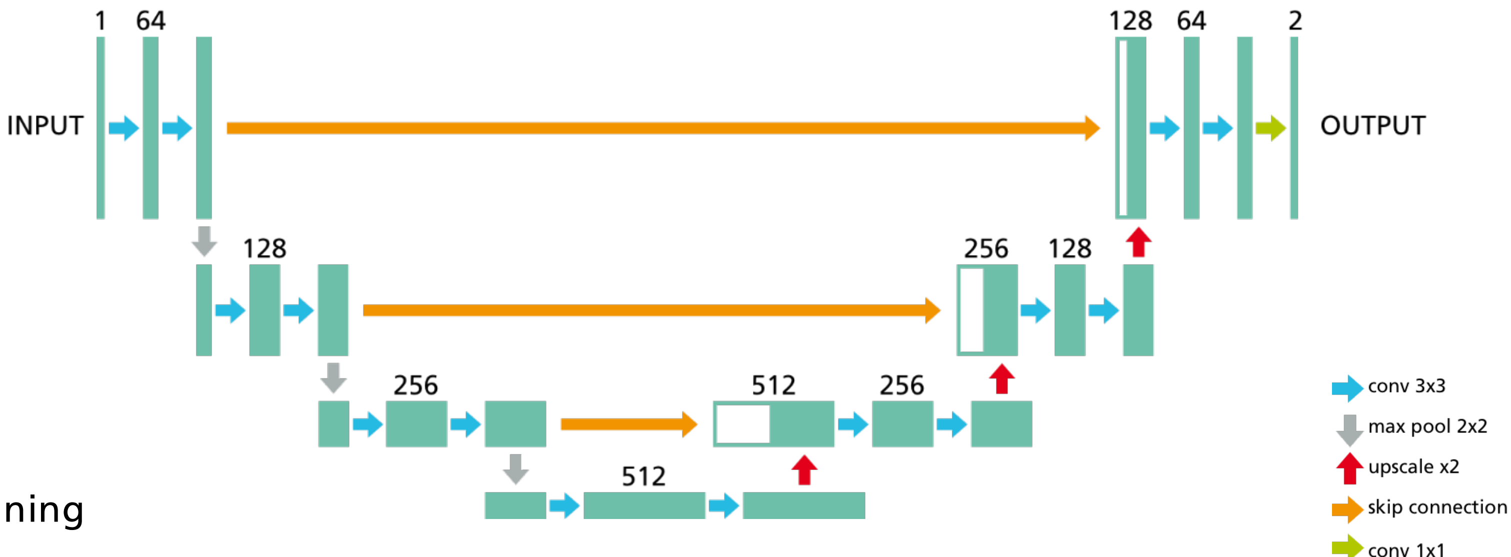
- Preprocessing
  - Rescaling raw GV to HU
  - Resampling to 2 mm isotropic voxel size
  - Padding with -1000 HU

FCN General Info

- Convolution block
  - Dropout p=0.5 in the upscaling path
  - ReLU activation function
  - Batch normalization
- Softmax as the final layer
- Training
  - Dice loss function
  - Adam optimizer

Liver Segmentation
Network Architecture and Training

- 2D U-net [1] with 4 resolution levels



- Training
  - Patch size: 148x148 (axial) or 148x44
  - Batch size 15
  - 10^{-5} learning rate
  - ~30k iterations / ~43 epochs / ~19 h

[1] Ronneberger O. et al., "U- Net: Convolutional Networks for Biomedical Image Segmentation", 2015.

Liver Segmentation
Postprocessing

- Biggest connected components of the majority vote mask

Liver Segmentation
Postprocessing

- Biggest connected components of the majority vote mask

transversal

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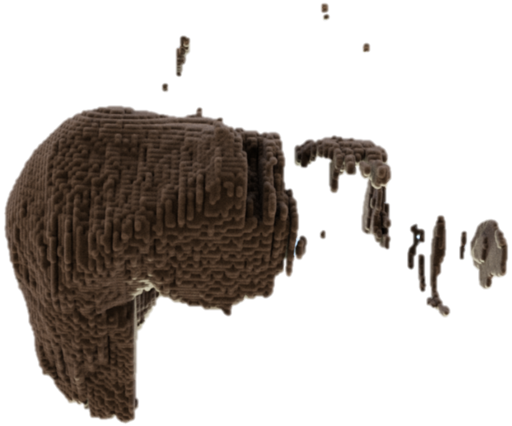
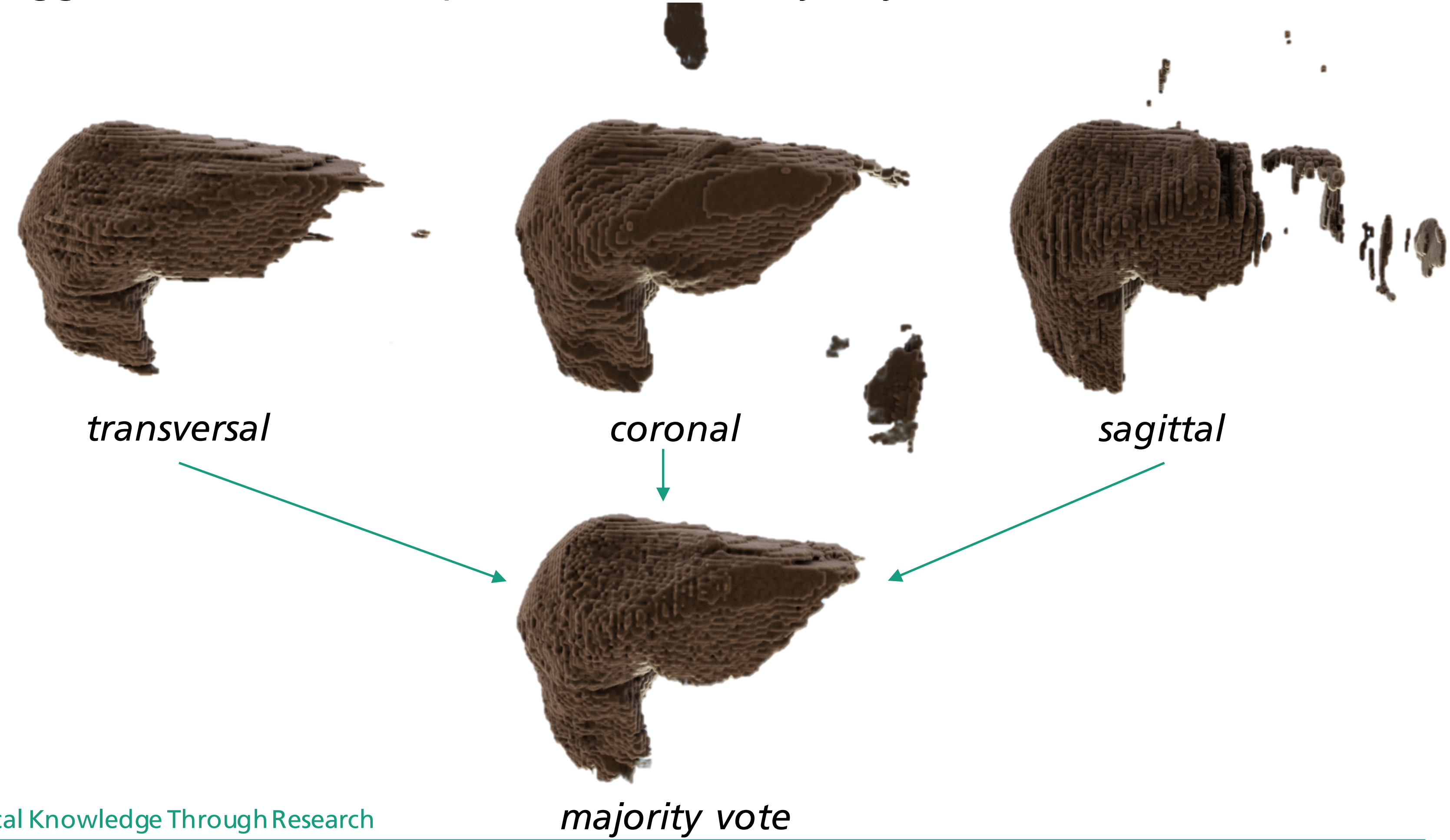


sagittal

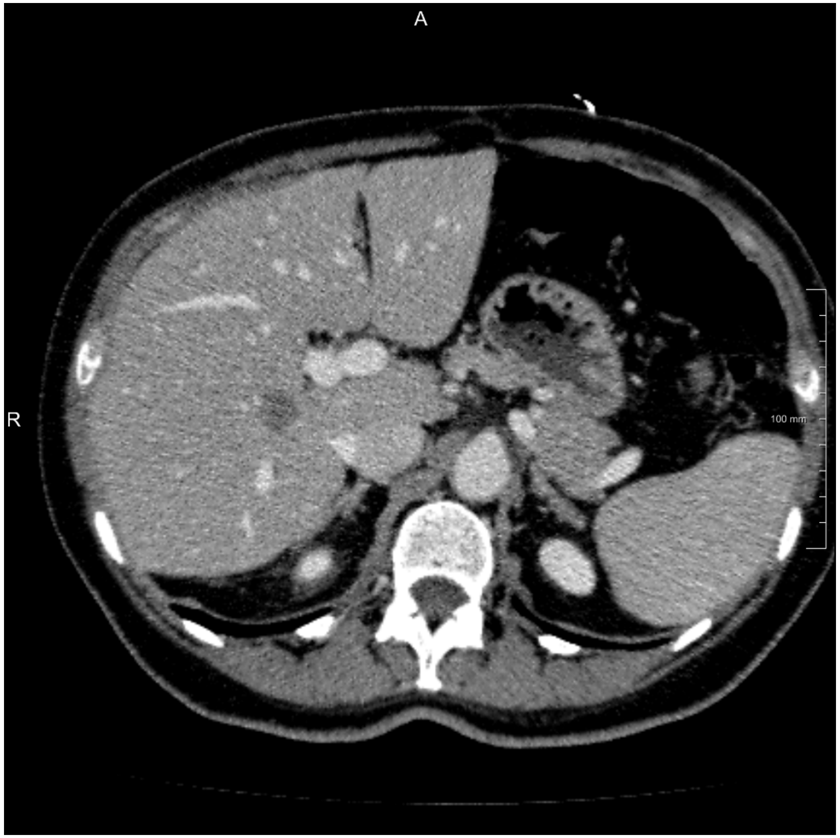
Liver Segmentation Postprocessing

- Biggest connected components of the majority vote mask



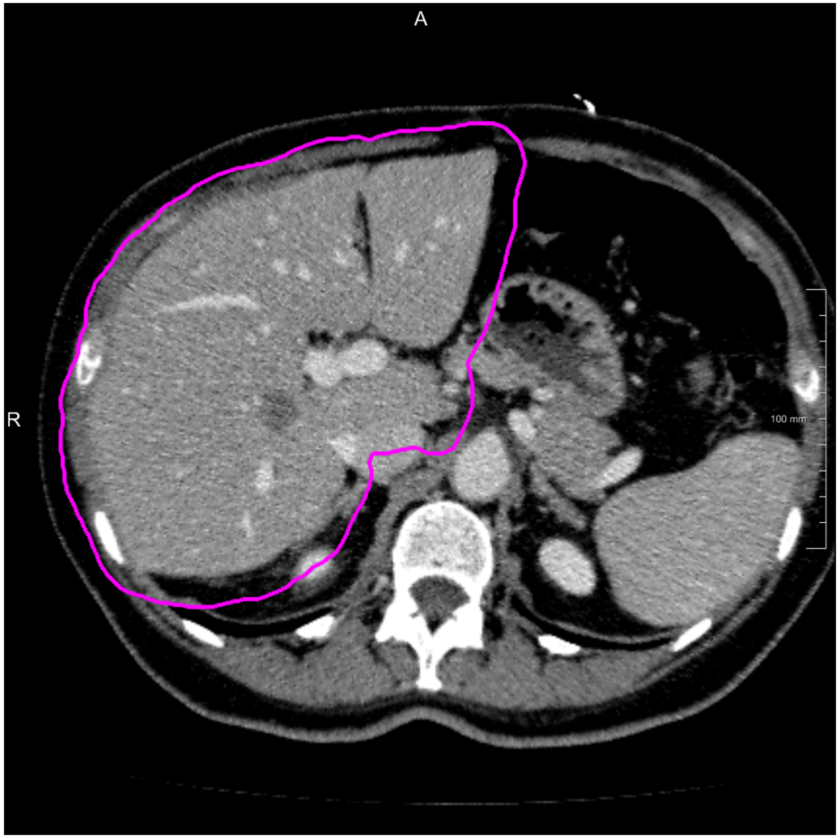
Tumor Segmentation
Data and Preprocessing

- LiTS dataset
- Preprocessing
  - Padding with -1000 HU



Tumor Segmentation
Data and Preprocessing

- LiTS dataset
- Preprocessing
  - Padding with -1000 HU
- Masked loss



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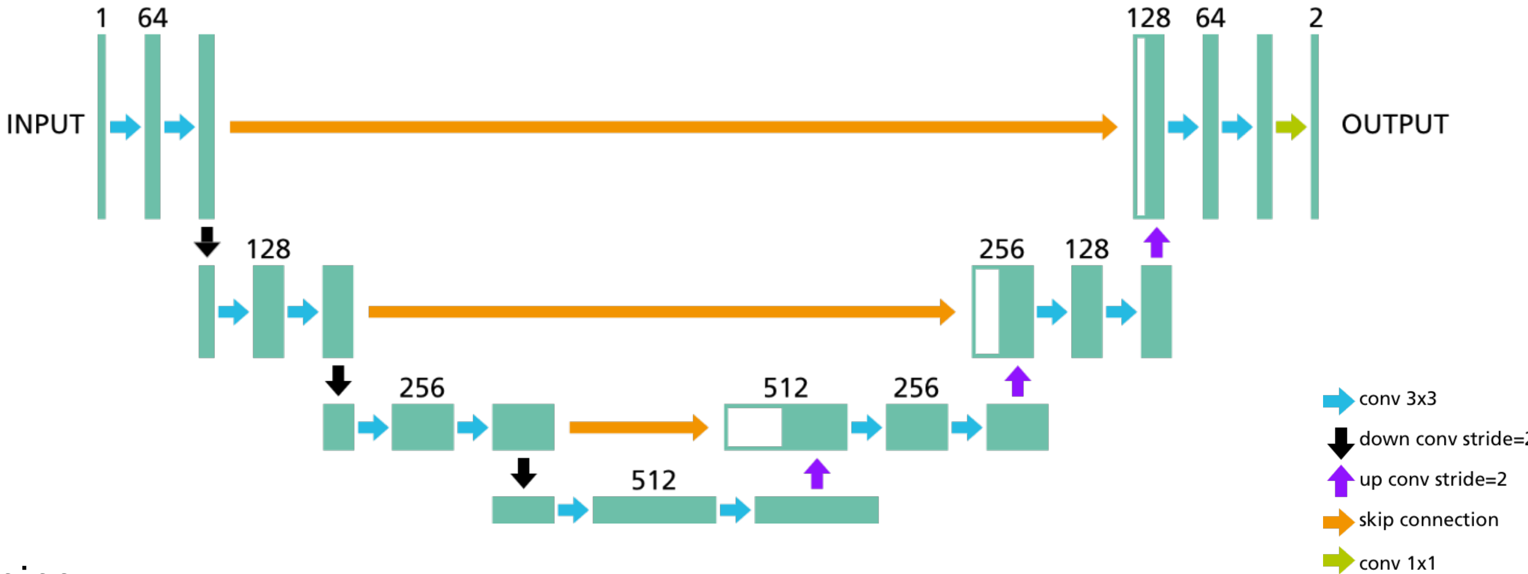
Tumor Segmentation
Network Architecture and Training

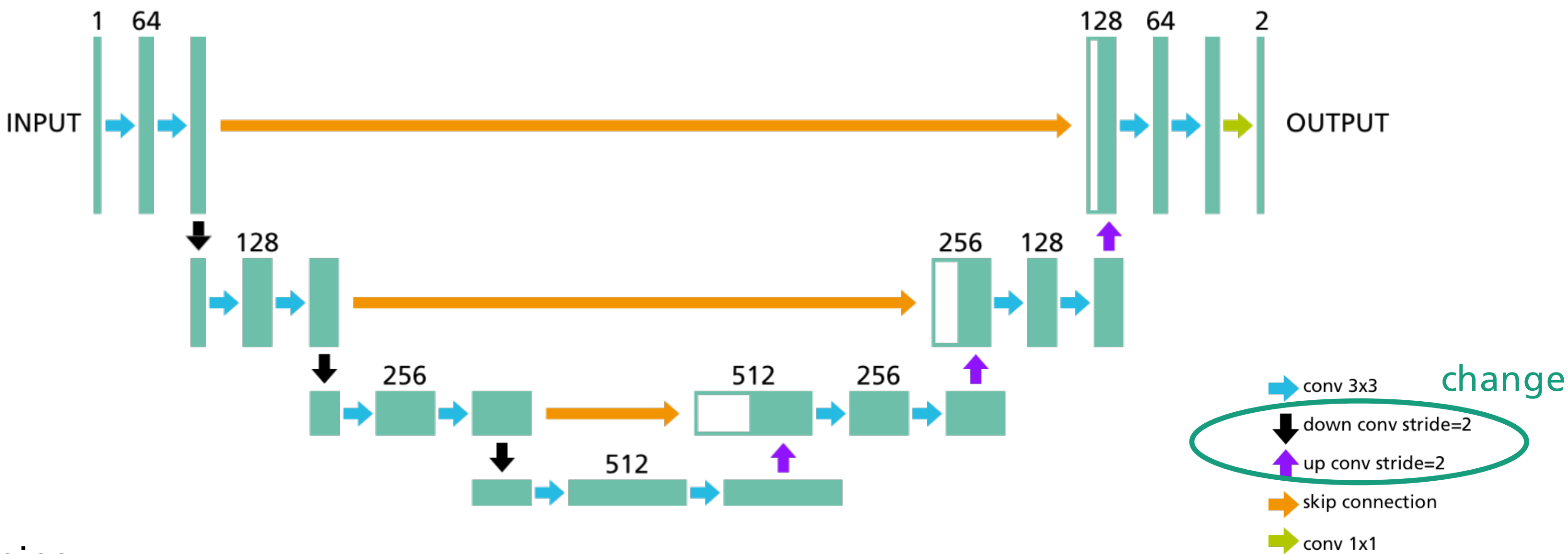
- Modified 2D U-net with 4 resolution levels



- Training
  - Patch size: 252x252 (axial)
  - Batch size 6
  - 5^{-5} learning rate
  - Random flipping
  - Only tumor patches
  - ~230k iterations / ~32 epochs / ~38 h

Tumor Segmentation
Network Architecture and Training

- Modified 2D U-net with 4 resolution levels



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Tumor Segmentation
Output of the FCN

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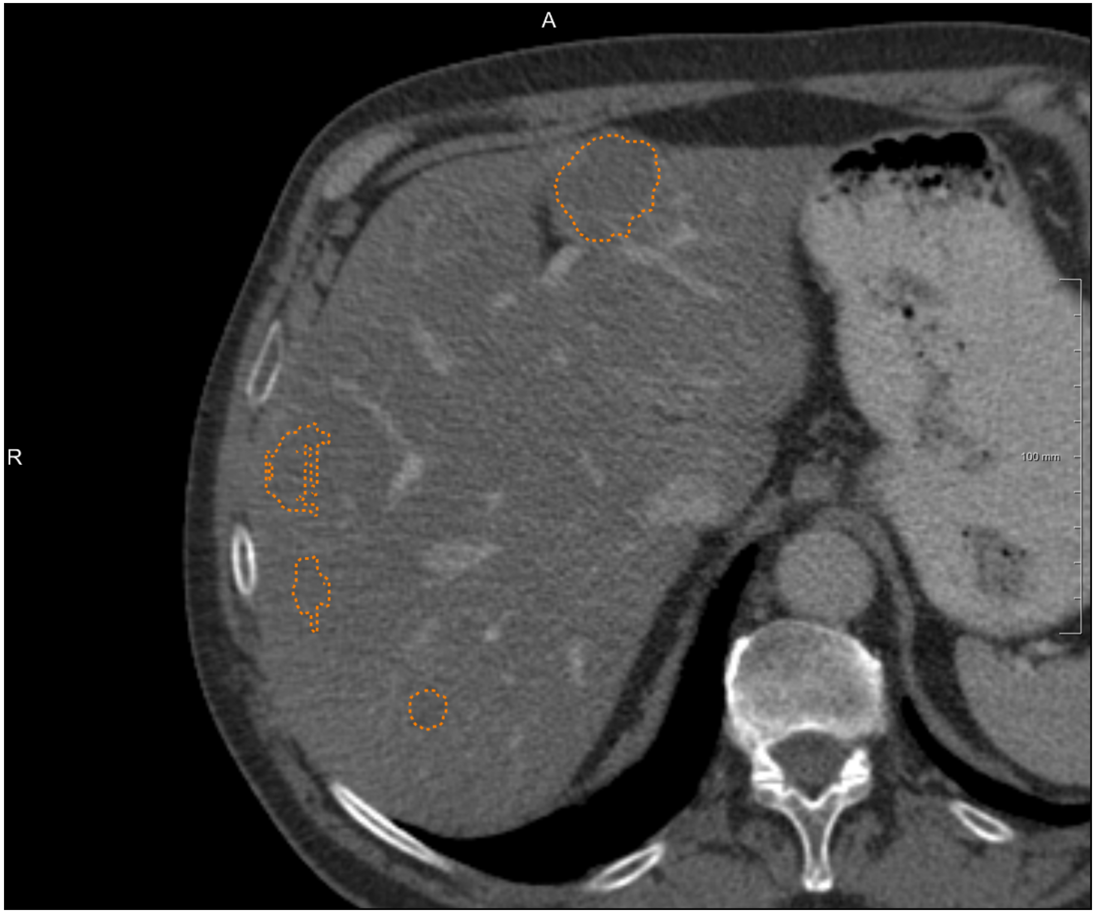

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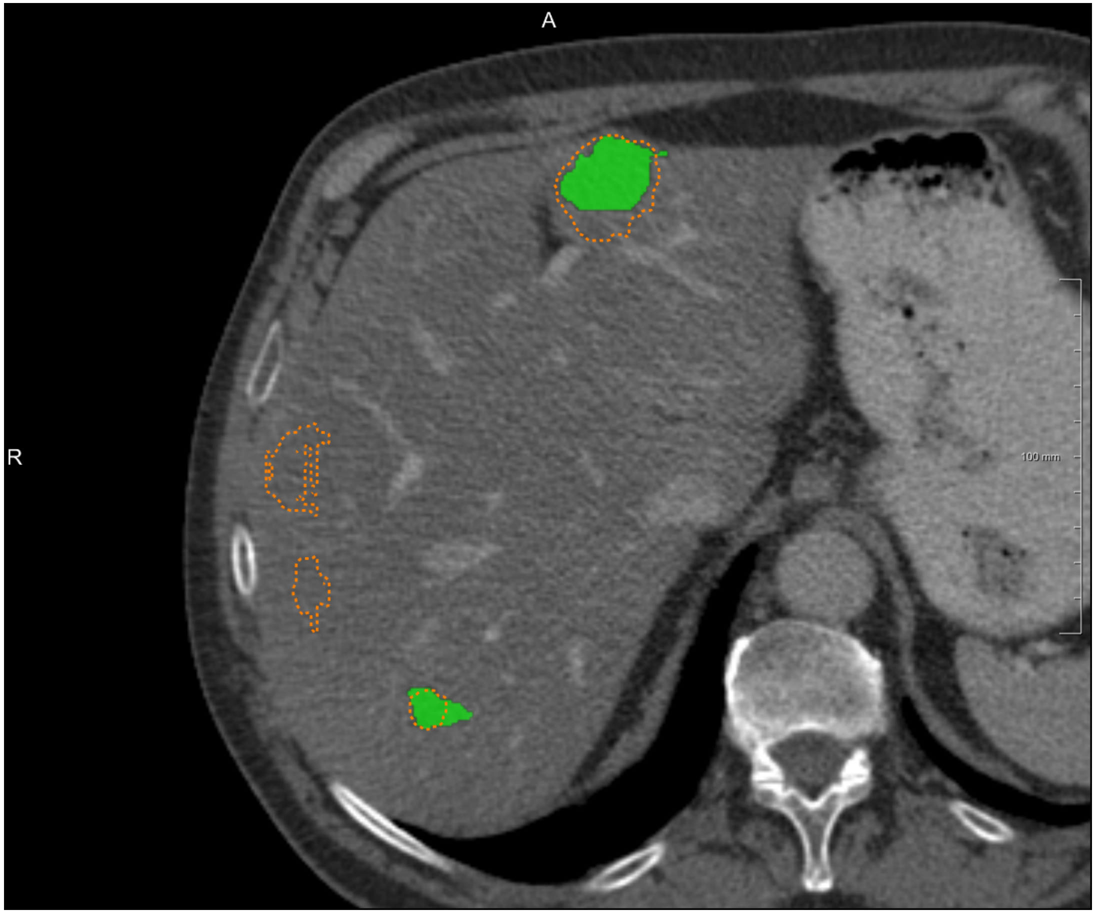

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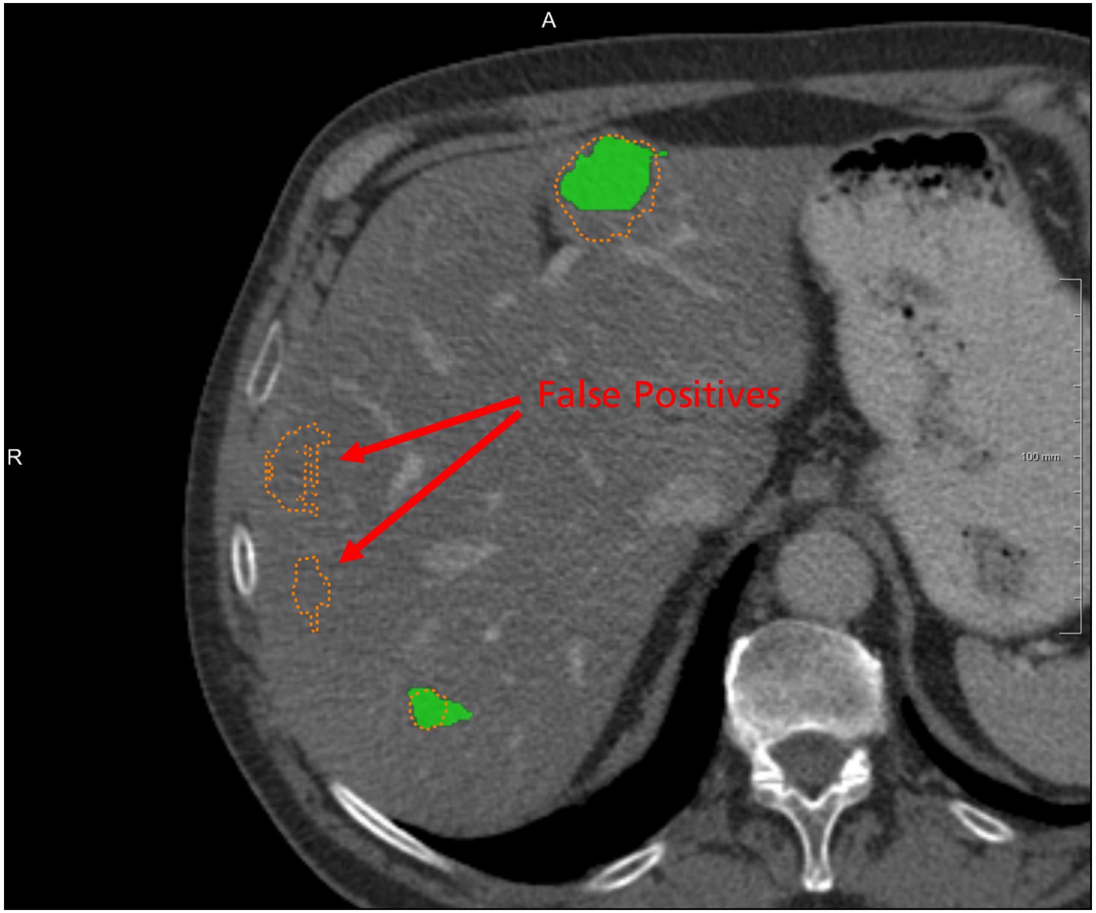

- False Positives (FPs) Problem

Tumor Segmentation
FPs Filtering

- Train another classifier to detect FPs
- 46 features based on:
  - CT intensity
  - Shape
  - DTF of the liver mask
- Random Forest (RF) accuracy ~90%

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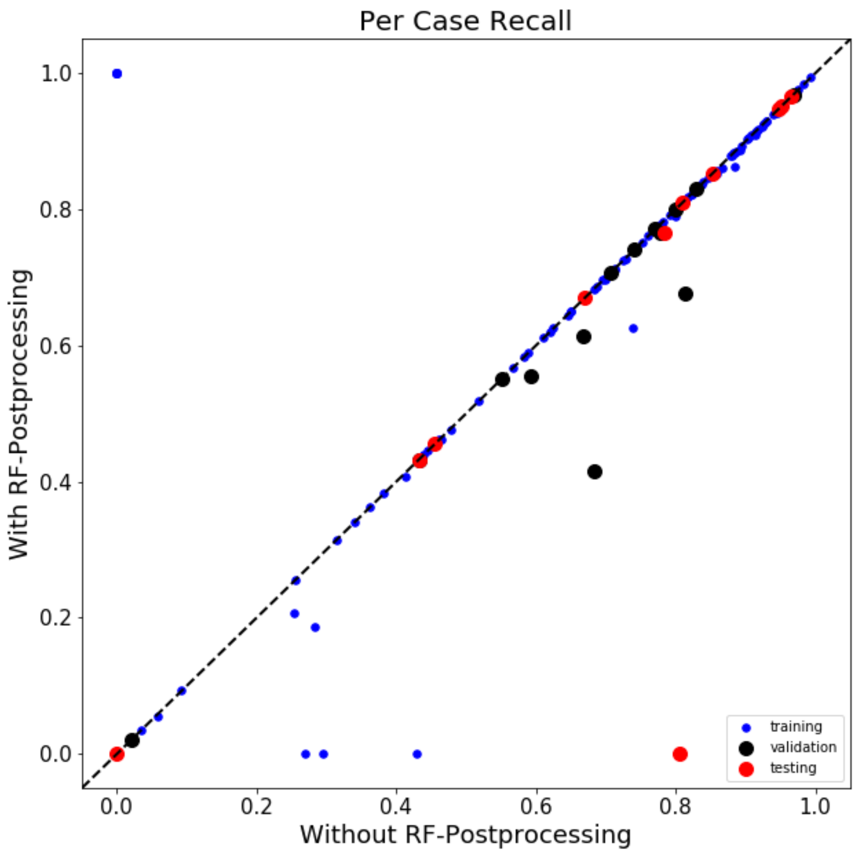
  - Recall



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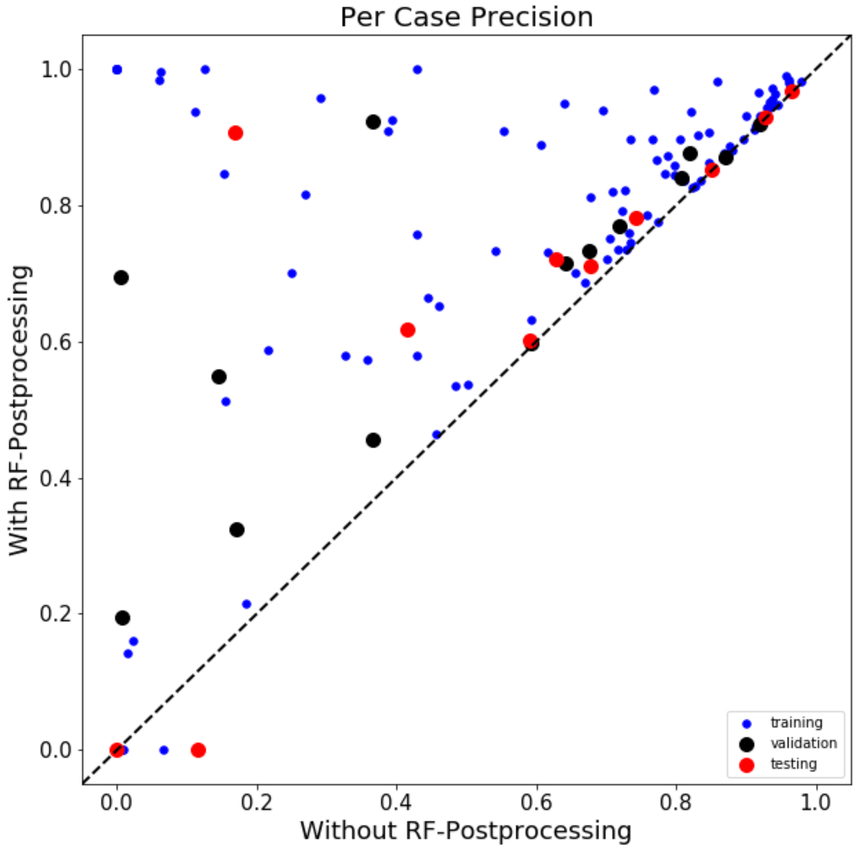

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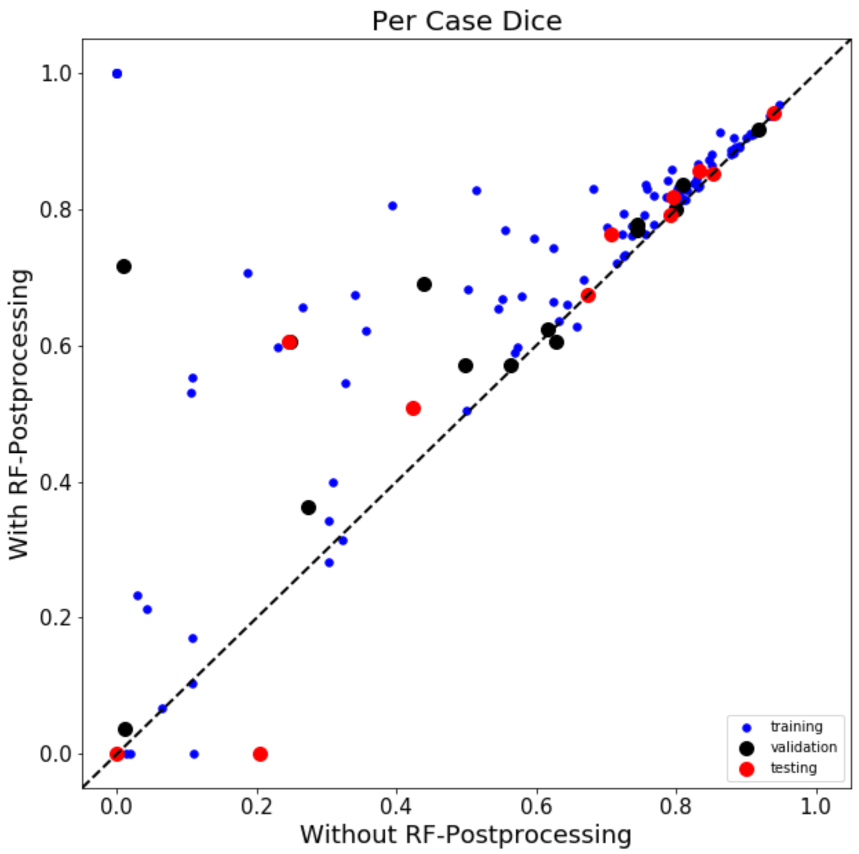
  - Recall ↓
  - Precision ↑
  - Dice ↑



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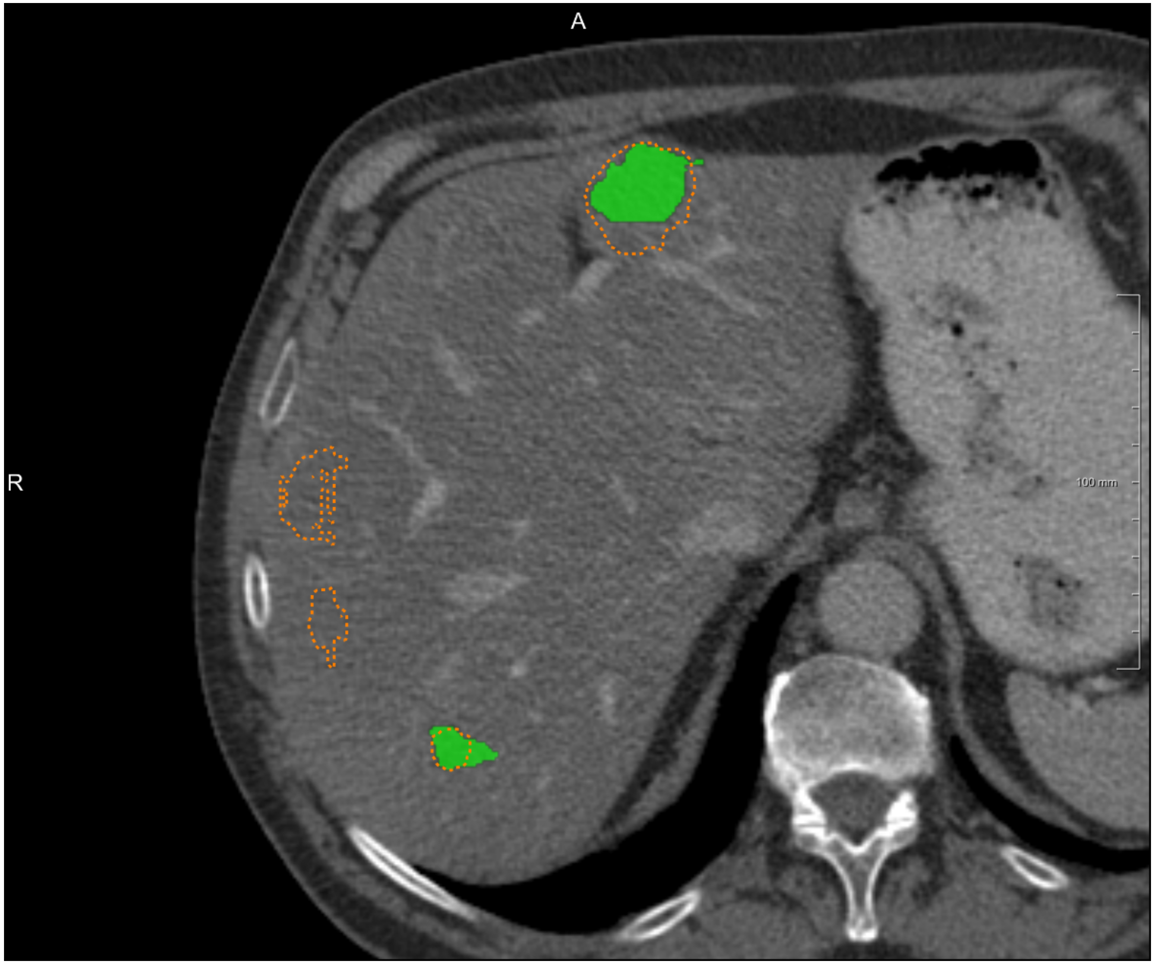
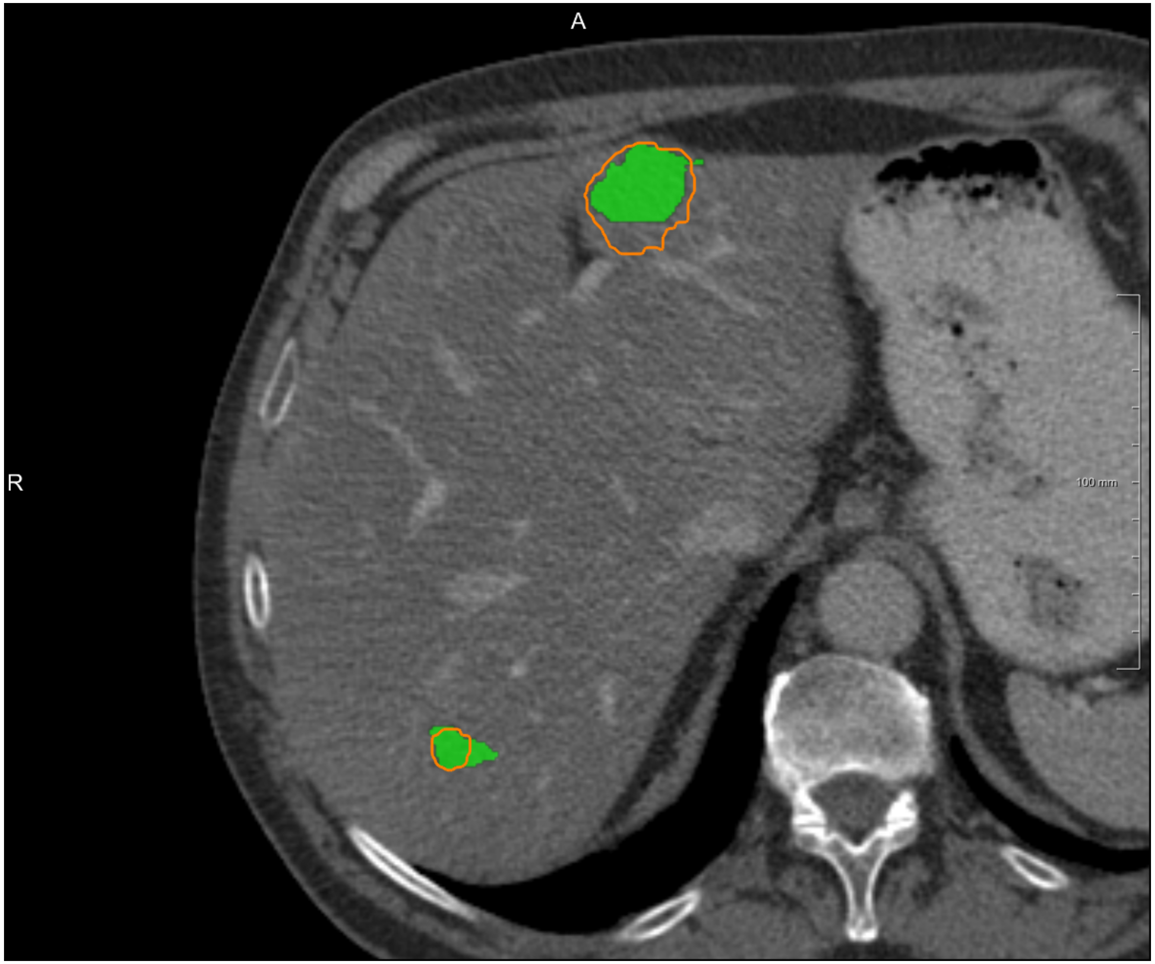
Tumor Segmentation
FPs Filtering Examples



Without RF-Postprocessing

Tumor Segmentation
FPs Filtering Examples



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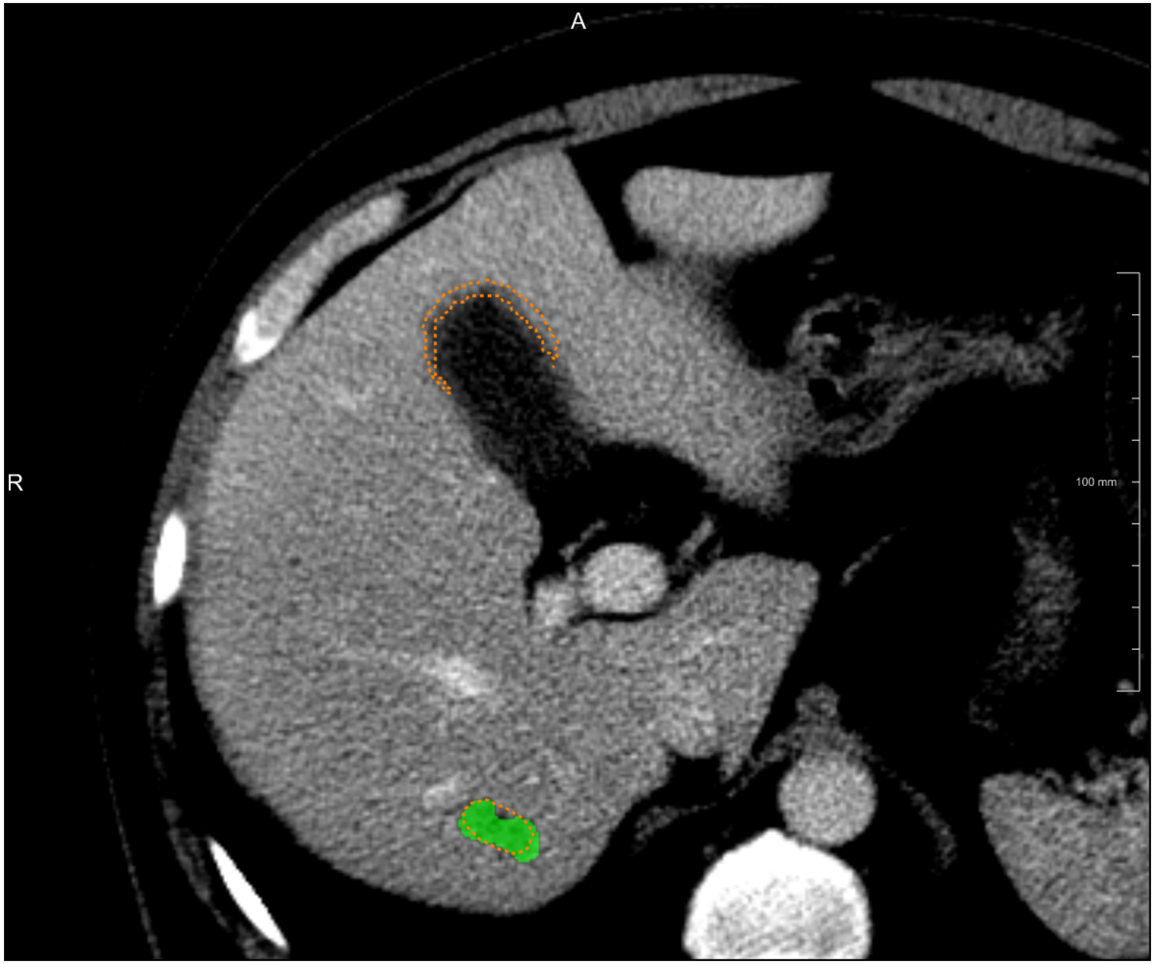

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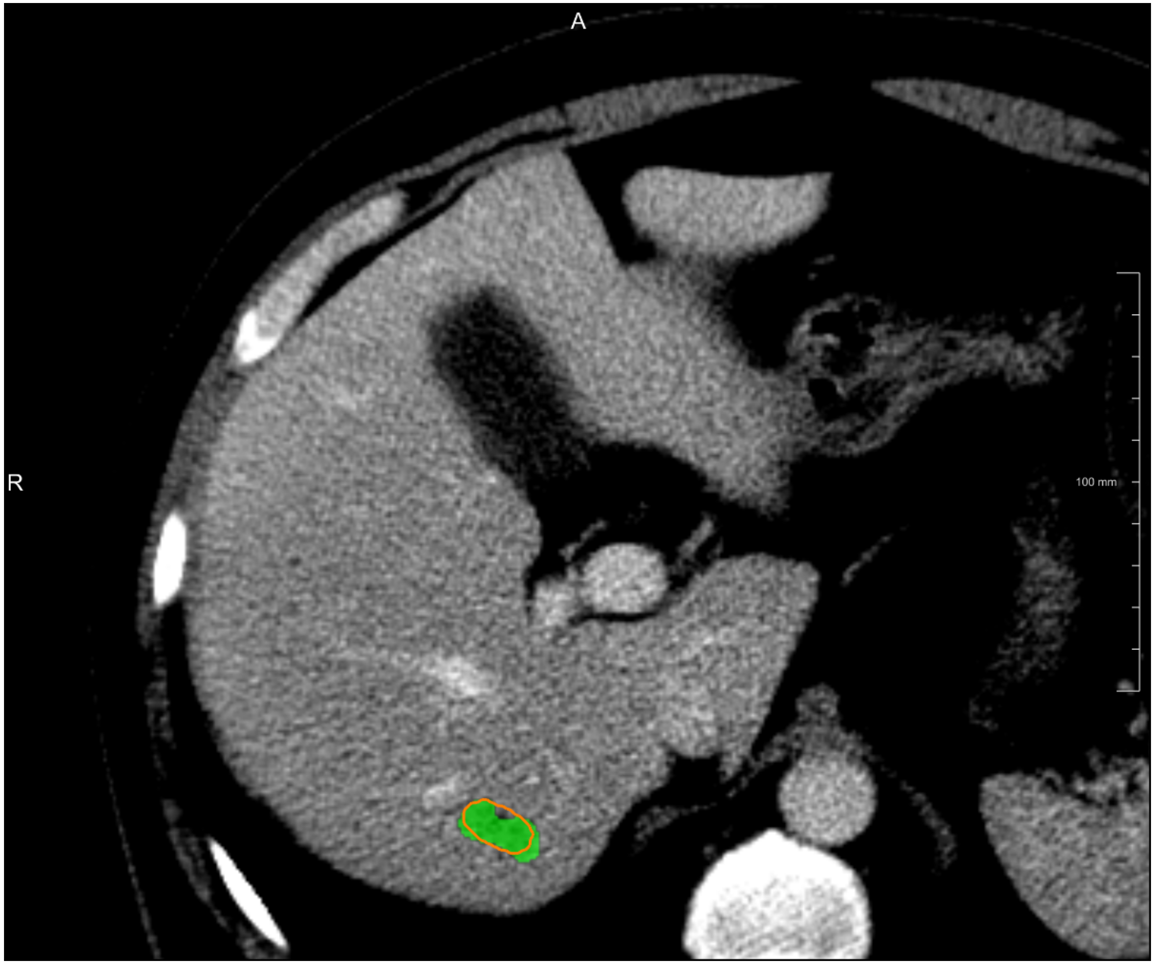

With RF-Postprocessing

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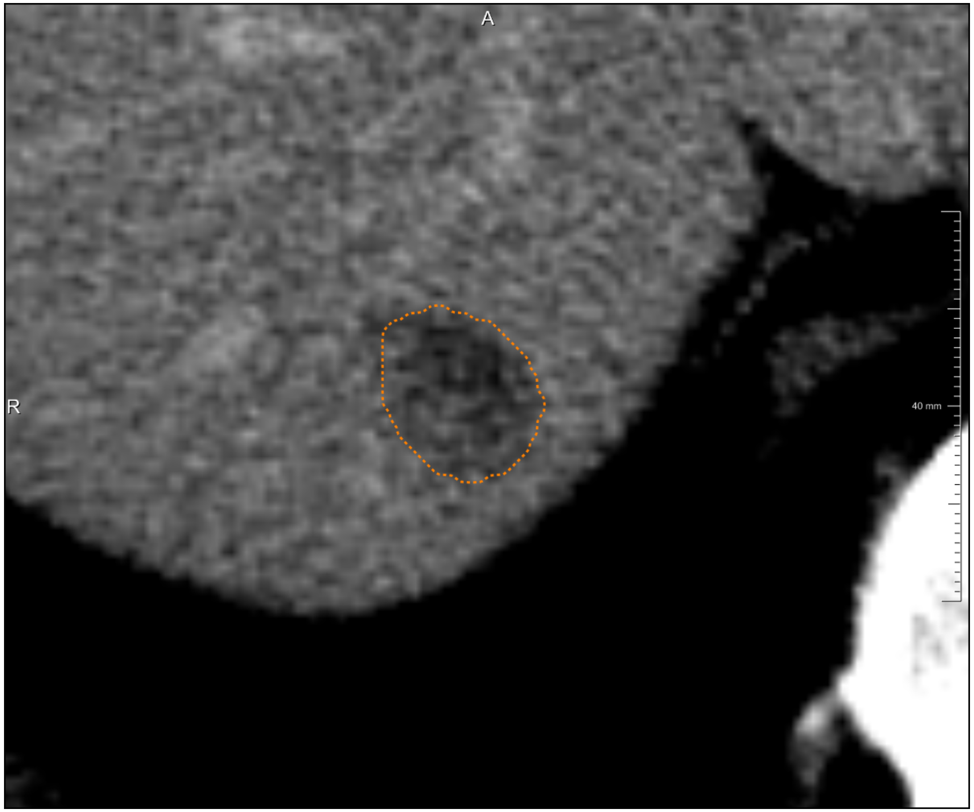
Tumor Segmentation
FPs Filtering with Tumor Refinement

- Use tumor candidates to initialize stroke-based semi-automatic segmentation tool [2]



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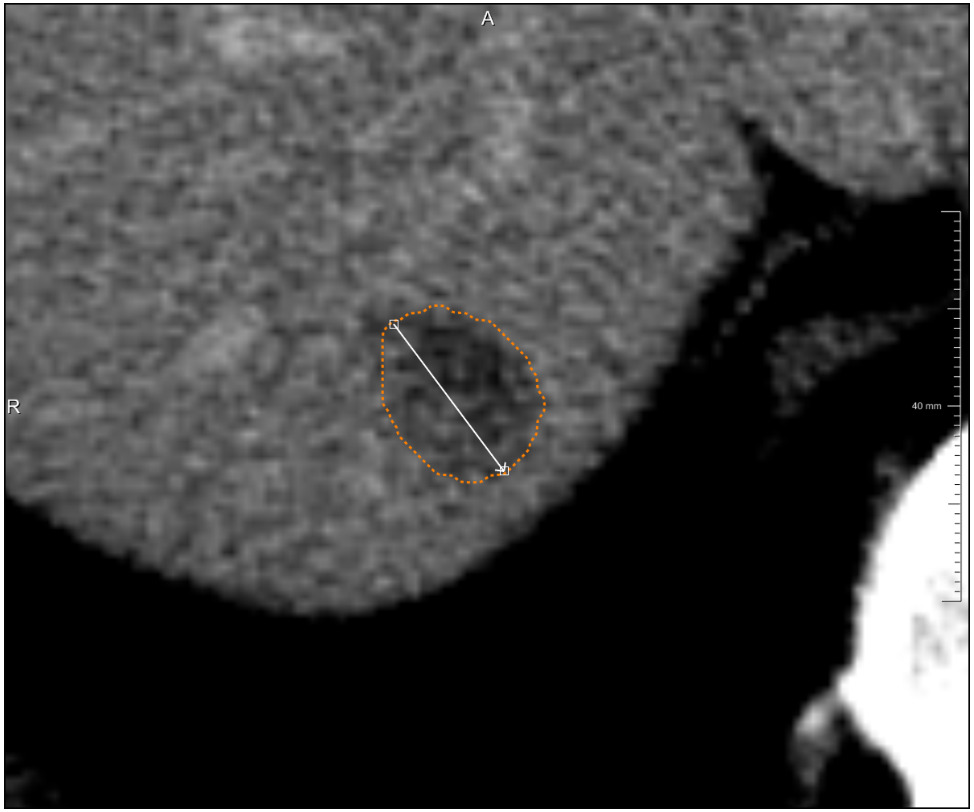

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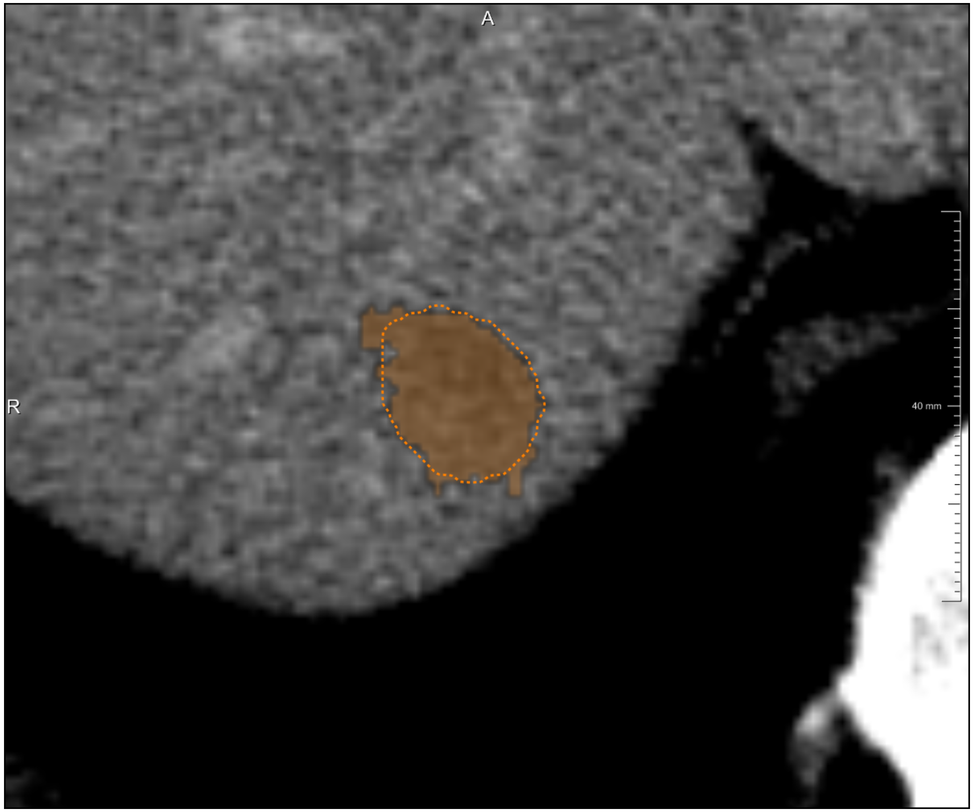

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Stroke application

- Segmentation refinement
- Additional features for RF classifier of the refined tumors

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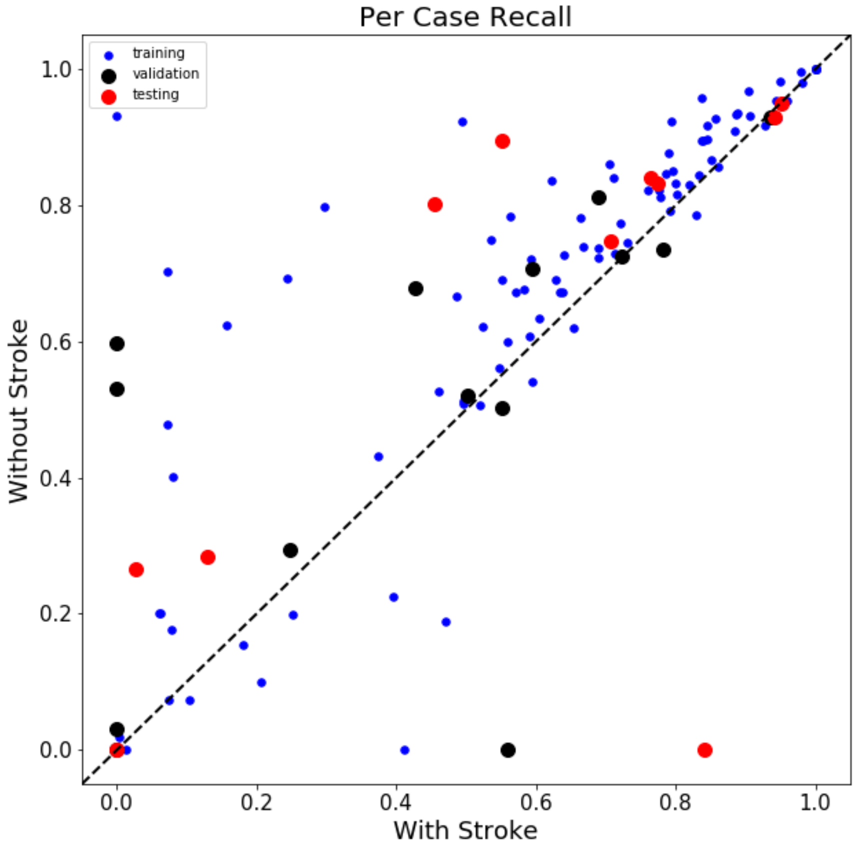

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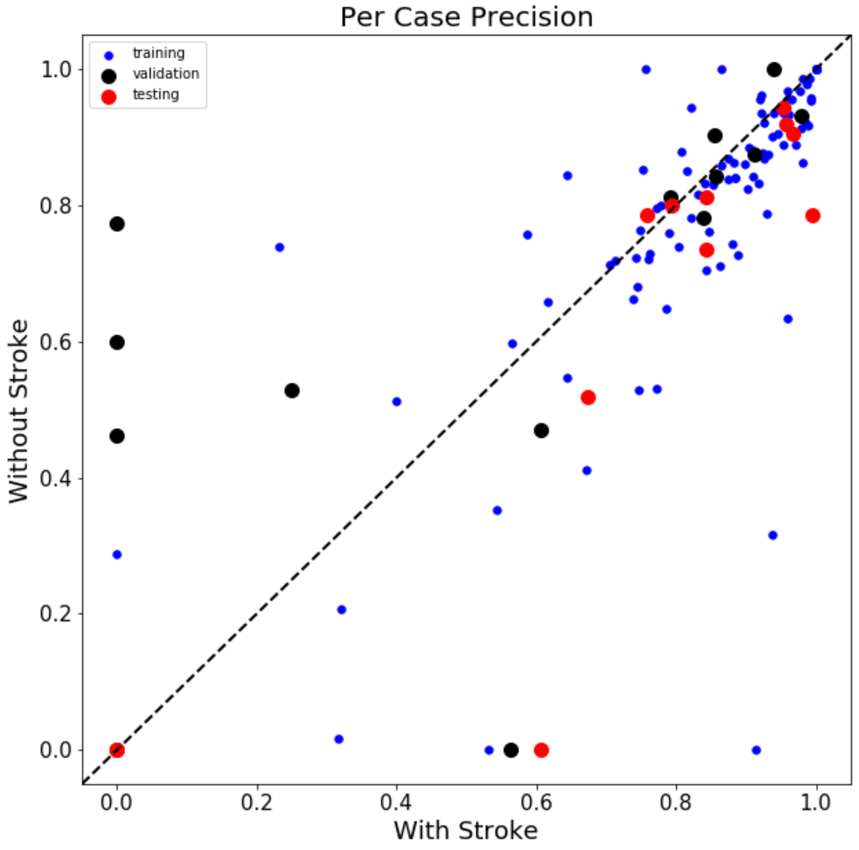
  - Recall
  - Precision



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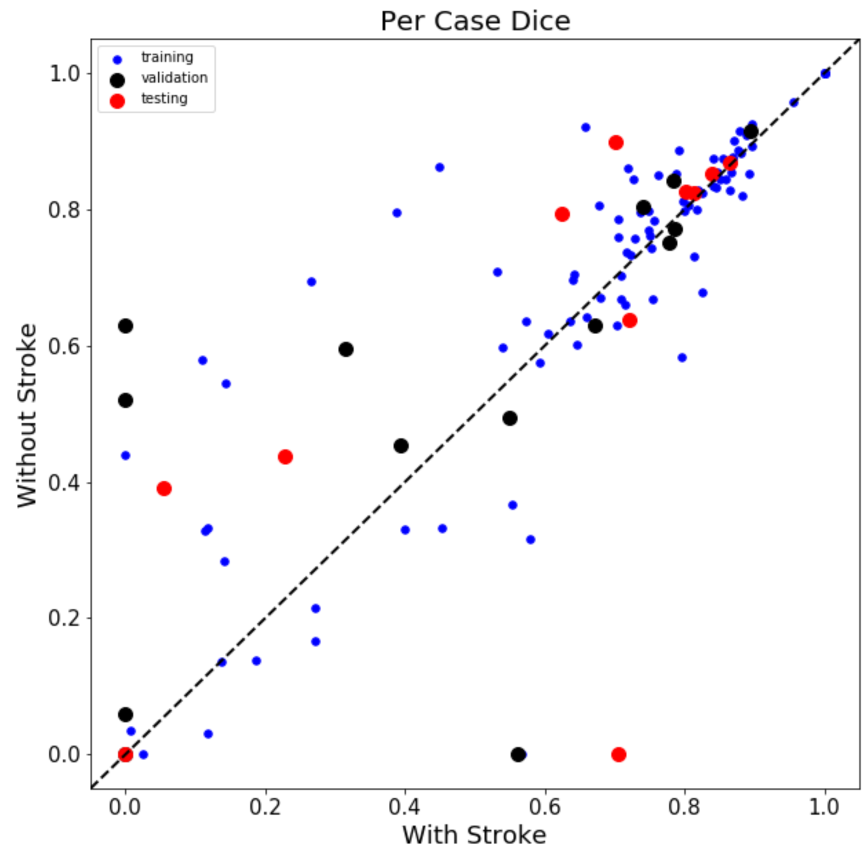

2.5D FCN Architecture

Idea:

- Add more context information
- 1st LiTS round winner used 2.5D [3]

[3] Han X. "Automatic Liver Lesion Segmentation Using A Deep Convolutional Neural Network Method." 2017.

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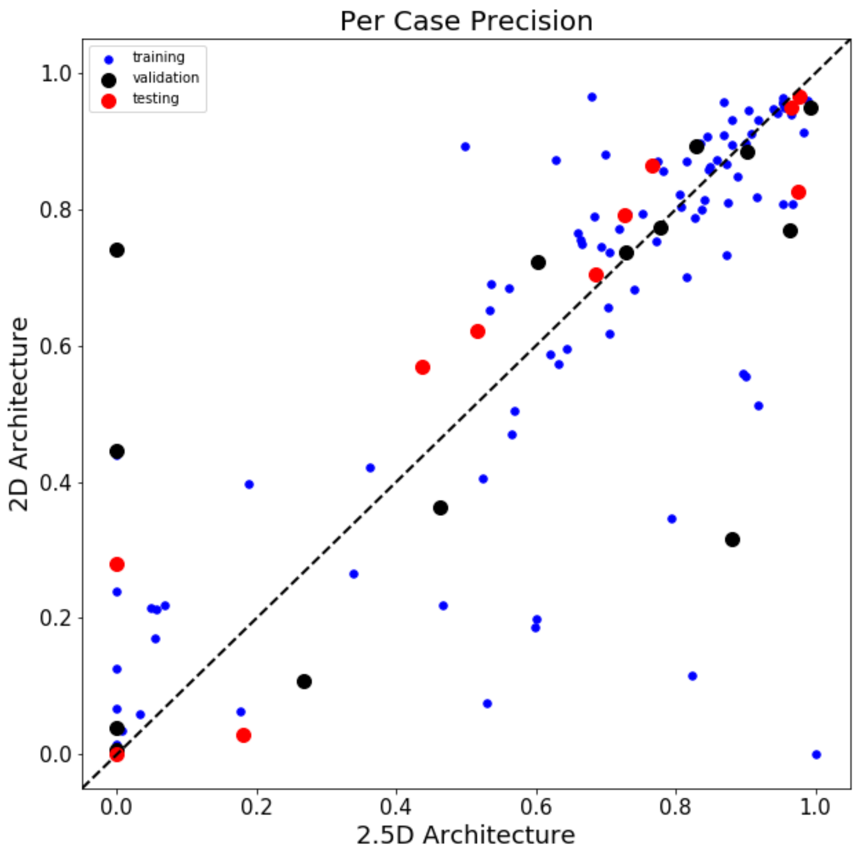
- 2.5D vs 2D:
  - Precision



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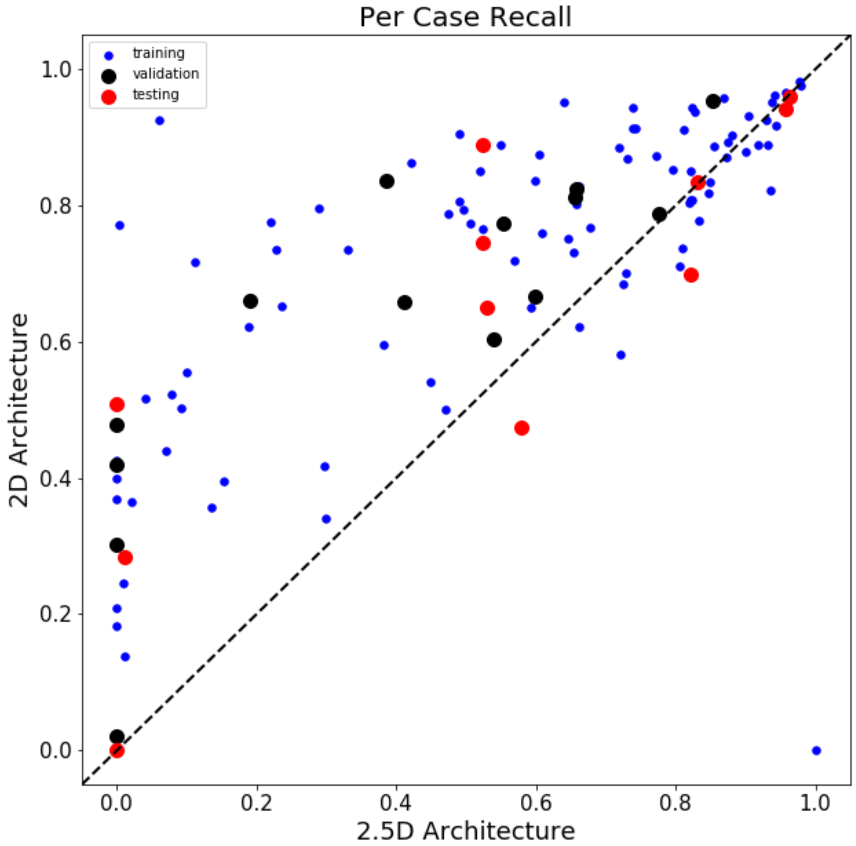

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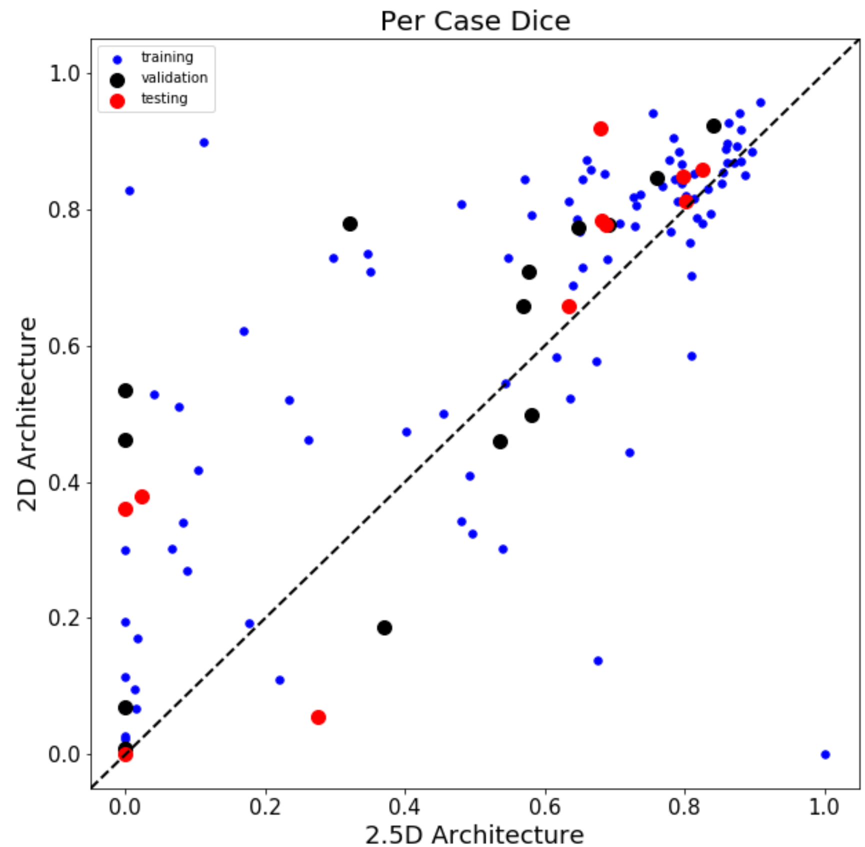

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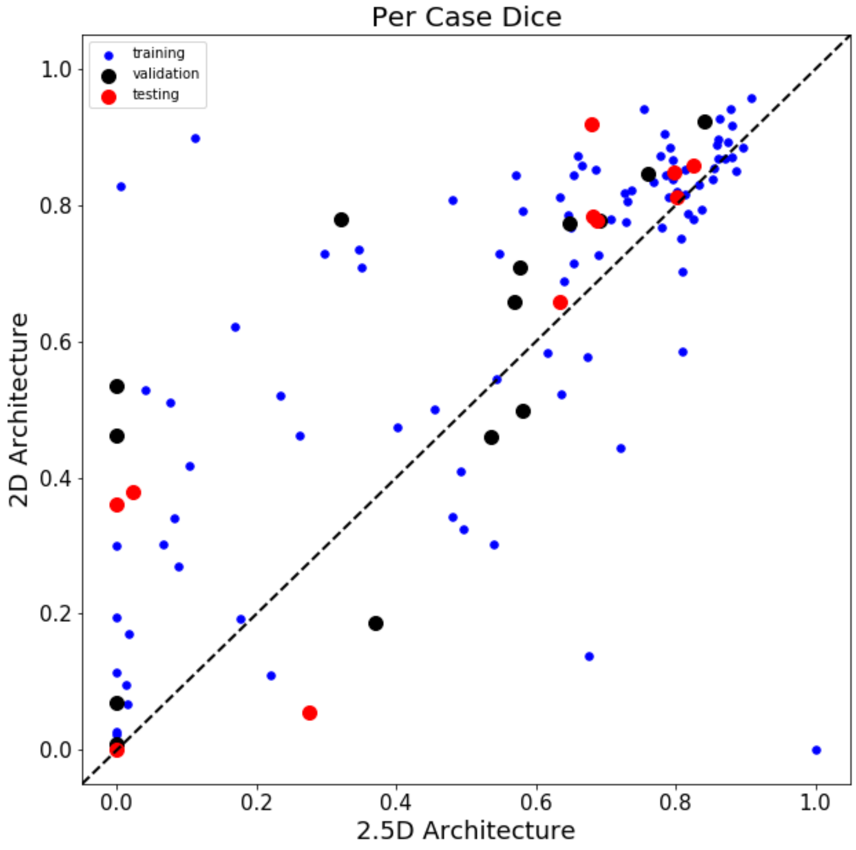
- Same observations for liver!



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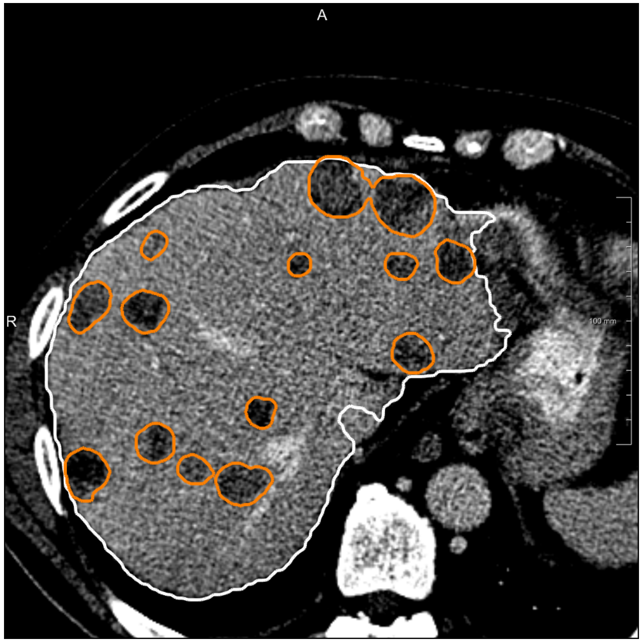

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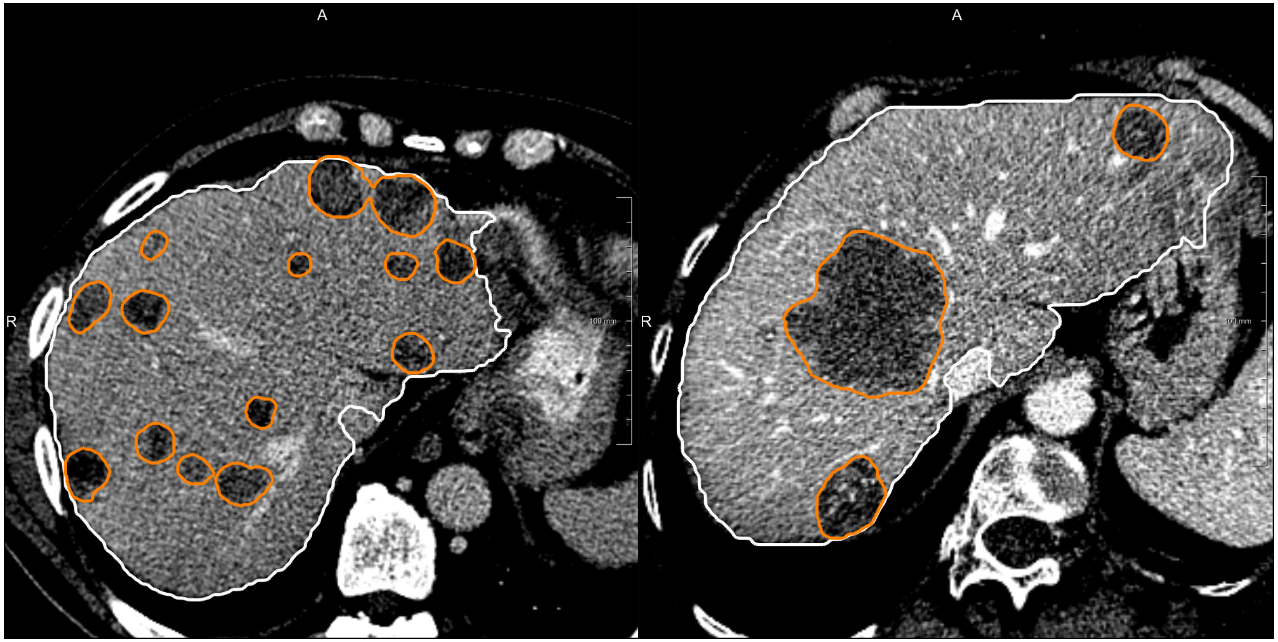

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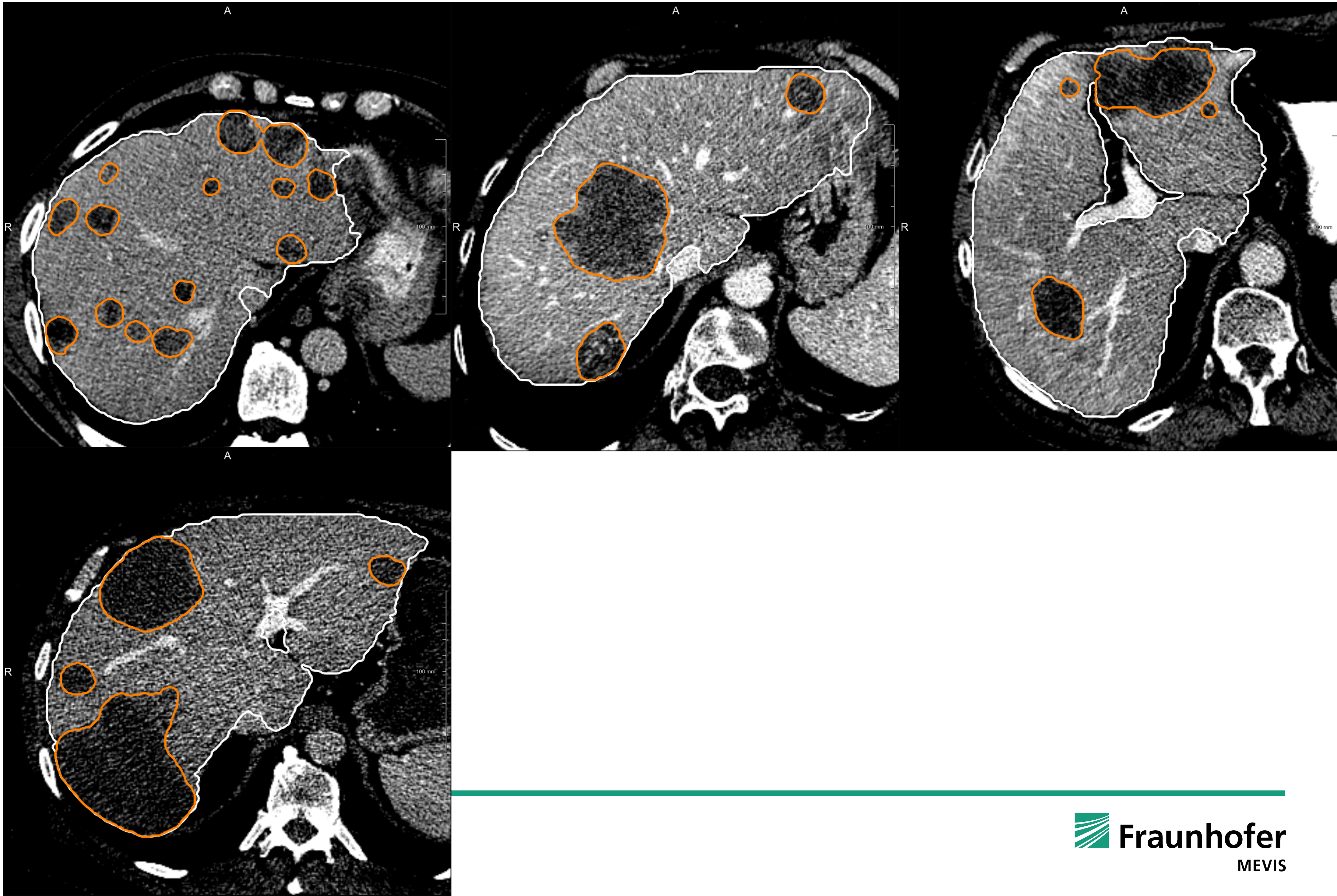

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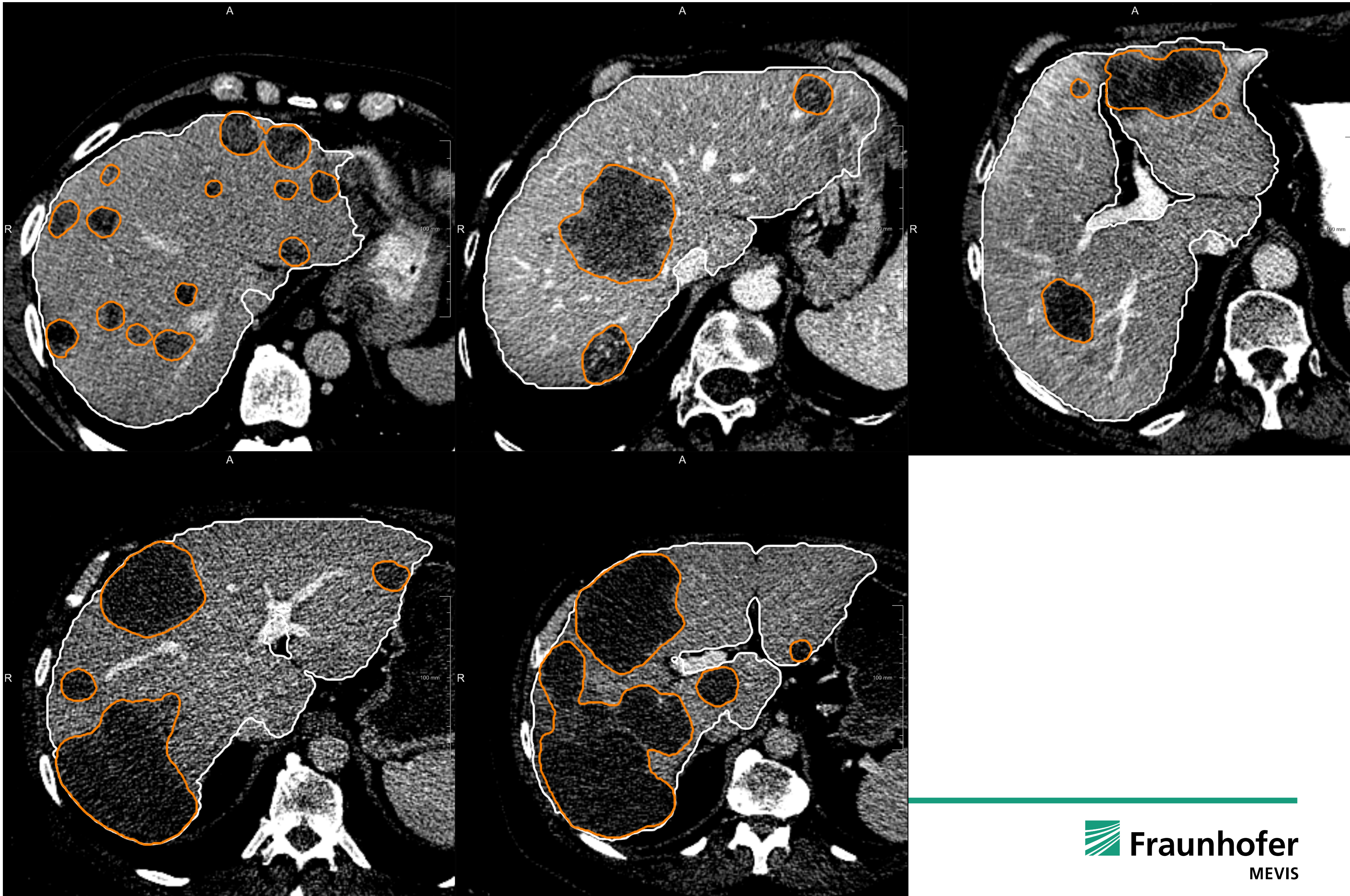

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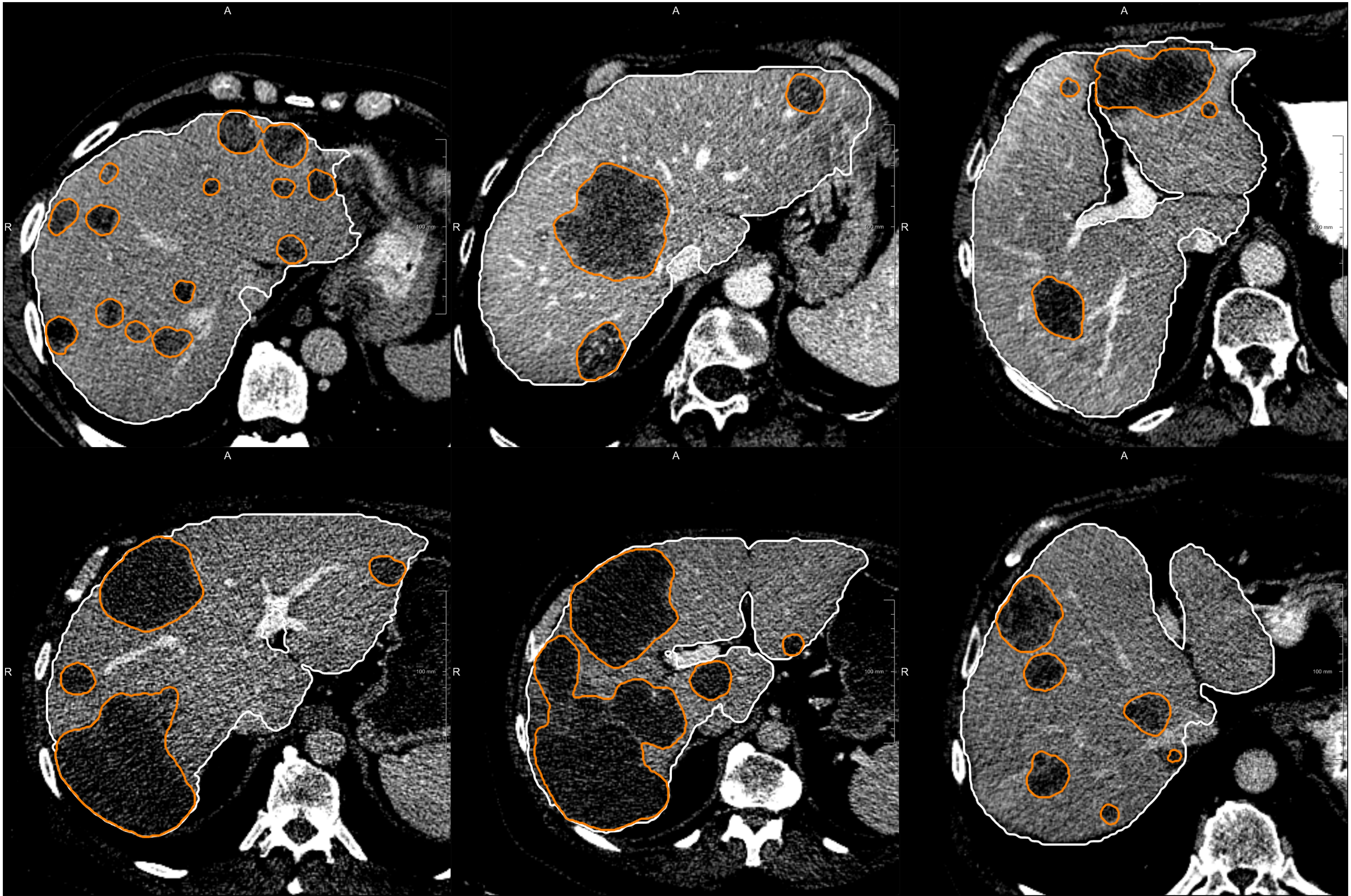
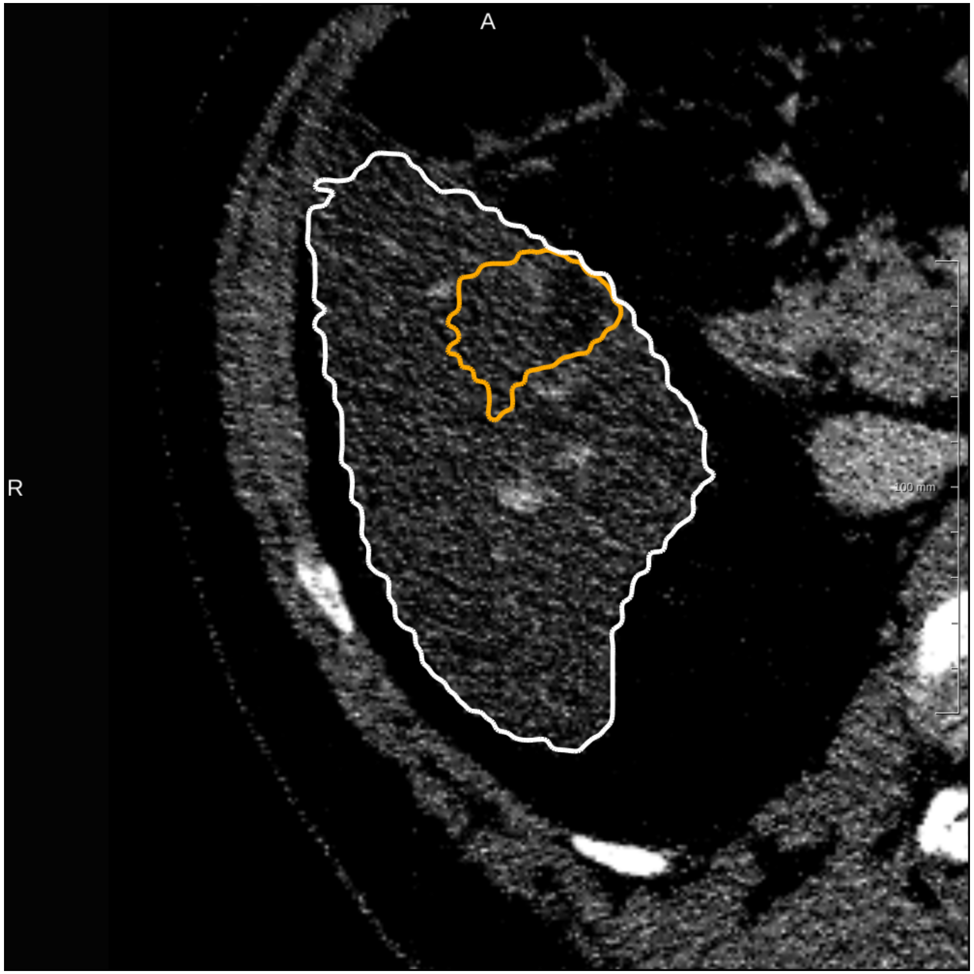


Problematic Cases



- Found tumor bigger than the reference

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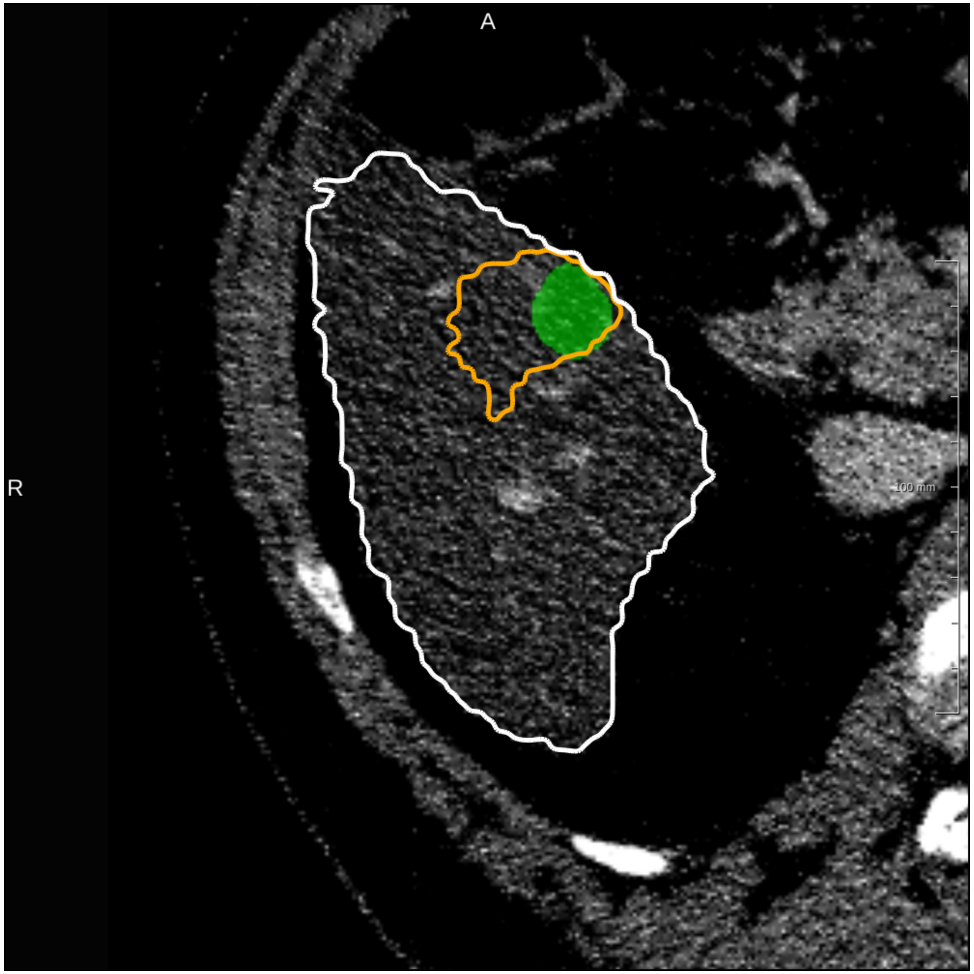

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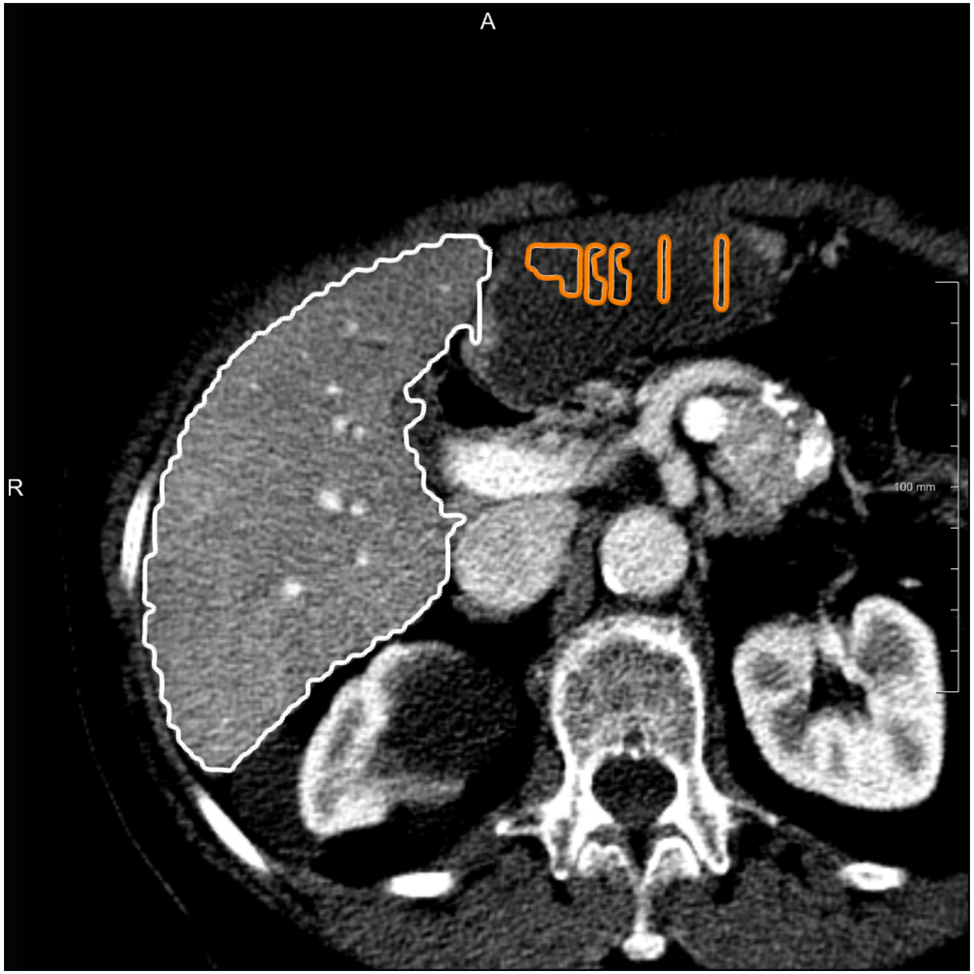

- Liver mask misses tumors located near organ’s border

Problematic Cases

- Big tumors are not fully segmented

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Problematic Cases

- Obvious(?) tumors are completely missed

LiTS Results

- Liver segmentation
  - Dice per case: 0.96
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OK

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OK

Further work required

Technical Setup

- Data loading and preprocessing
  - MeVisLab
- Deep Learning Toolkits
  - RedLeaf
  - Lasagne
  - Theano
- Evaluation
  - Challengr

Conclusions

- We proposed a fully automatic method for liver and liver lesion segmentation based on FCNs

- False positive tumors were filtered with a high accuracy using image intensity and shape based features

- Providing more context to the network (2.5D) decreased the segmentation quality

- Further work is required to make tumor segmentation clinically applicable

Outlook

- Different architectures
  - Adversarial networks
  - Recurrent networks
- Other training strategies
  - Curriculum learning

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Thank you for your attention ☺

Questions?