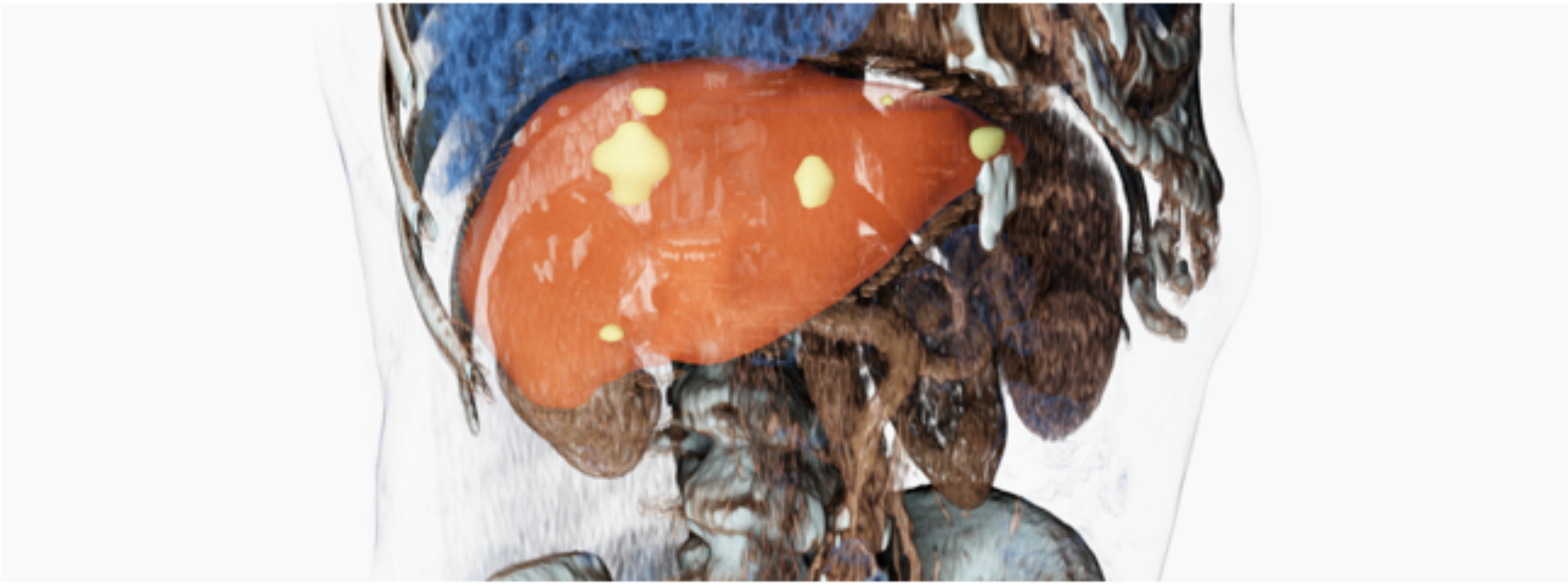
# NEURAL NETWORK BASED AUTOMATIC LIVER AND LIVER TUMOR SEGMENTATION

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



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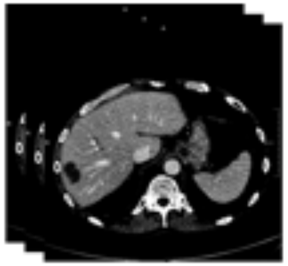
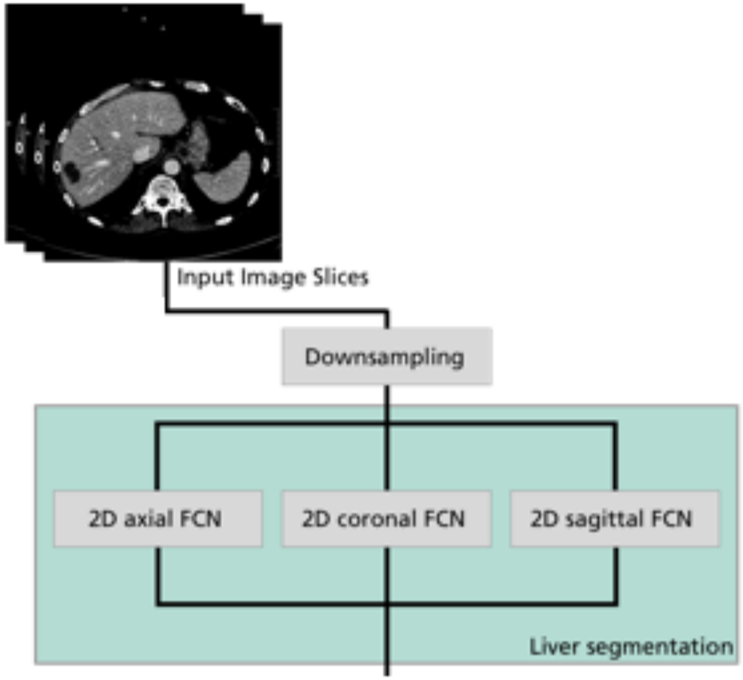
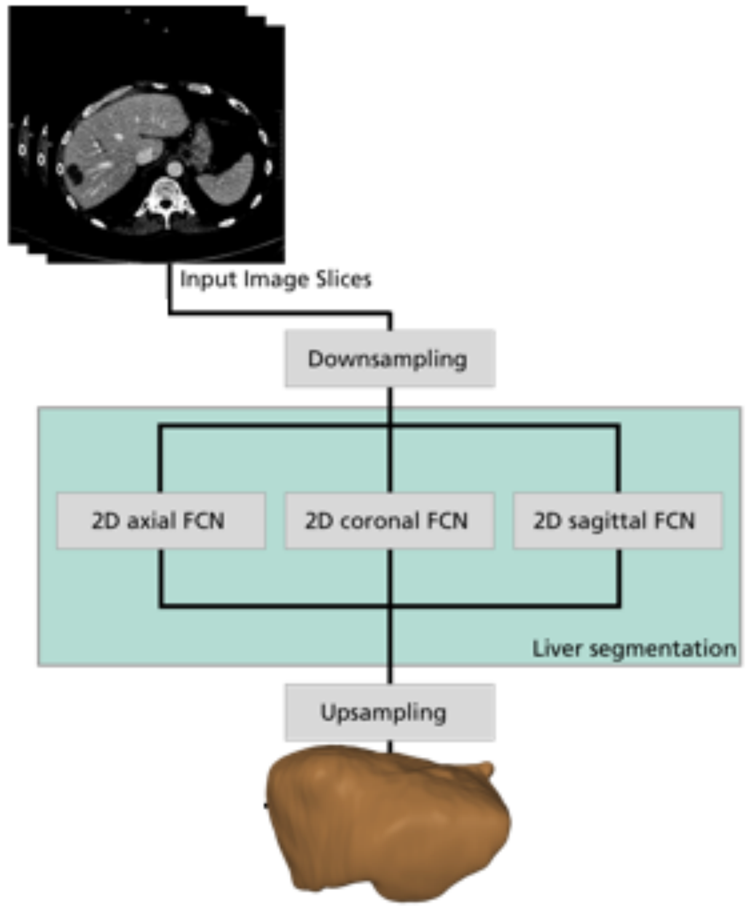

Input Image Slices


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



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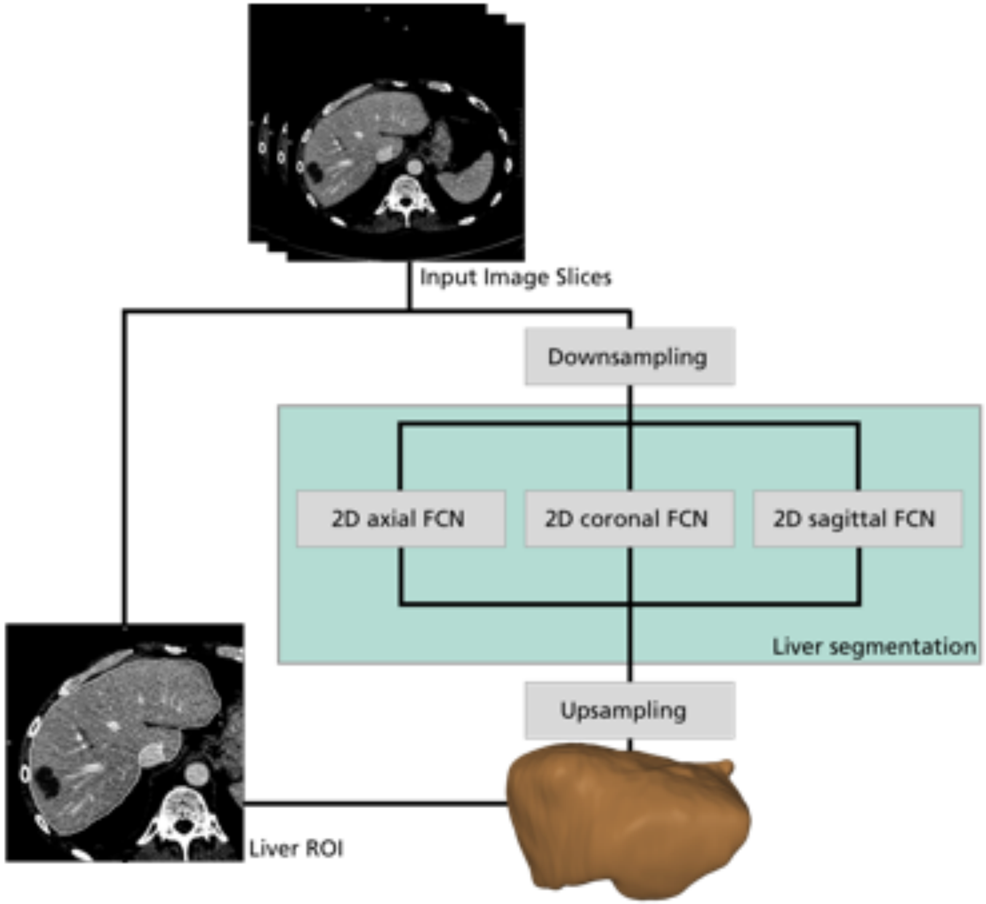
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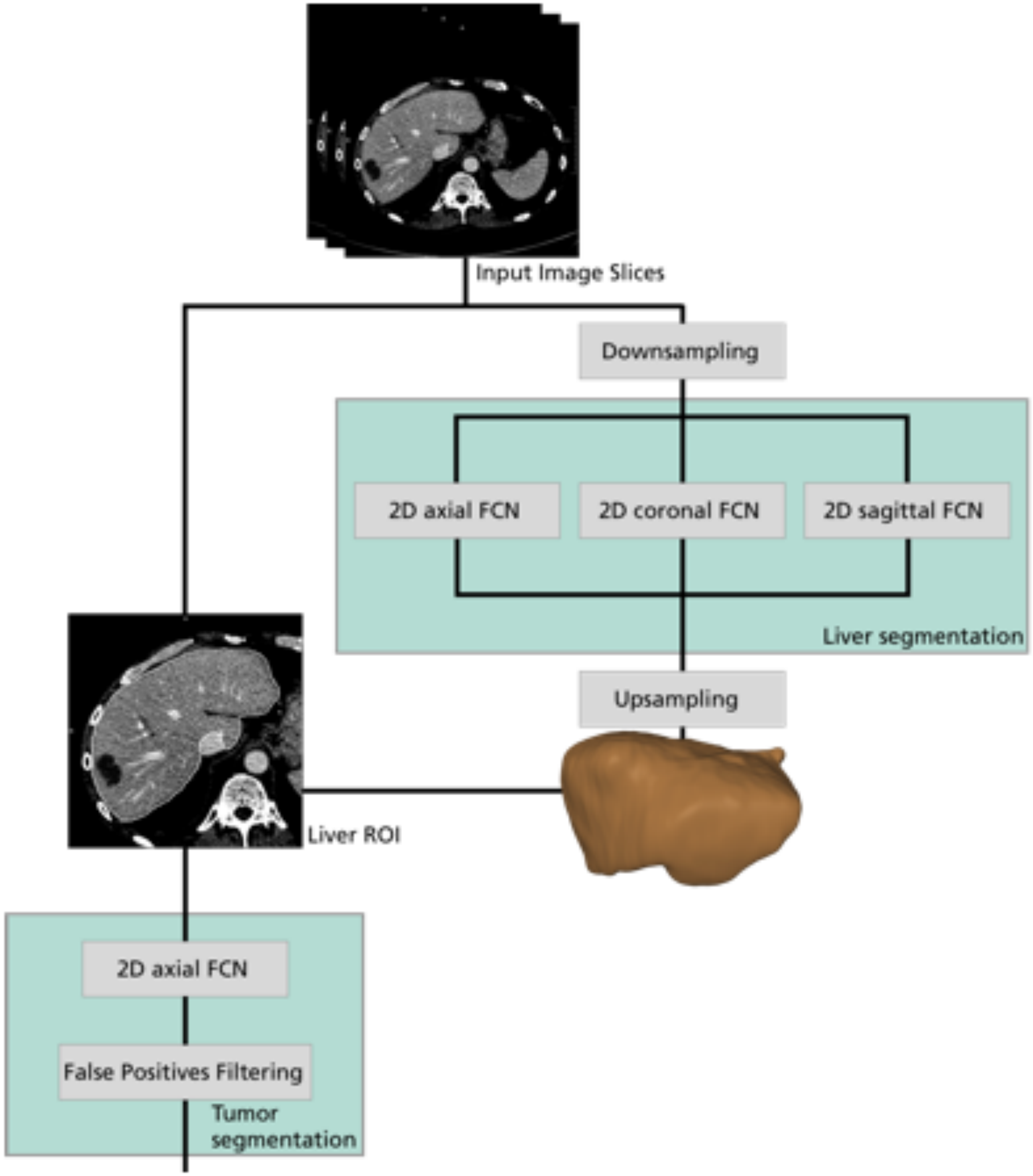
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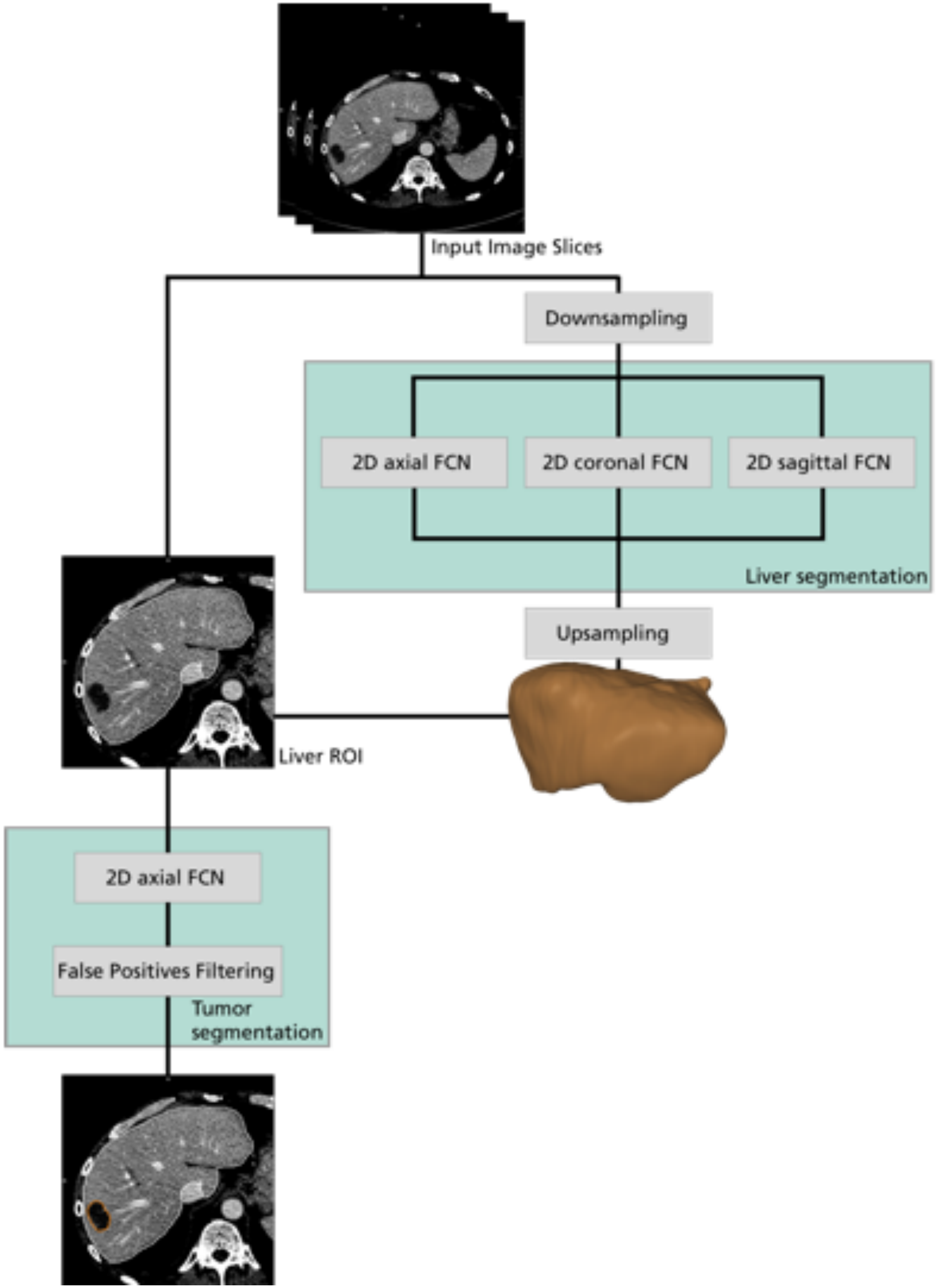
False Positives Filtering
Tumor
segmentation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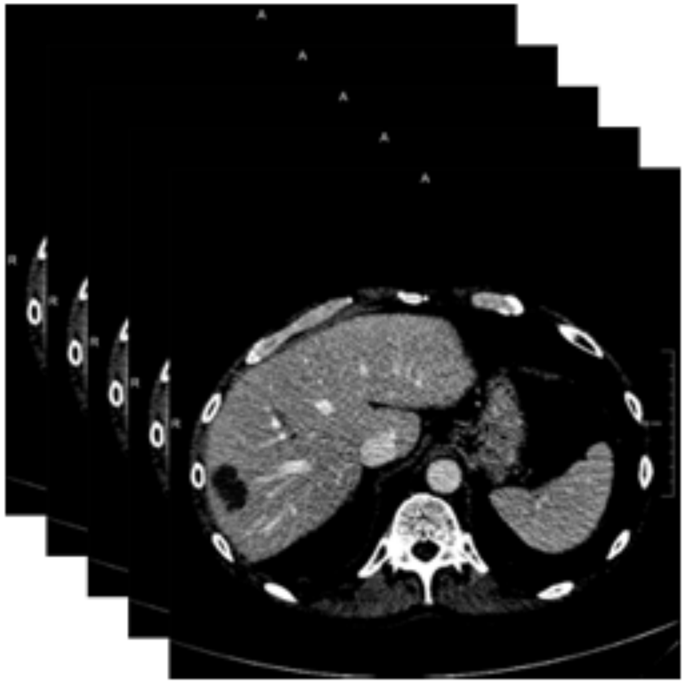
# Datasets

- 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

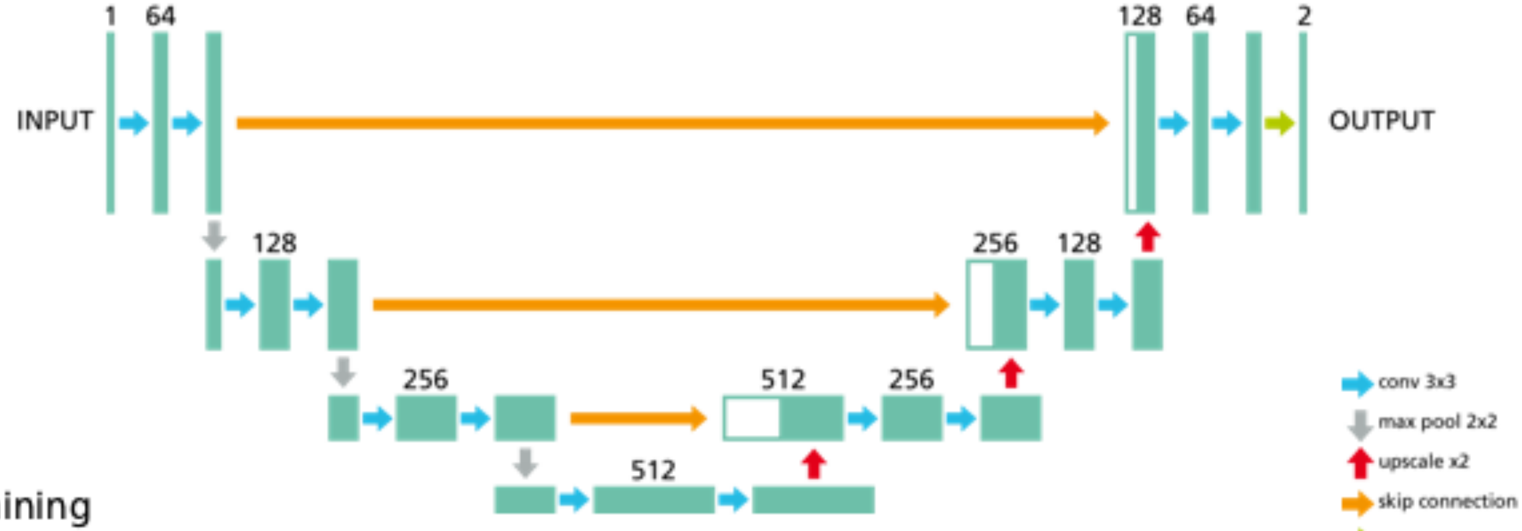
- Two training datasets
  - LiTS
  - Liver surgery planning
- Preprocessing
  - Rescaling raw GV to HU
  - Resampling to 2 mm isotropic voxel size
  - Padding with -1000 HU

# 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.



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# Liver Segmentation
# Postprocessing

- Biggest connected components of the majority vote mask

## Liver Segmentation
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*transversal*

# Liver Segmentation Postprocessing

- Biggest connected components of the majority vote mask

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*transversal* *coronal* *sagittal*

# Liver Segmentation
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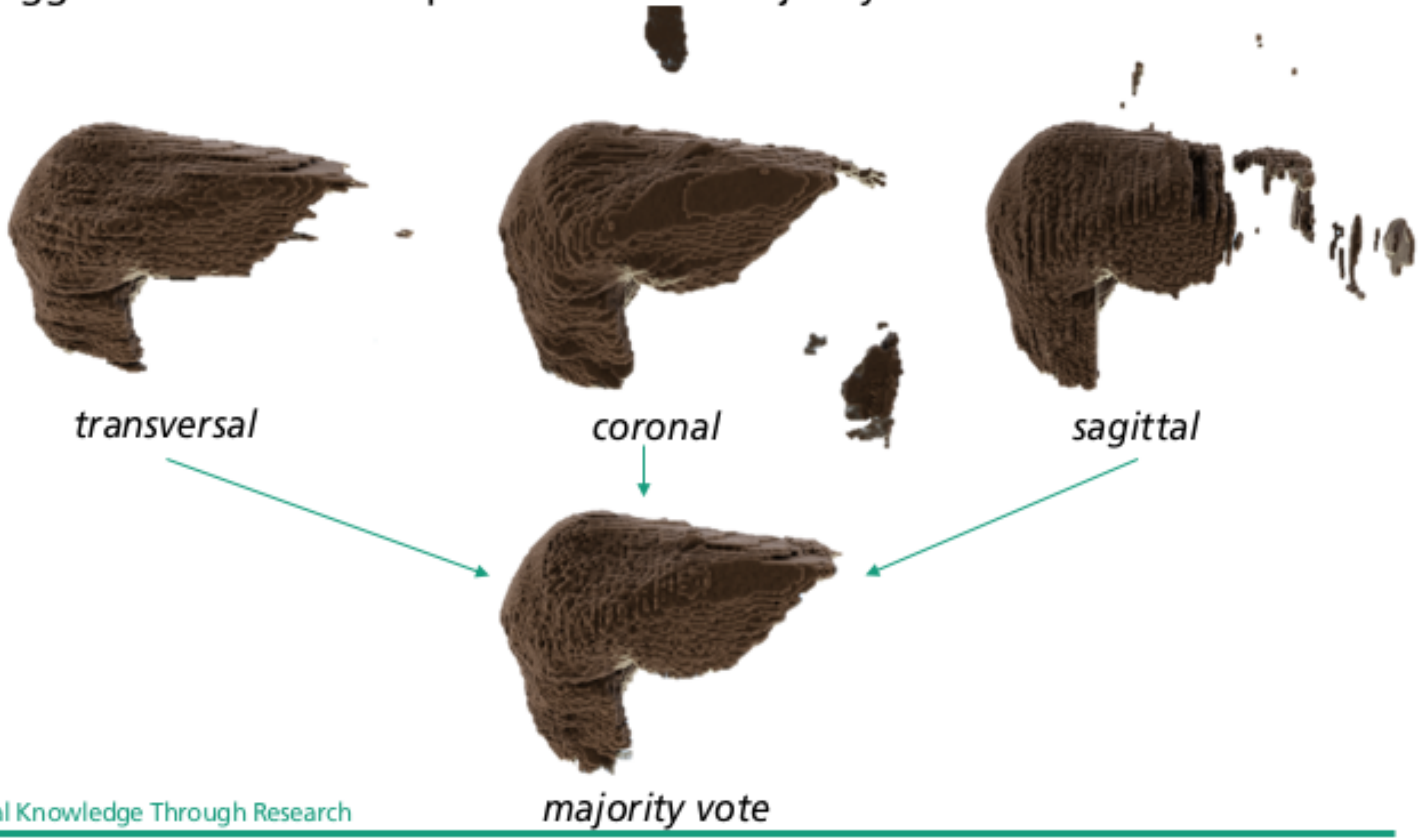

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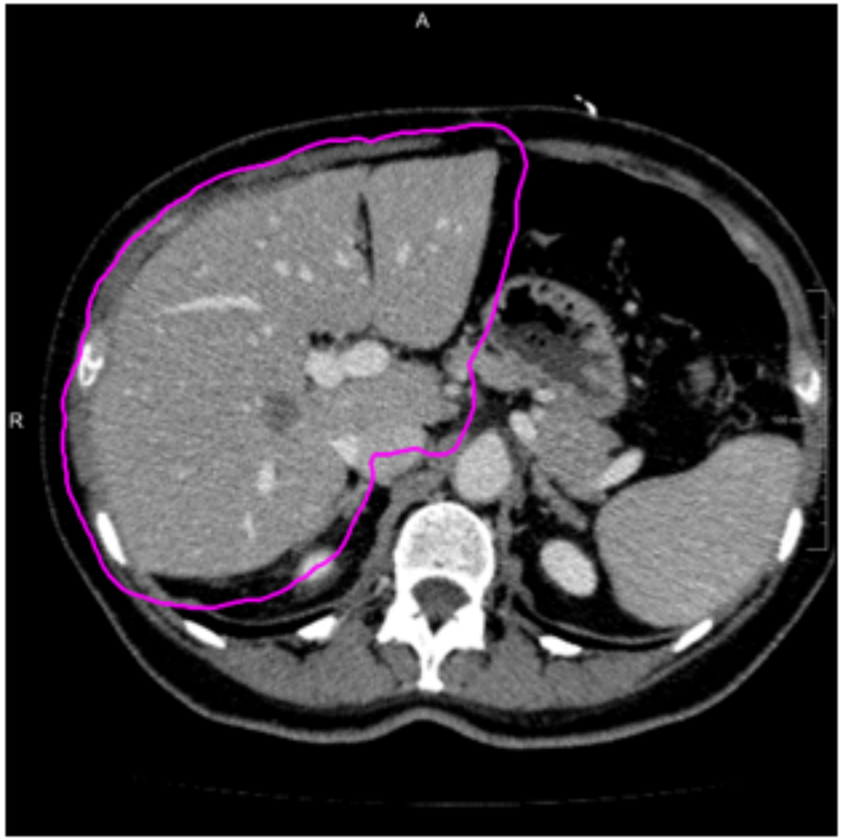
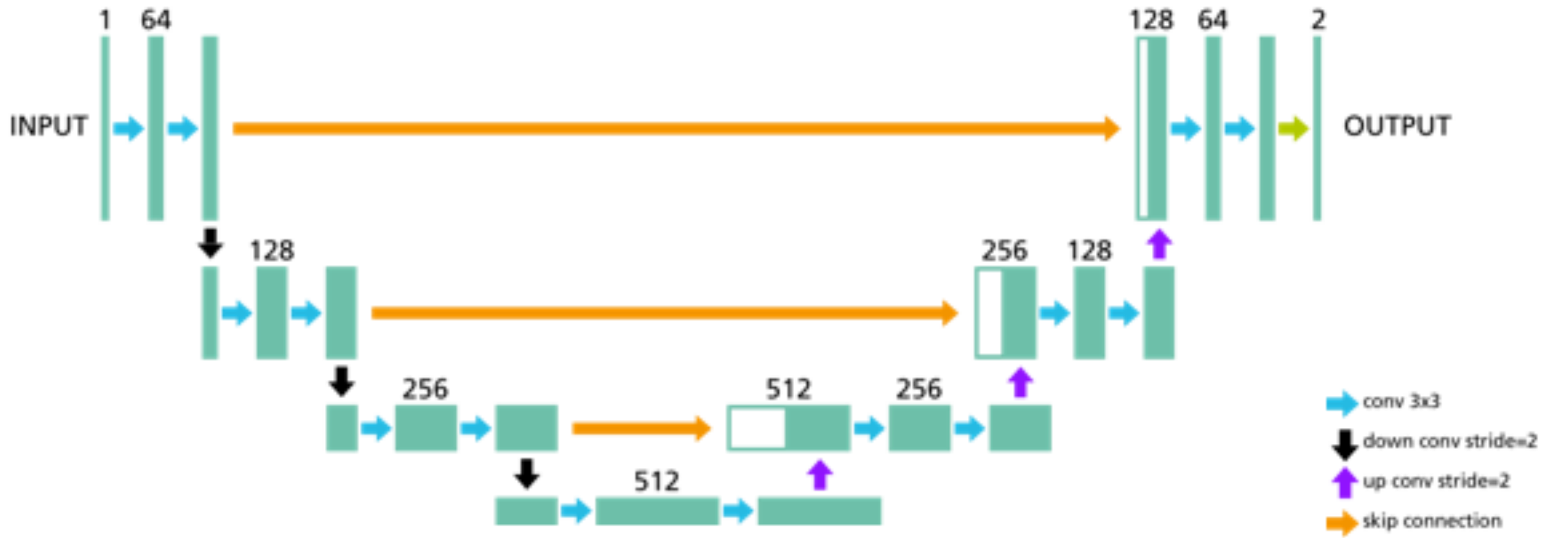
- Masked loss



# 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





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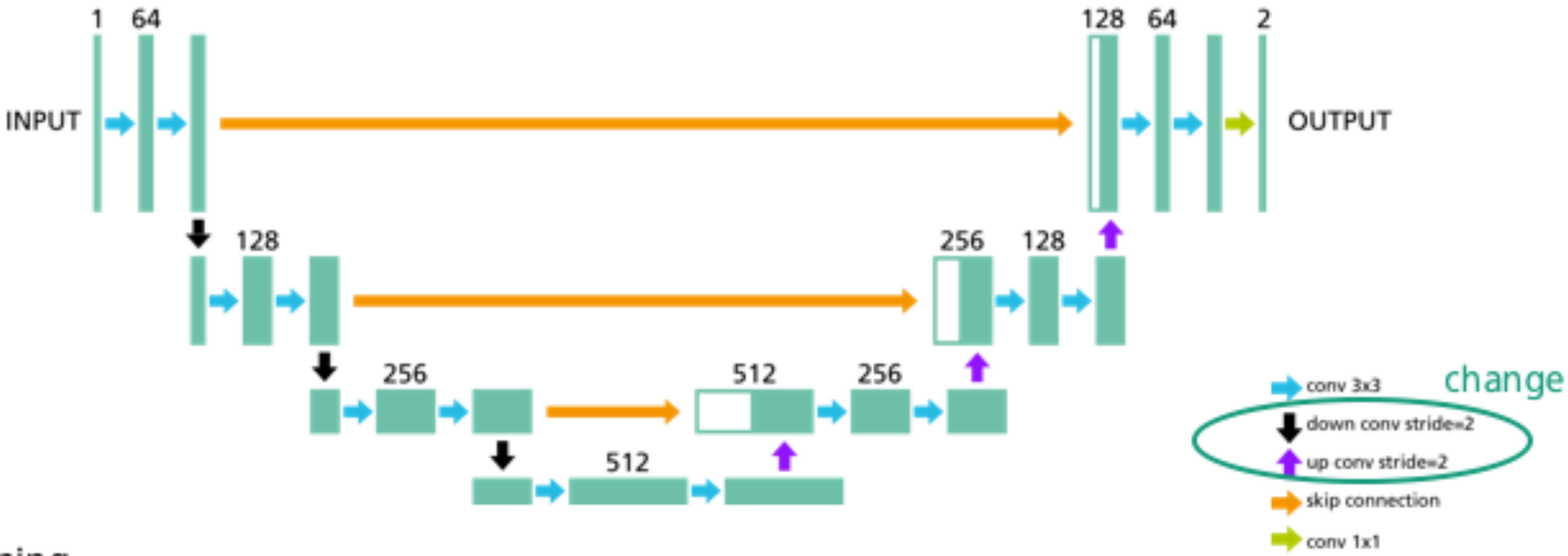


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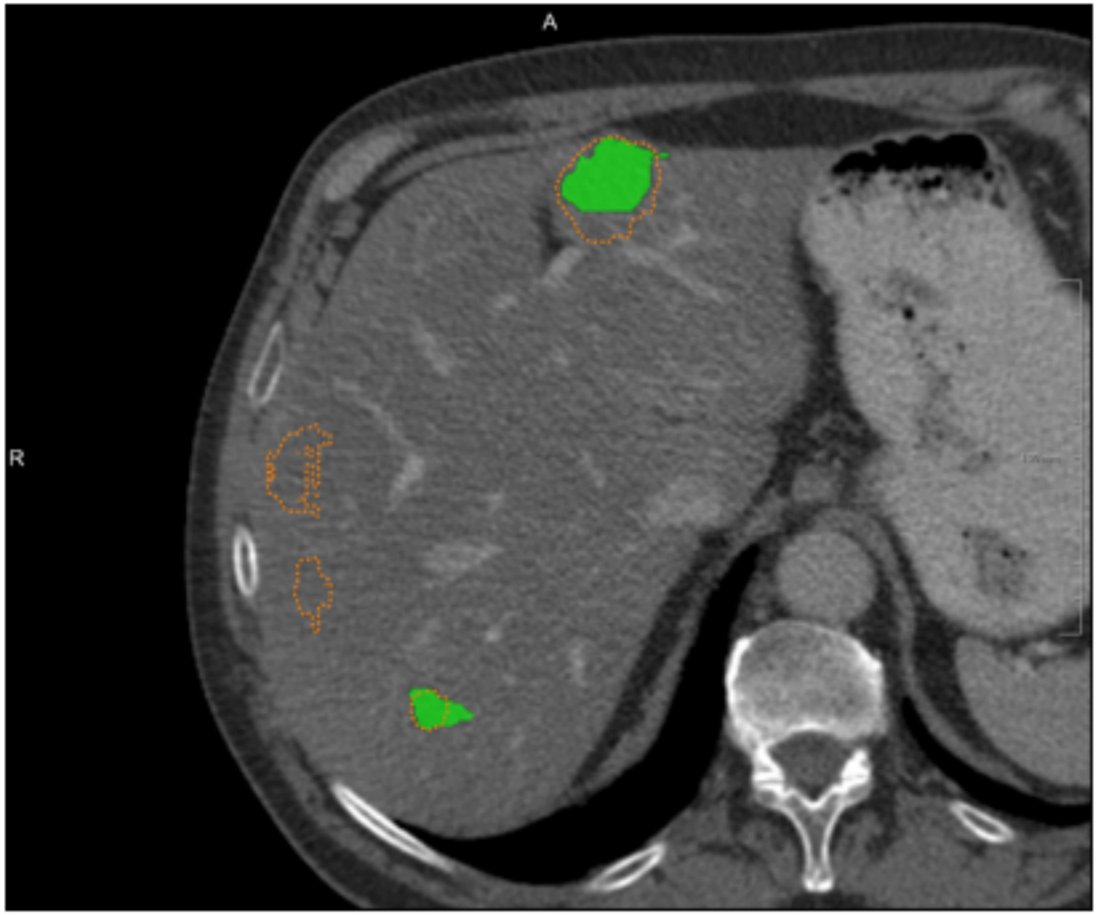

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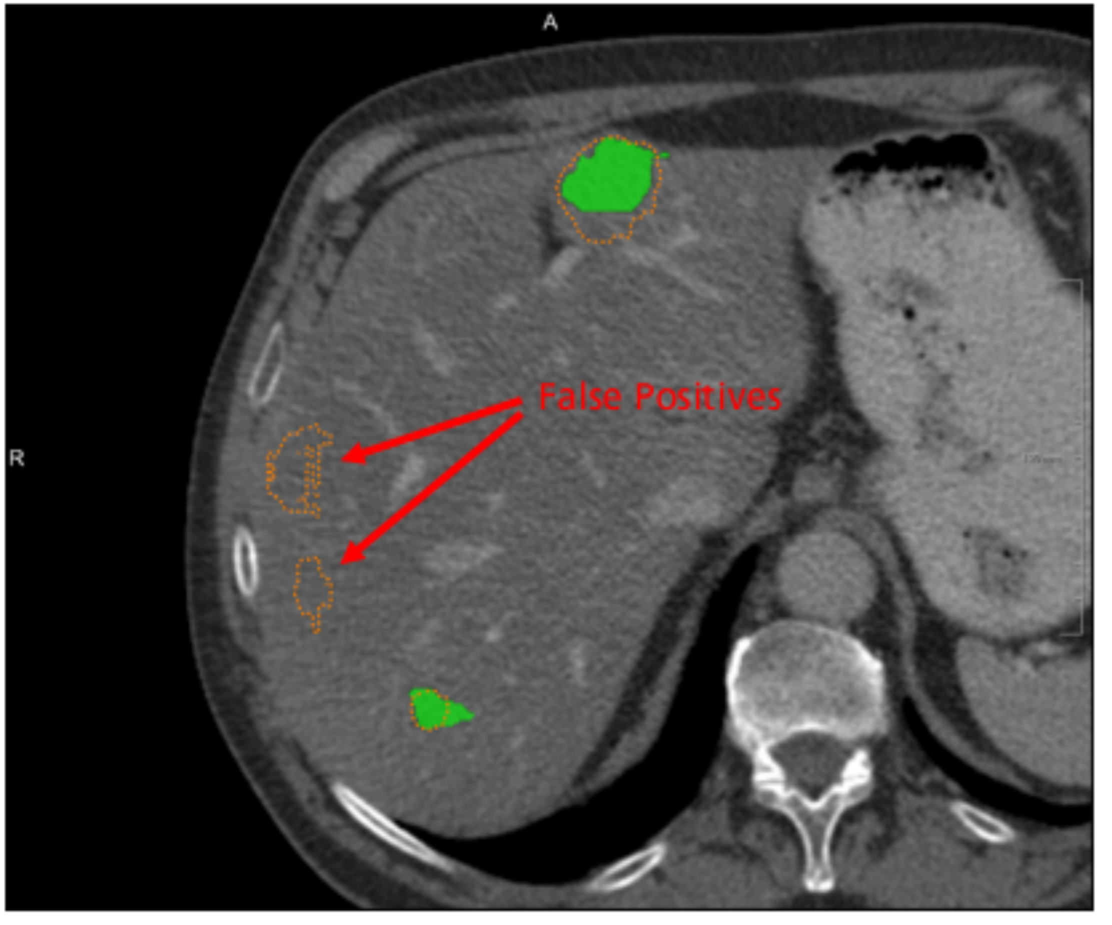


- False Positives (FPs) Problem

# Tumor Segmentation
# FPs Filtering

- Train another classifier to detect FPs
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  - Shape
  - DTF of the liver mask
- Random Forest (RF) accuracy ~90%

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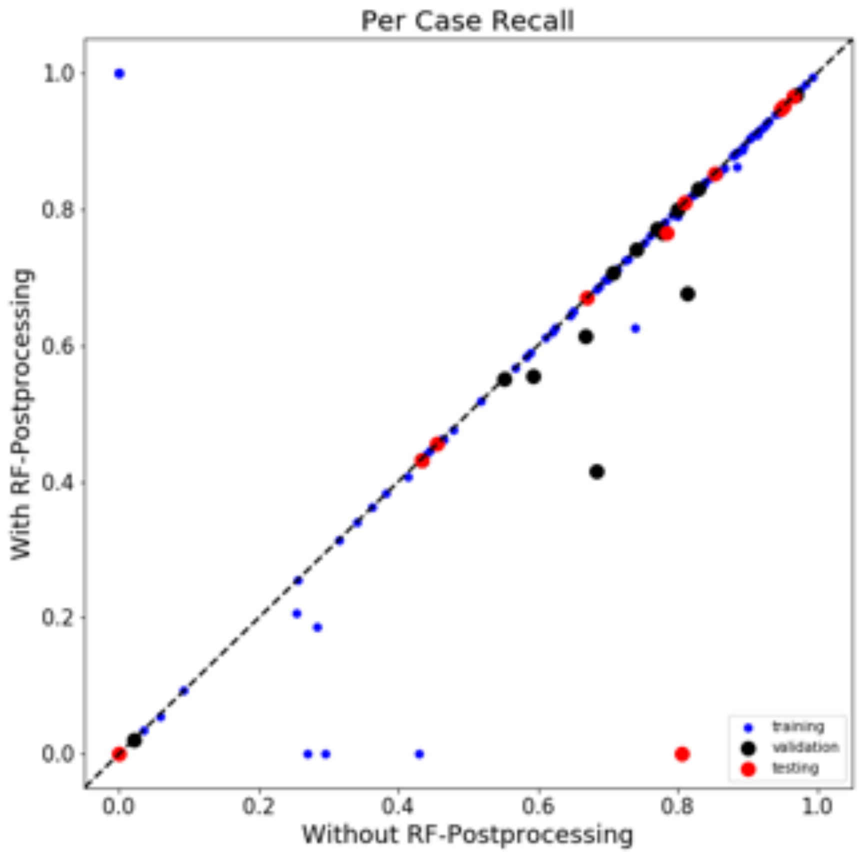

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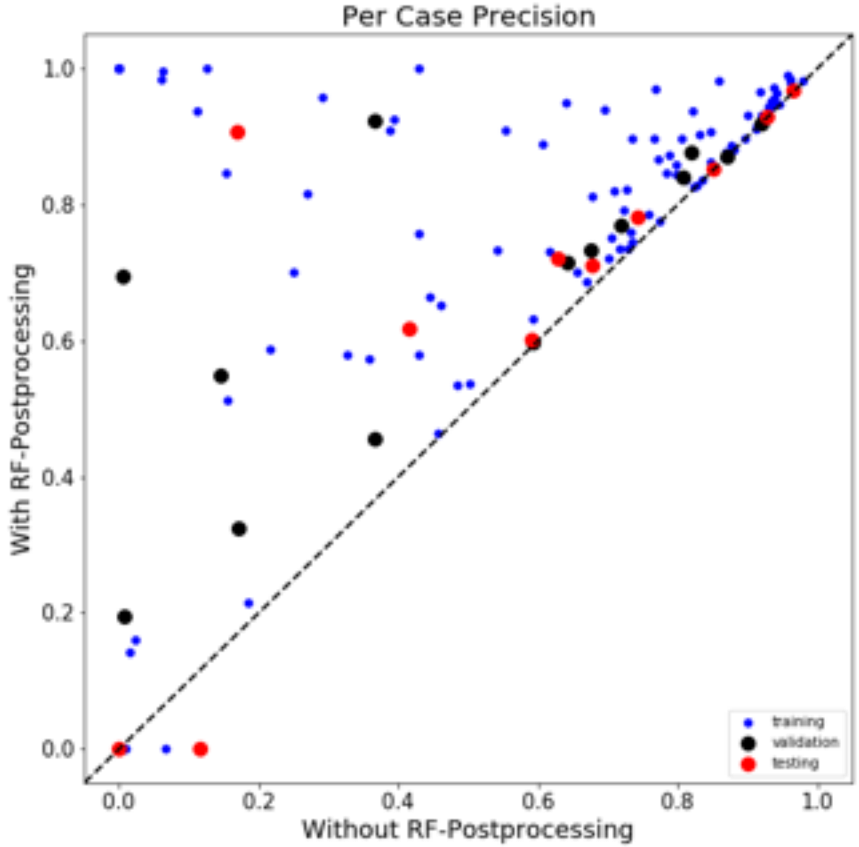

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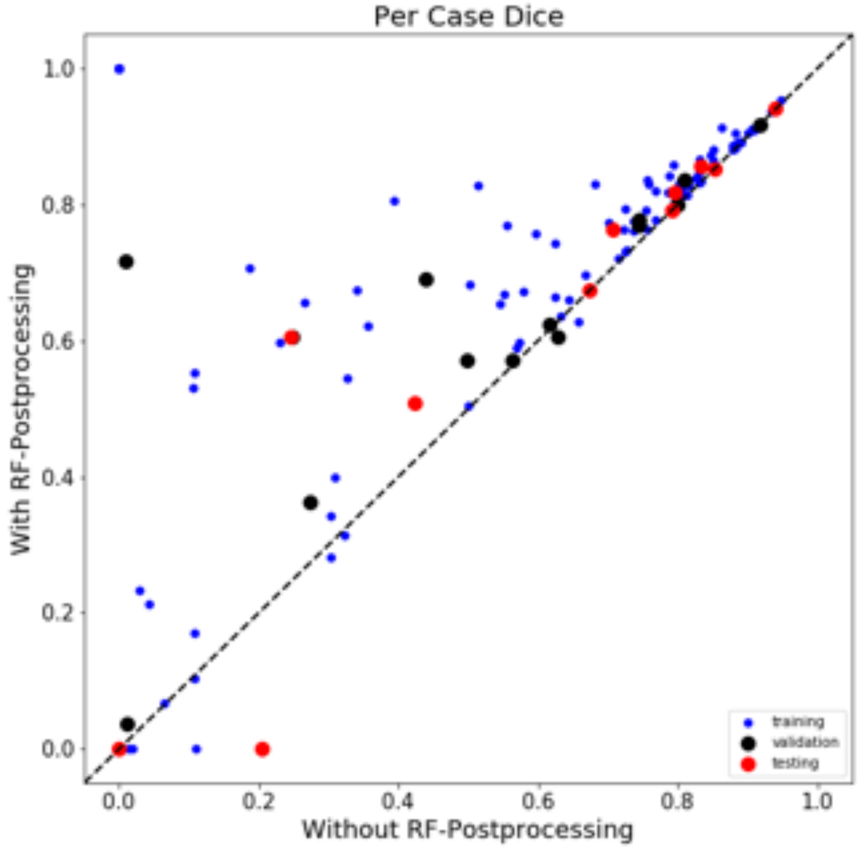






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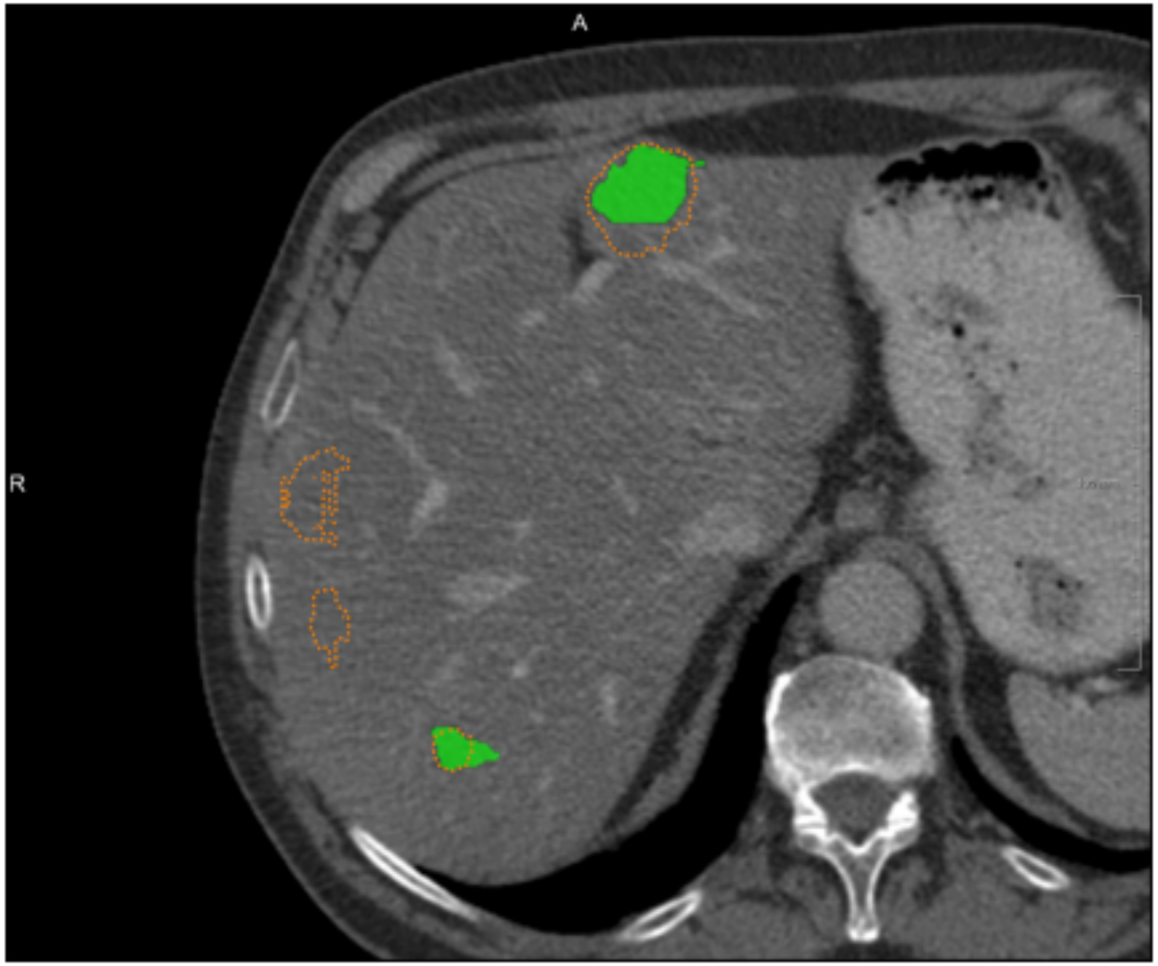
# Tumor Segmentation
# FPs Filtering Examples




Without RF-Postprocessing

# Tumor Segmentation
# FPs Filtering Examples


With RF-Postprocessing

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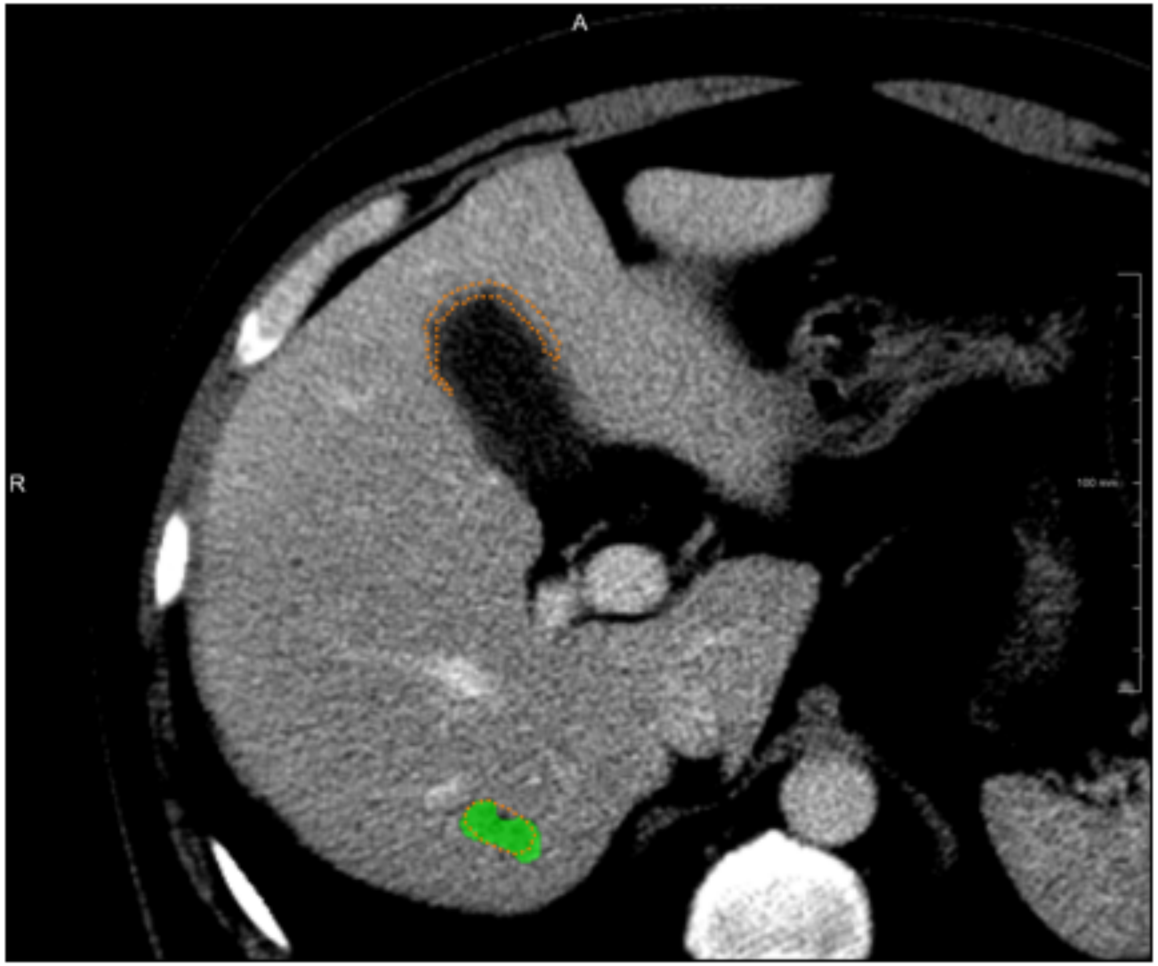


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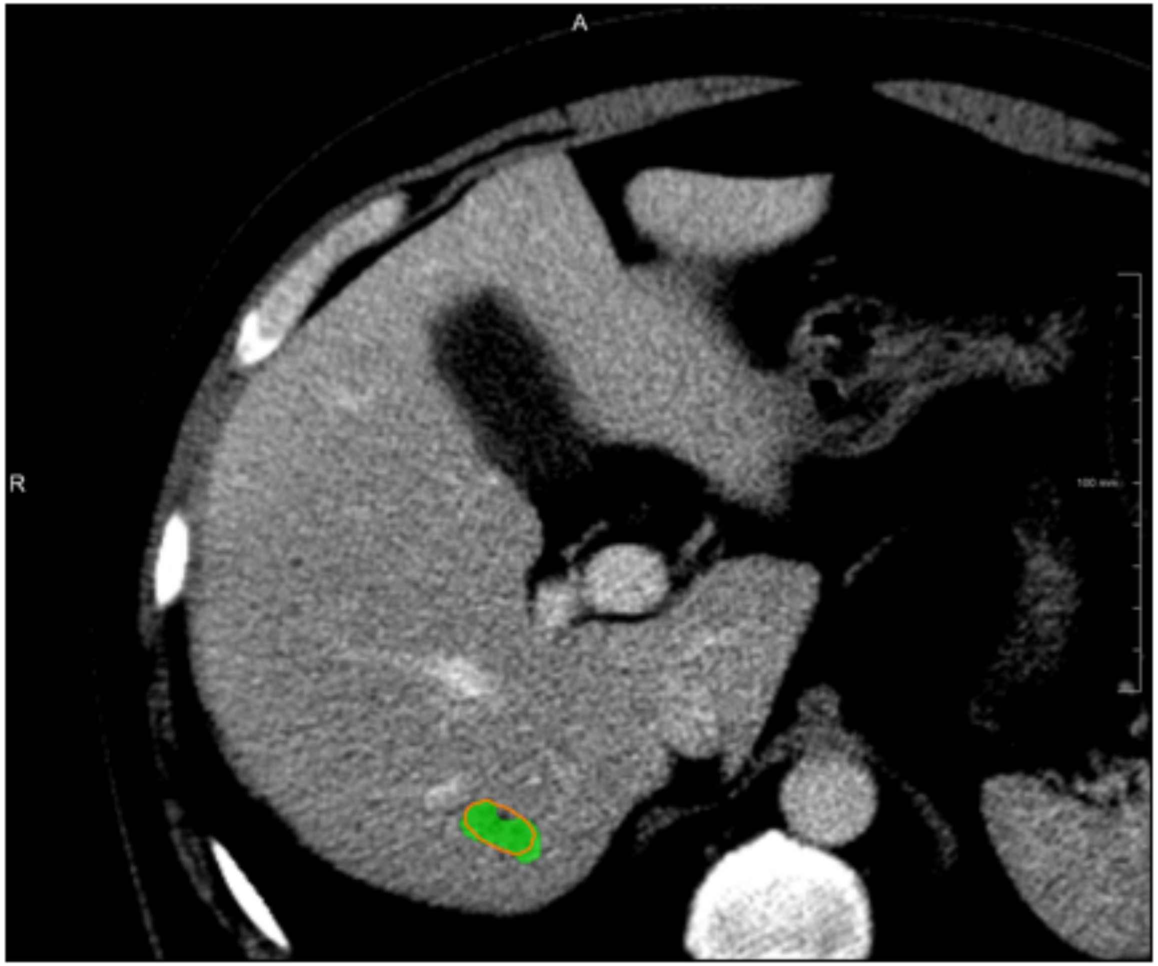
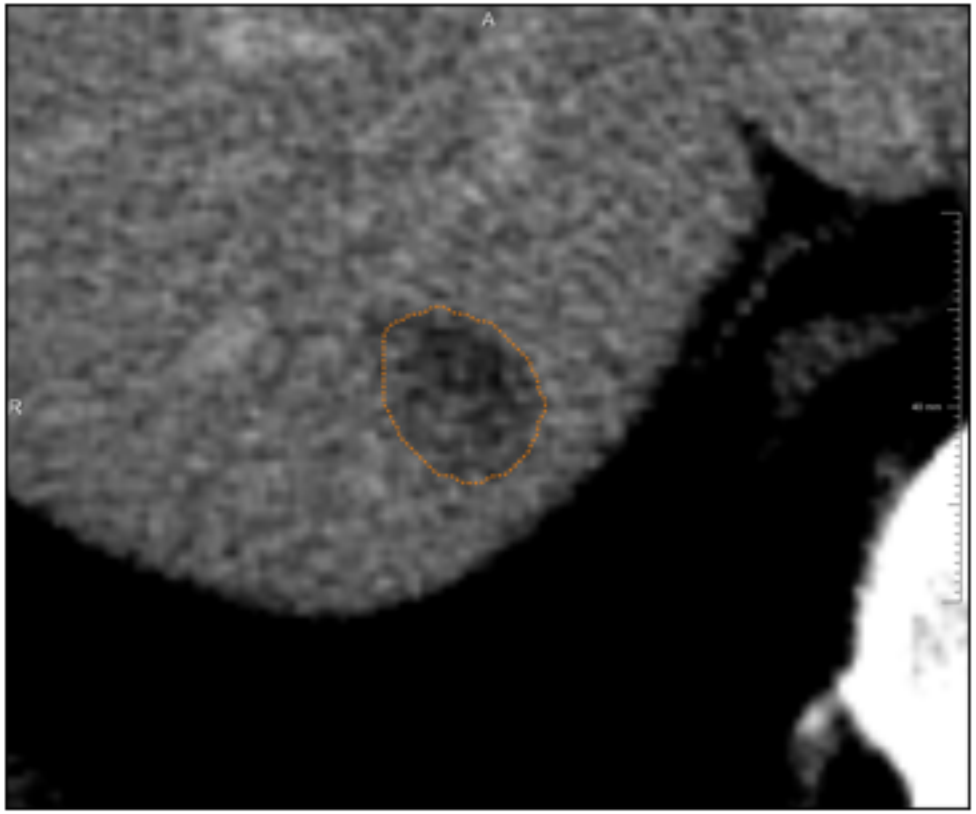



With RF-Postprocessing

# Tumor Segmentation
## FPs Filtering with Tumor Refinement

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

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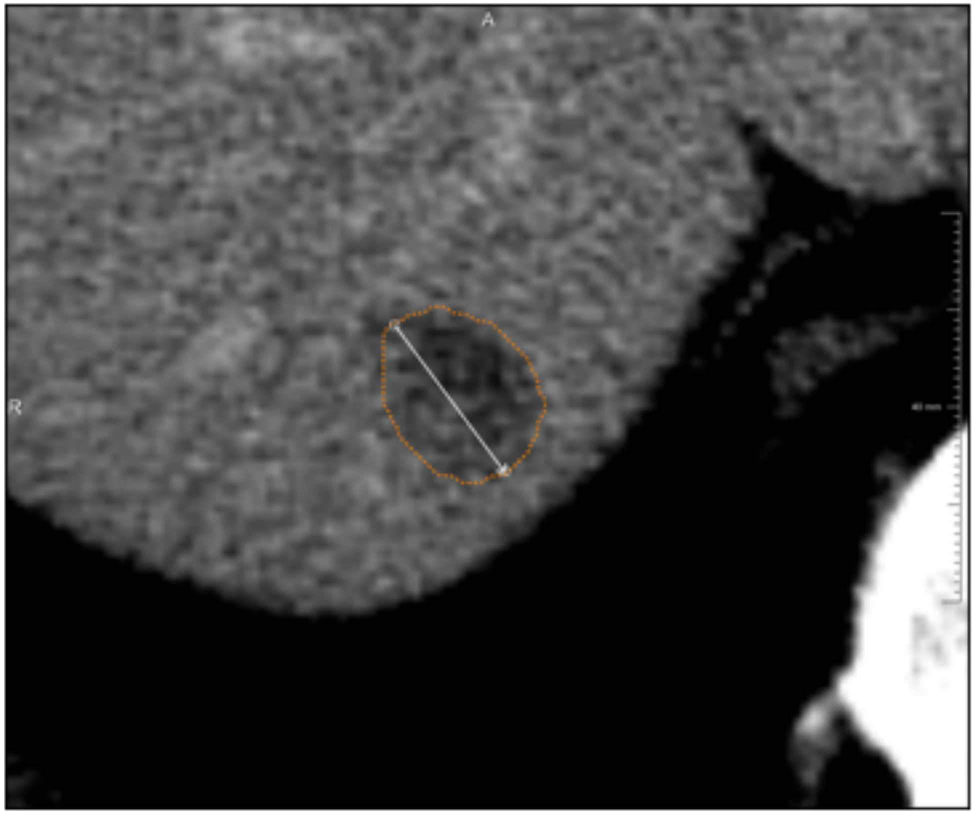


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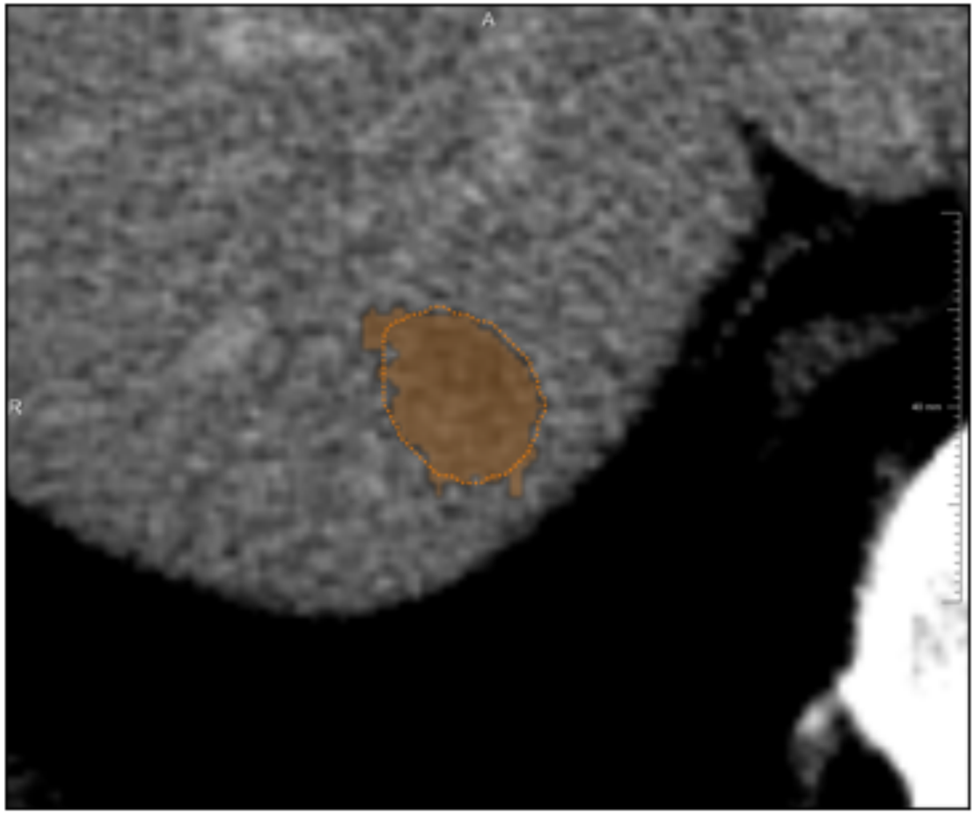


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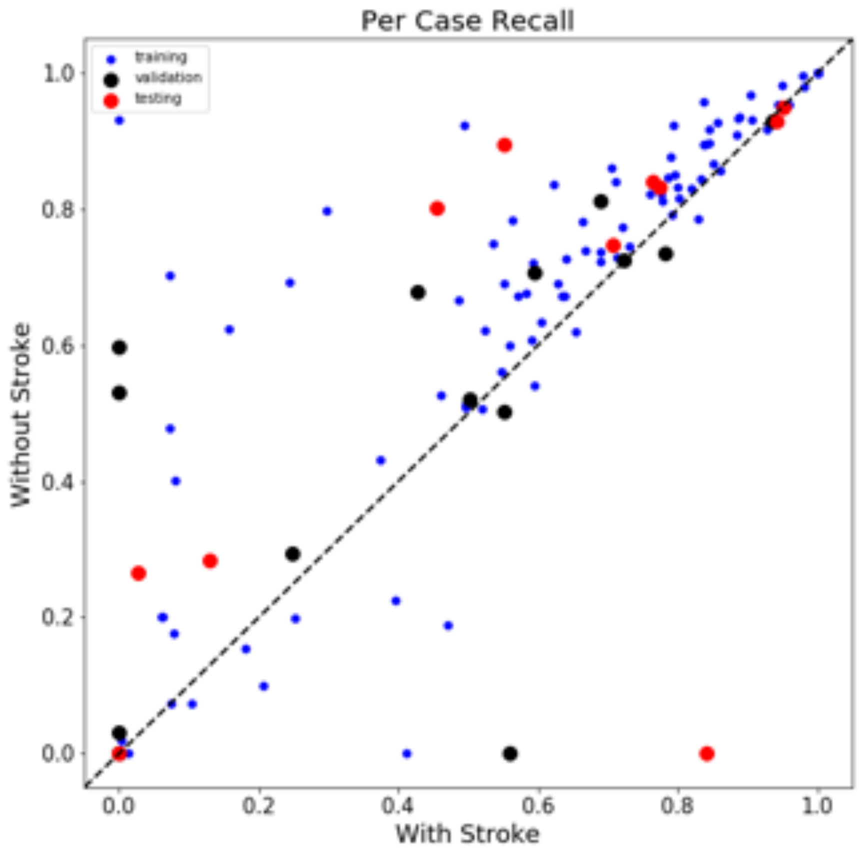






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# Tumor Segmentation
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Stroke application

- Segmentation refinement
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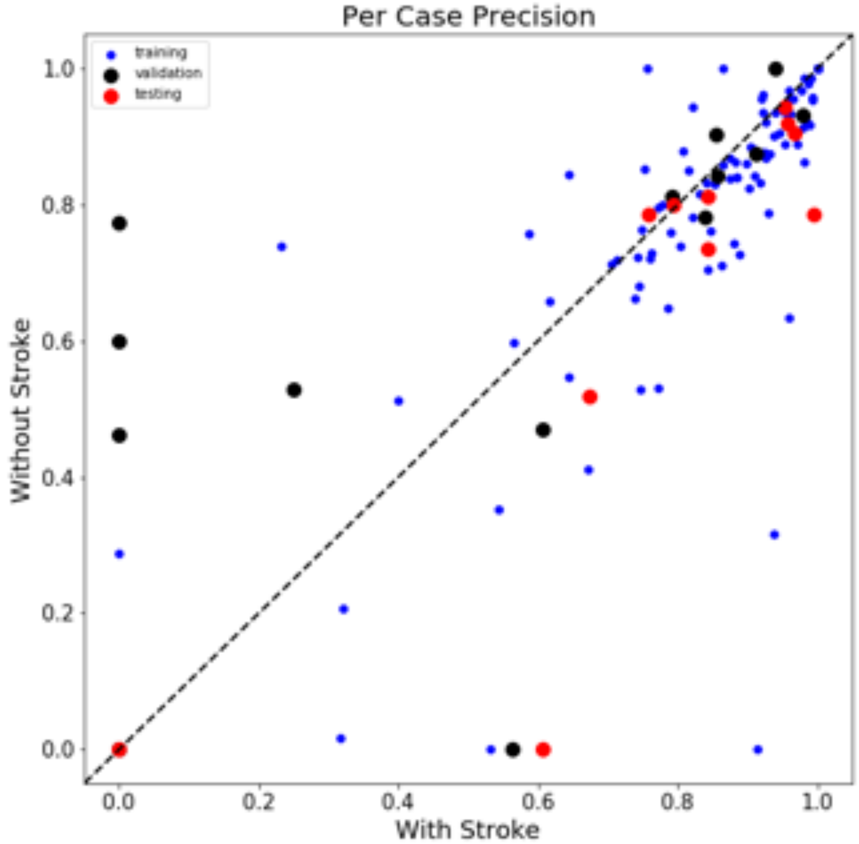
- Stroke vs No-Stroke:
  - Recall ↓
  - Precision ↑





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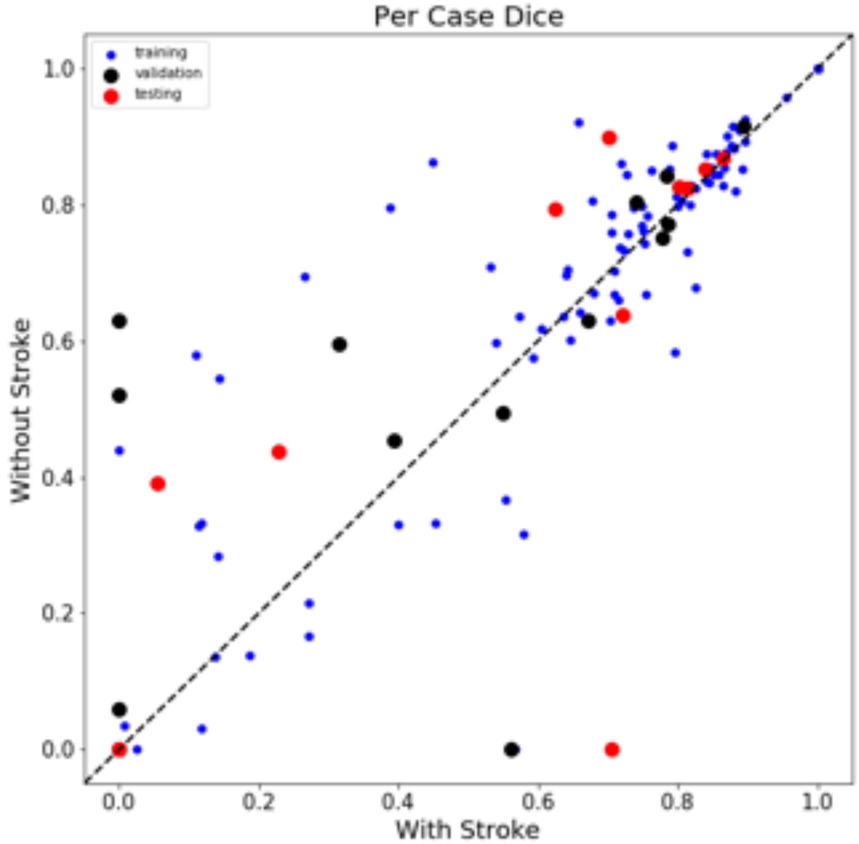

# 2.5D FCN Architecture

Idea:

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

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- 2.5D vs 2D:
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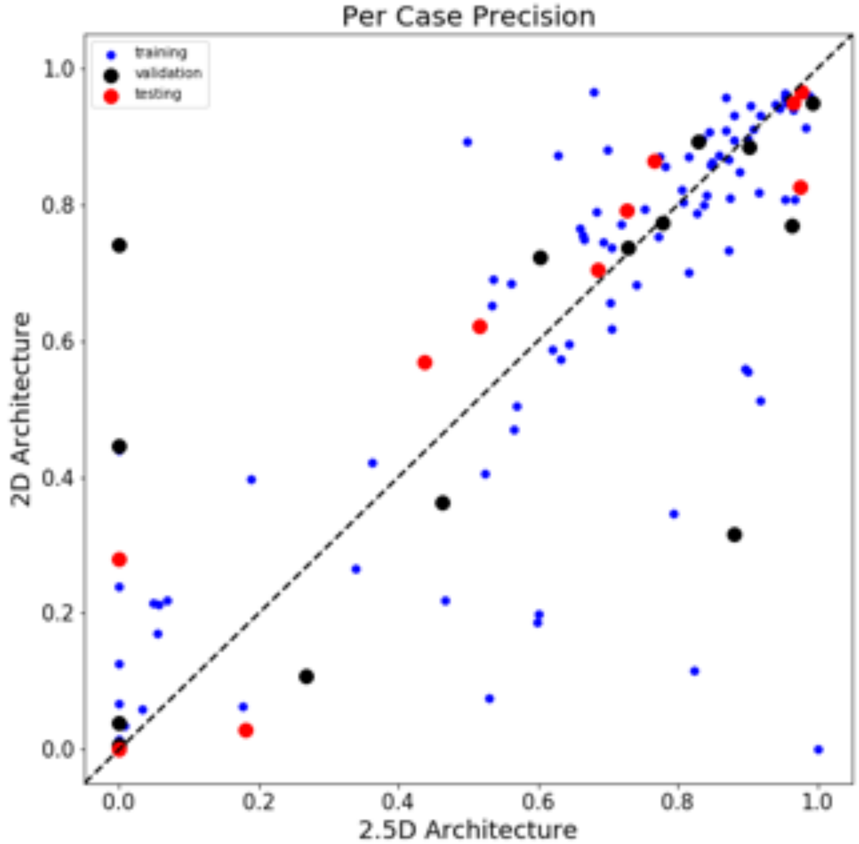


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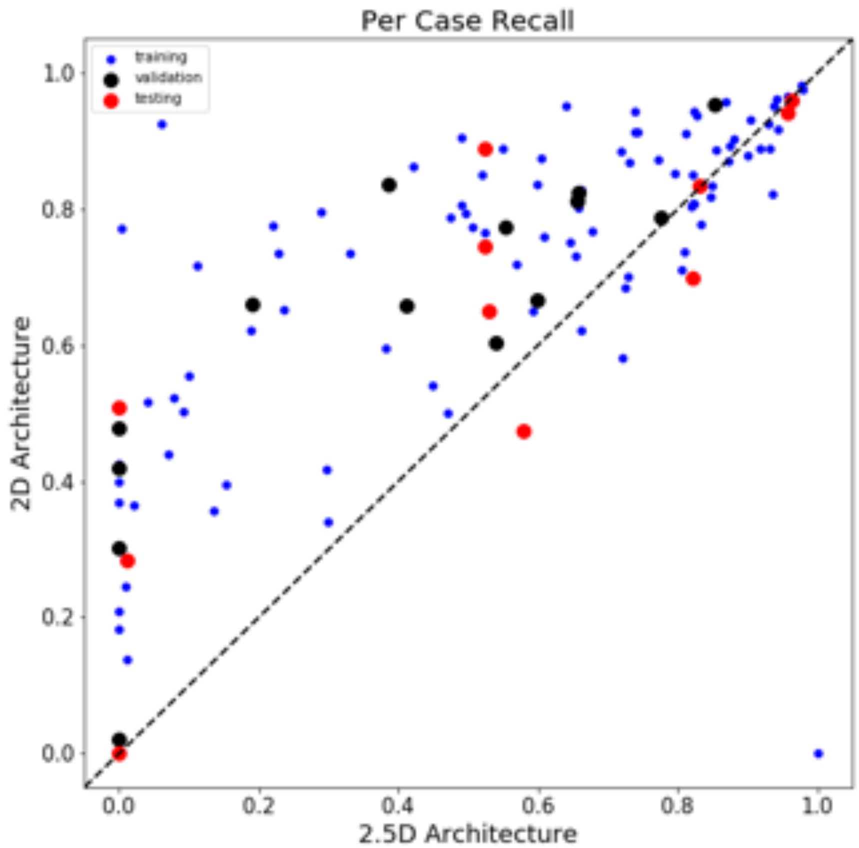



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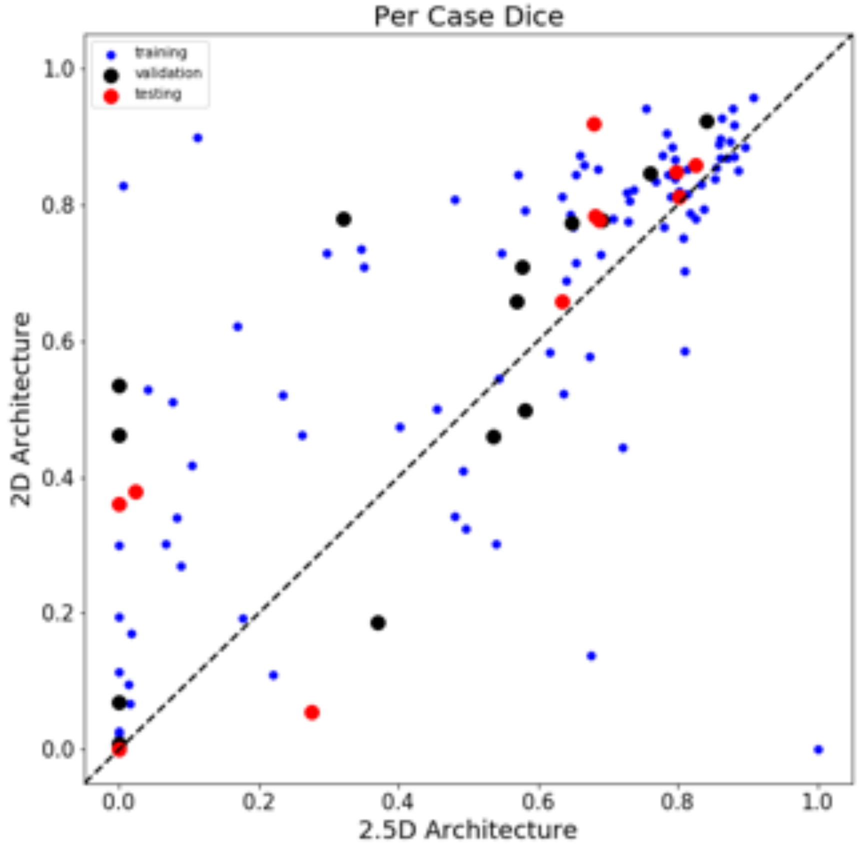


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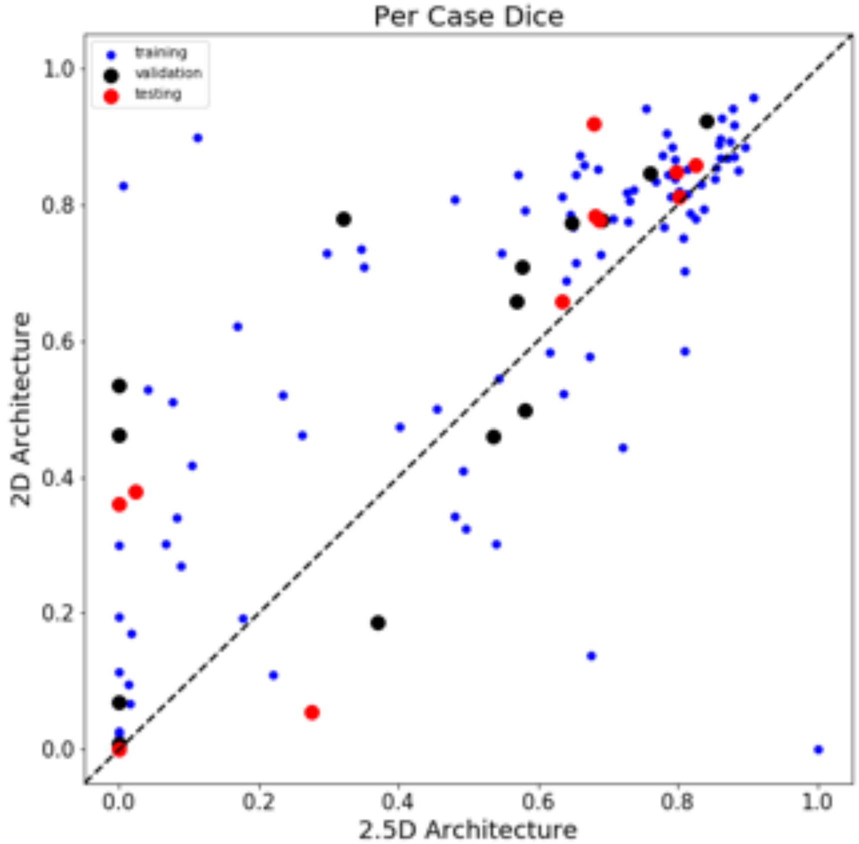
- Same observations for liver!





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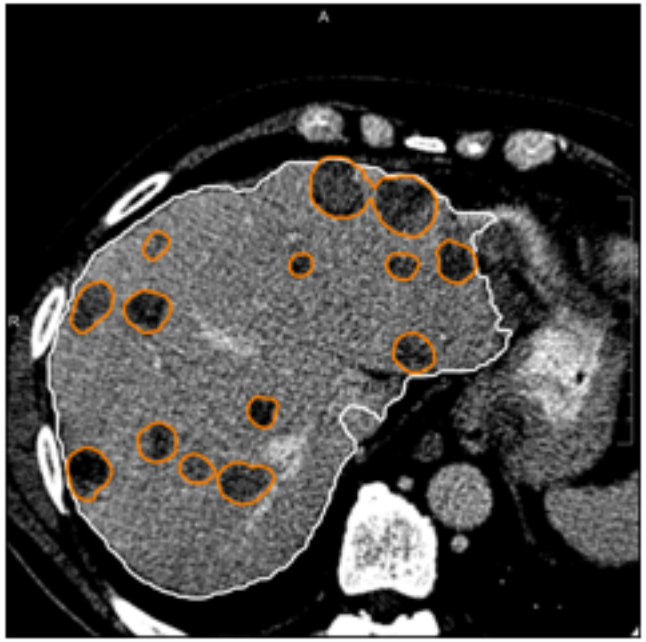

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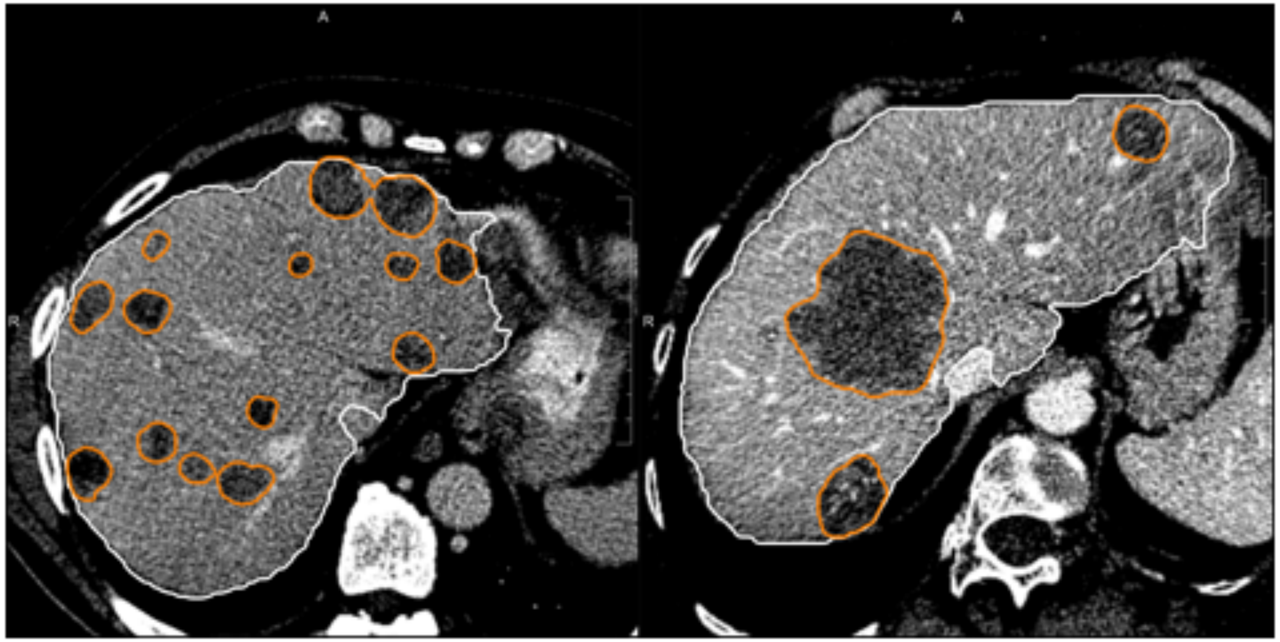

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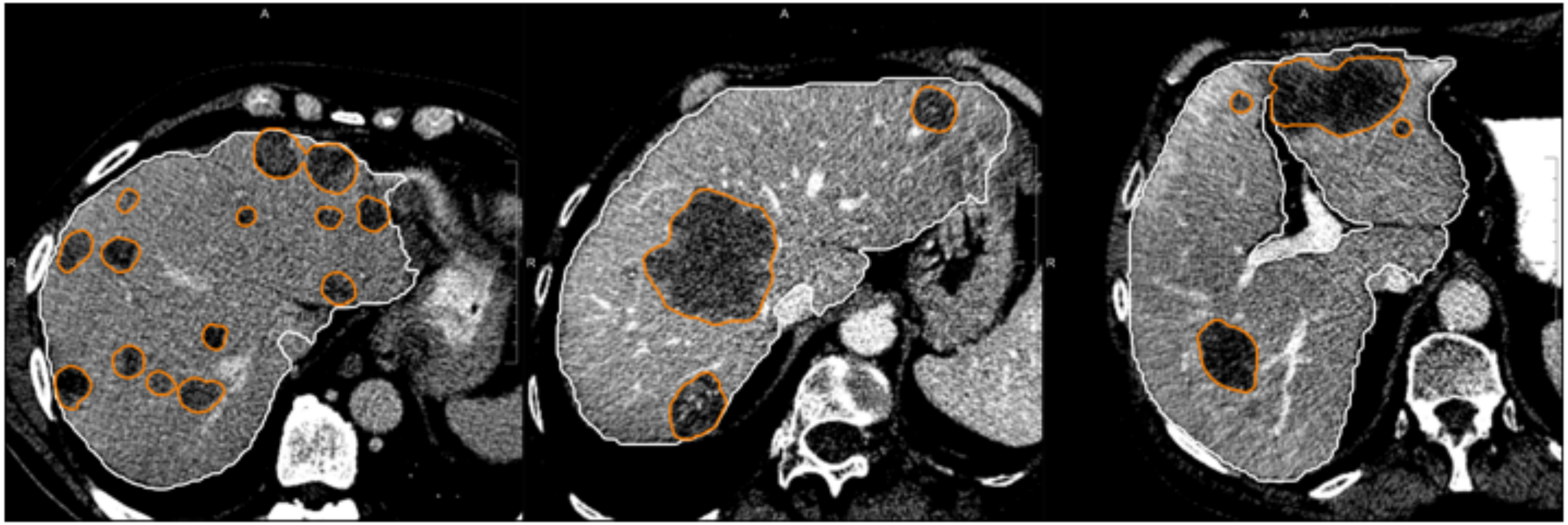






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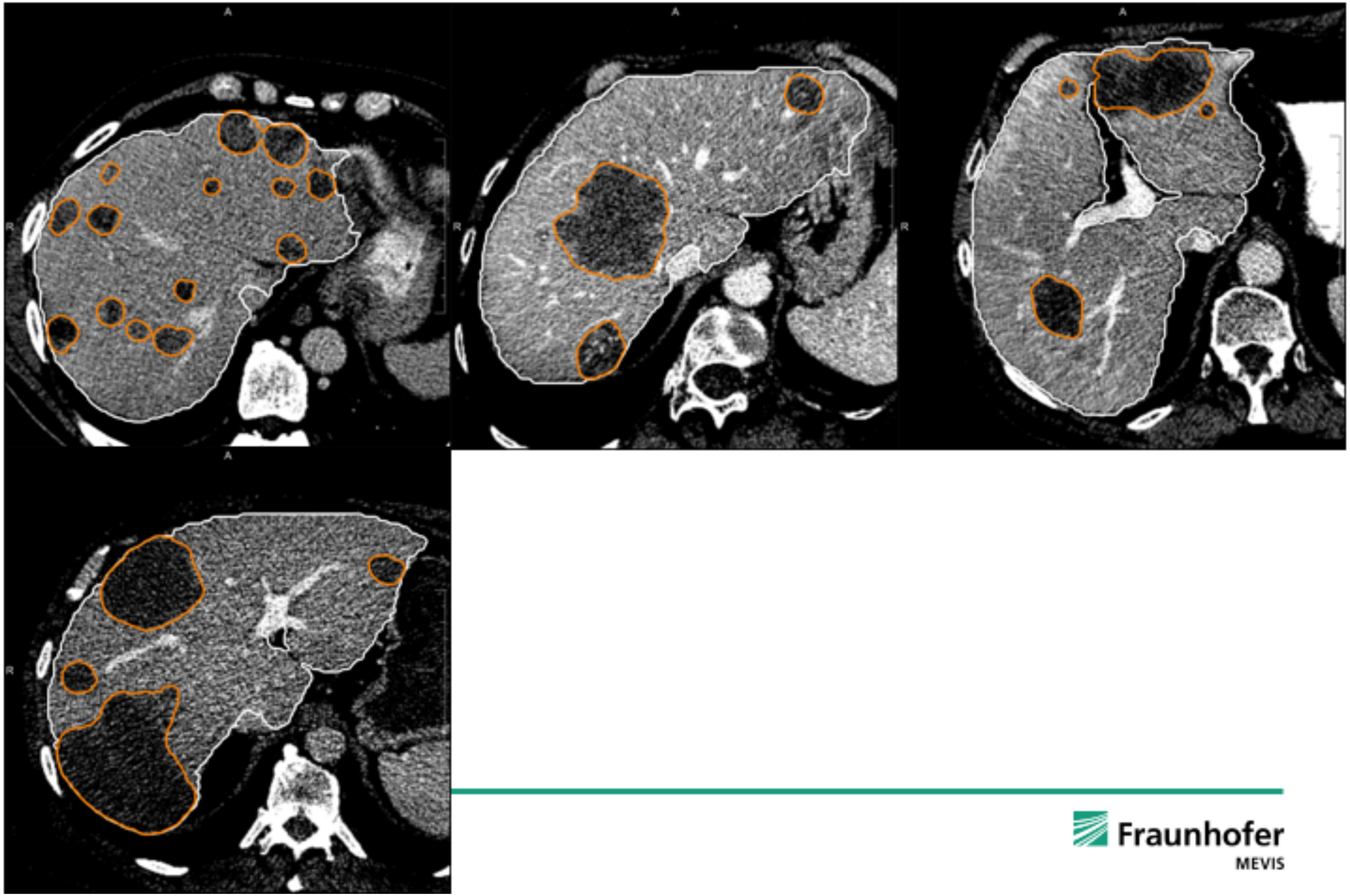
# Examples



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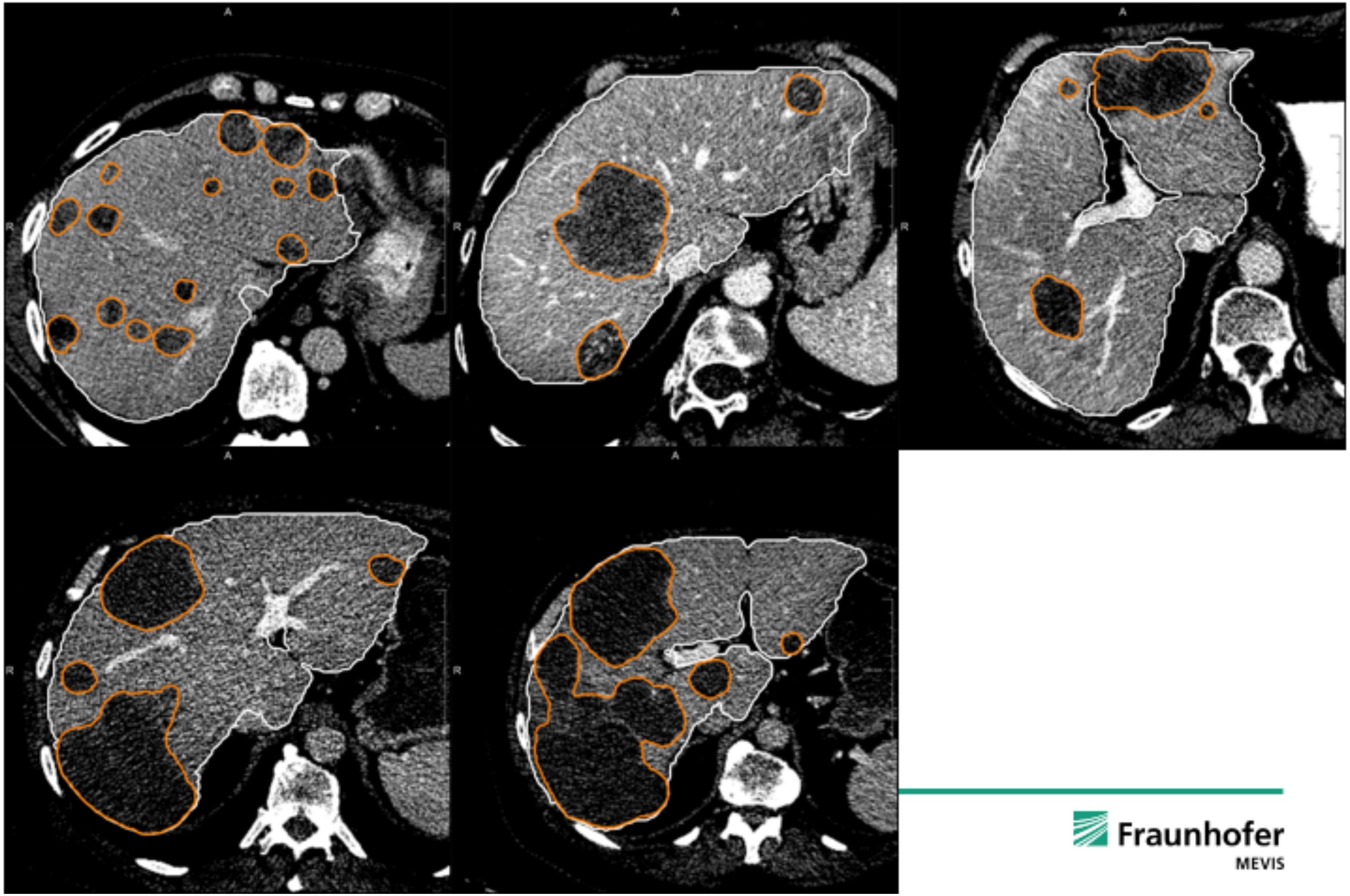

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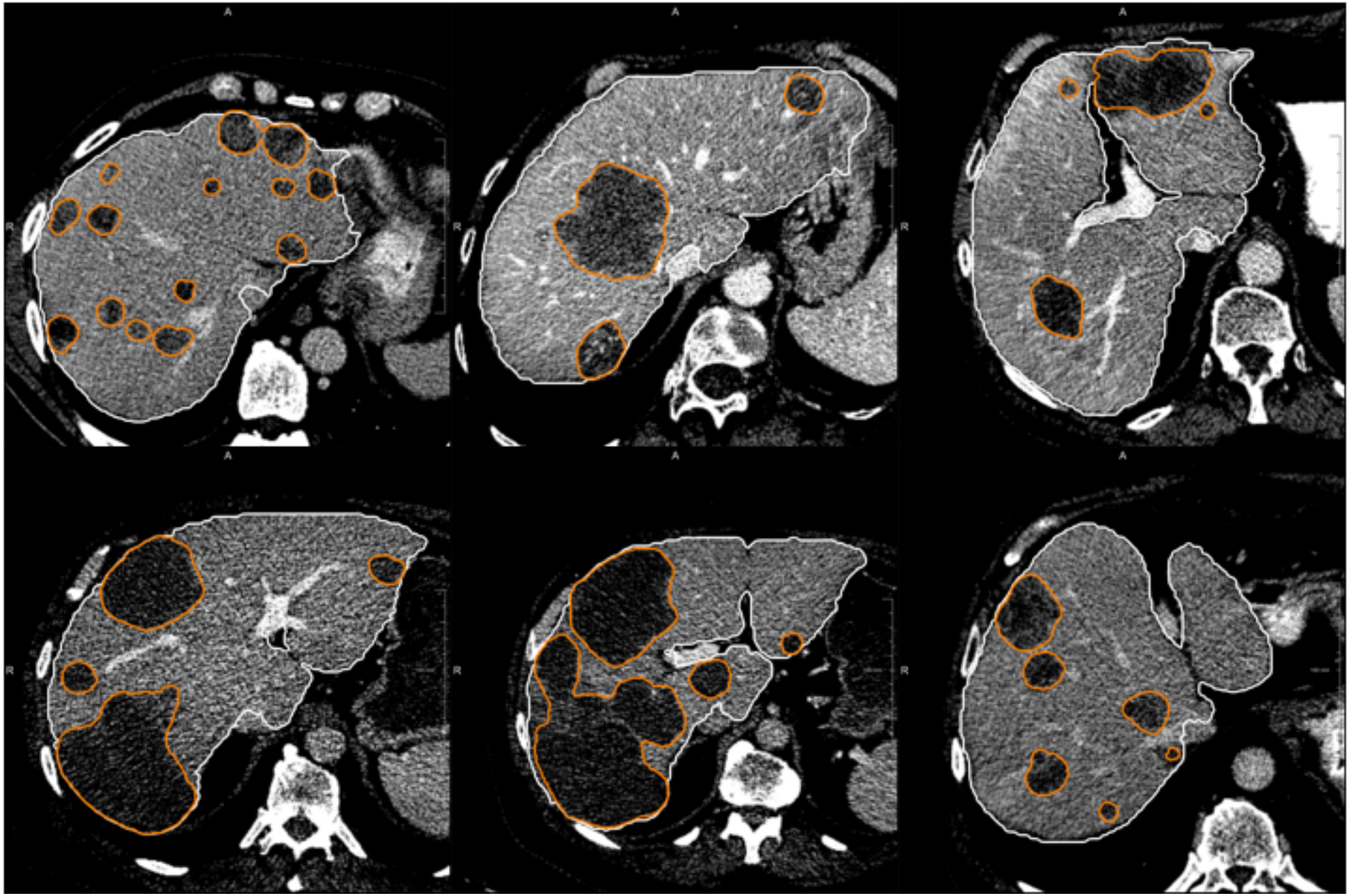
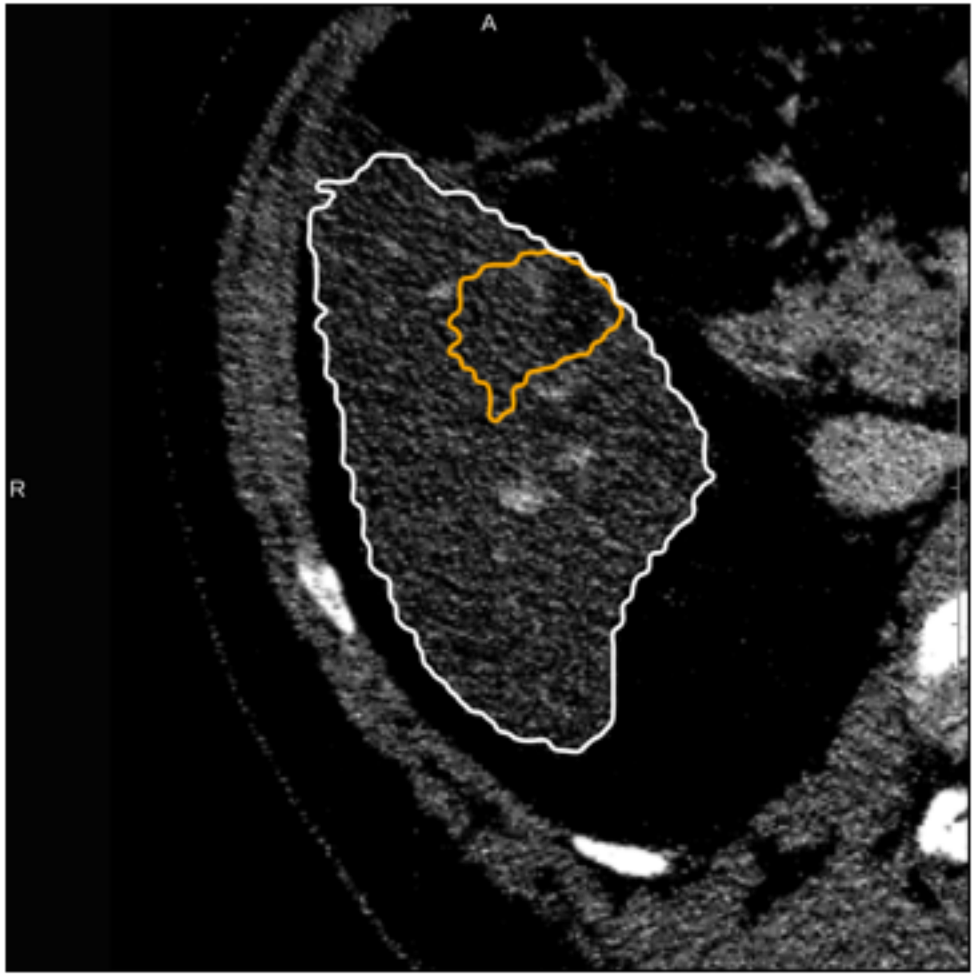


# Problematic Cases

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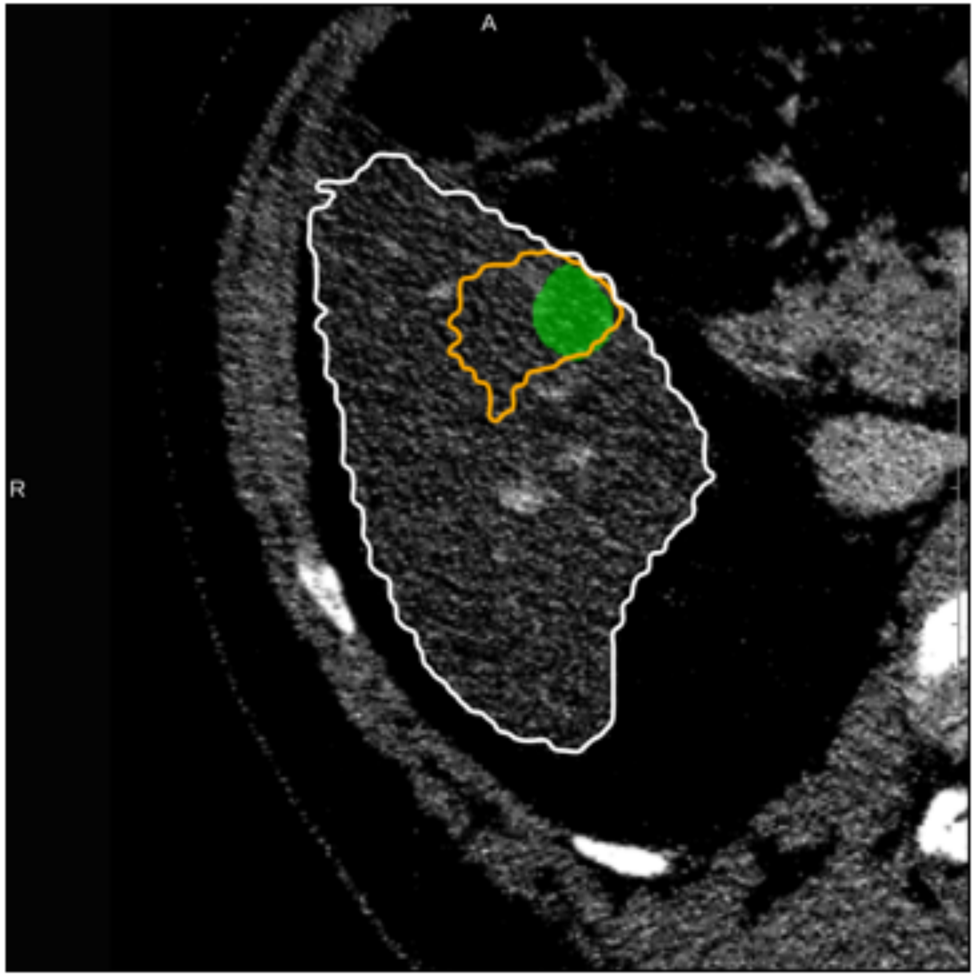


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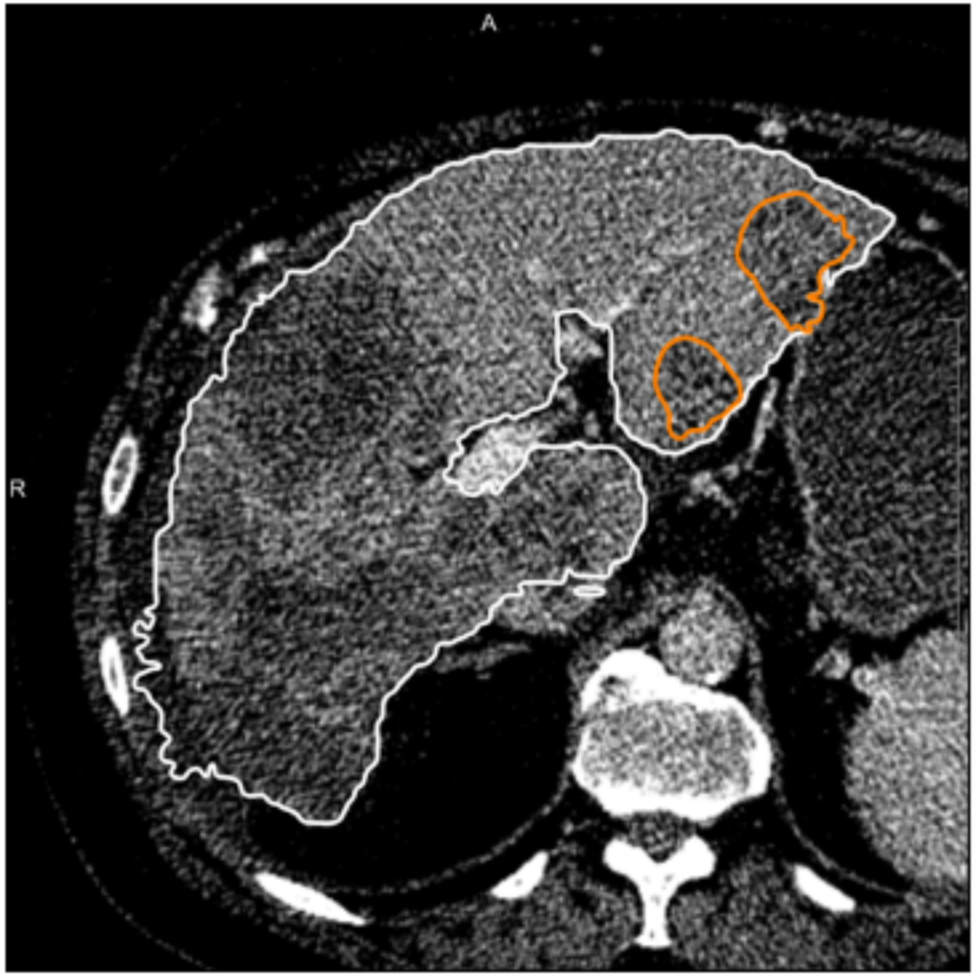
# Problematic Cases


- Liver mask misses tumors located near organ's border

# Problematic Cases


- Big tumors are not fully segmented

# Problematic Cases




- Obvious(?) tumors are completely missed

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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?**