AUTOMATIC LIVER AND TUMOR SEGMENTATION IN LATE-PHASE MRI USING FULLY CONVOLUTIONAL NEURAL NETWORKS

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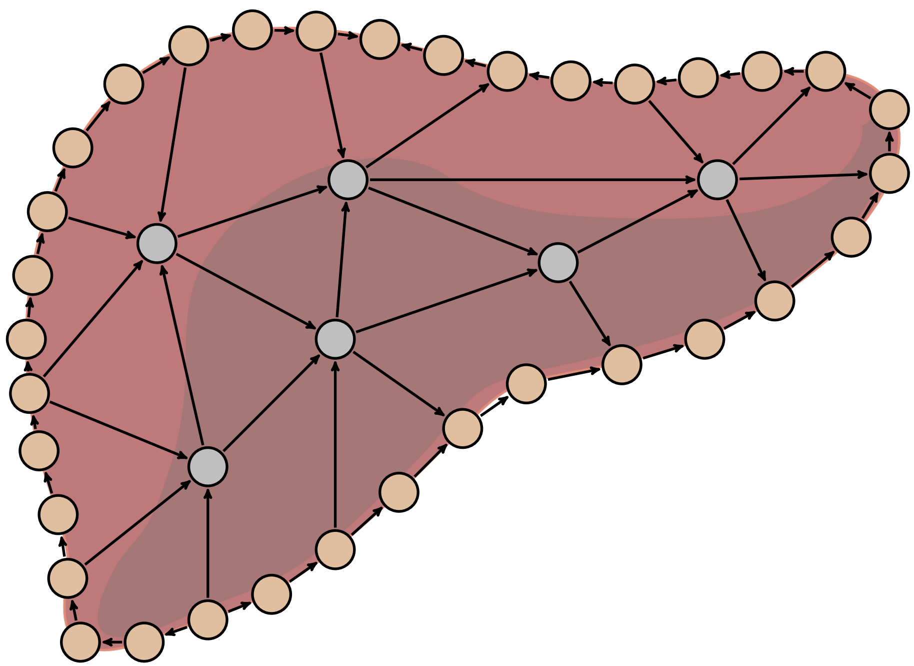

Medical Knowledge Through Research

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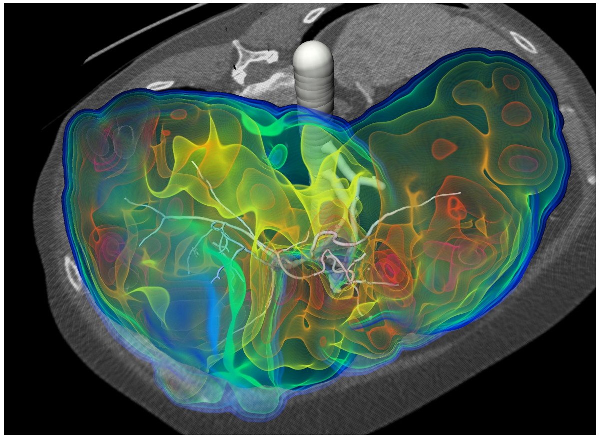
Background

- Liver & tumor segmentation is required for many liver interventions
- Radioembolisation
  - Basis for tumor load computation
  - Required for dose computation
- Manual or semi-automatic segmentation
  - Tedious and time consuming
  - inter-observer variability
- Well studied problem for CT
  - LiTS challenge 2017 (3rd place out of 28 teams) [1]



[1] http://lits-challenge.com/

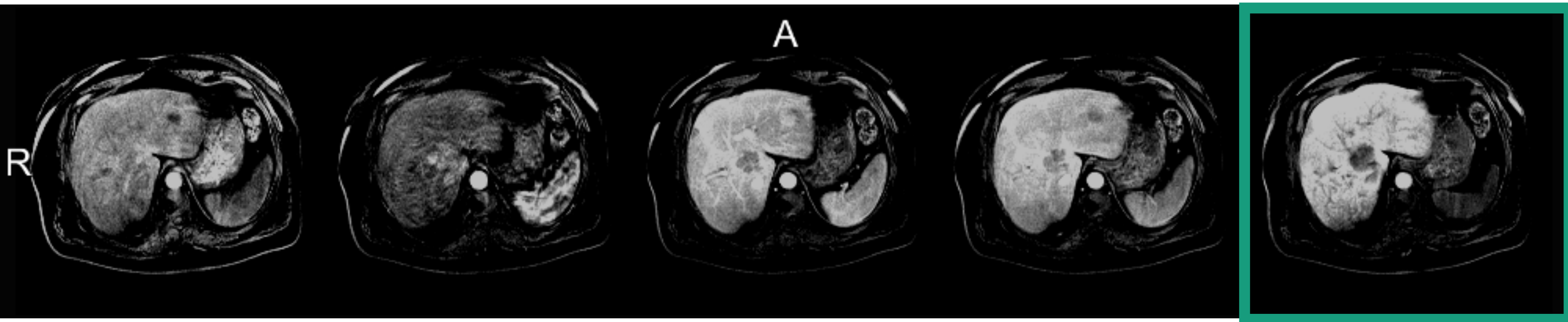
Goal

- Develop automatic DL-based algorithm for:
  - Liver segmentation
  - Liver tumor segmentation
- Comparison with:
  - Reference annotations
  - Clinical routine segmentations
  - Results reported in the literature
- Extends our previous work [1]

[1] Schenk A et al., "Deep learning for liver segmentation and volumetry in late phase MRI", ECR 2018.

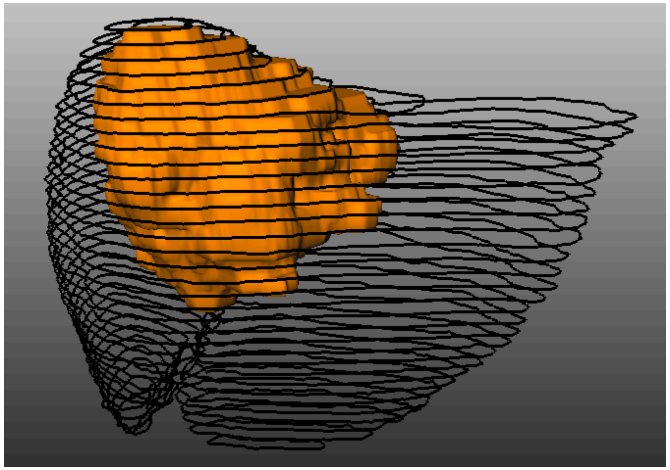
Data

- 90 patients with primary liver cancer and/or liver metastases
  - 76 scheduled for radioembolisation
- DCE-MRI
  - Acquired at Städtisches Klinikum Dresden, Germany
  - 3T Discovery MRI, GE Healthcare Systems, USA
  - Contrast agent Gd-EOB-EDPA (Primovist®, Bayer Healthcare)
  - LAVA sequence



Native 20s 60s 120s 15 min

Manual segmentations



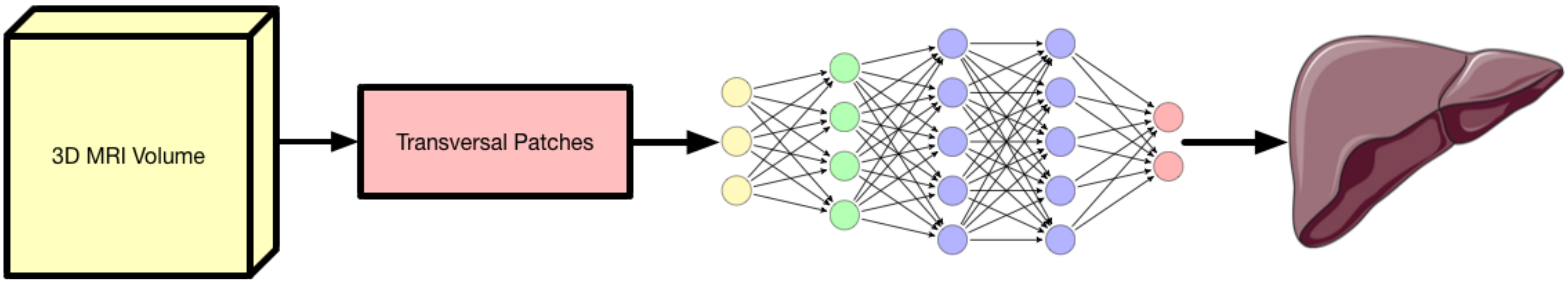
- Reference
  - Very precise and time consuming
  - Done by radiological assistants and reviewed by a radiologist
  - Used for training of deep learning models

- Routine
  - According to clinical routine standards
  - Defined by one radiologist and two residents
  - Contouring and interpolation software [1]

[1] Weiler F et al., "Building blocks for clinical research in adaptive radiotherapy", CURAC 2015.

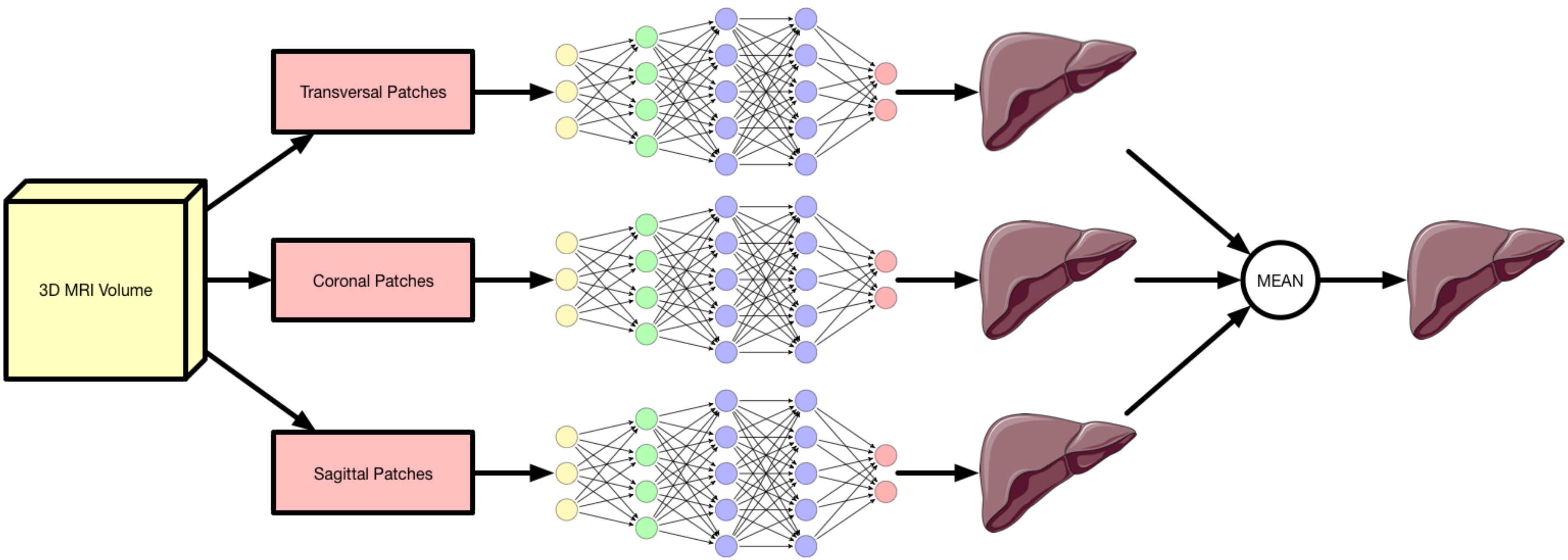
Segmentation Pipelines

- Axial



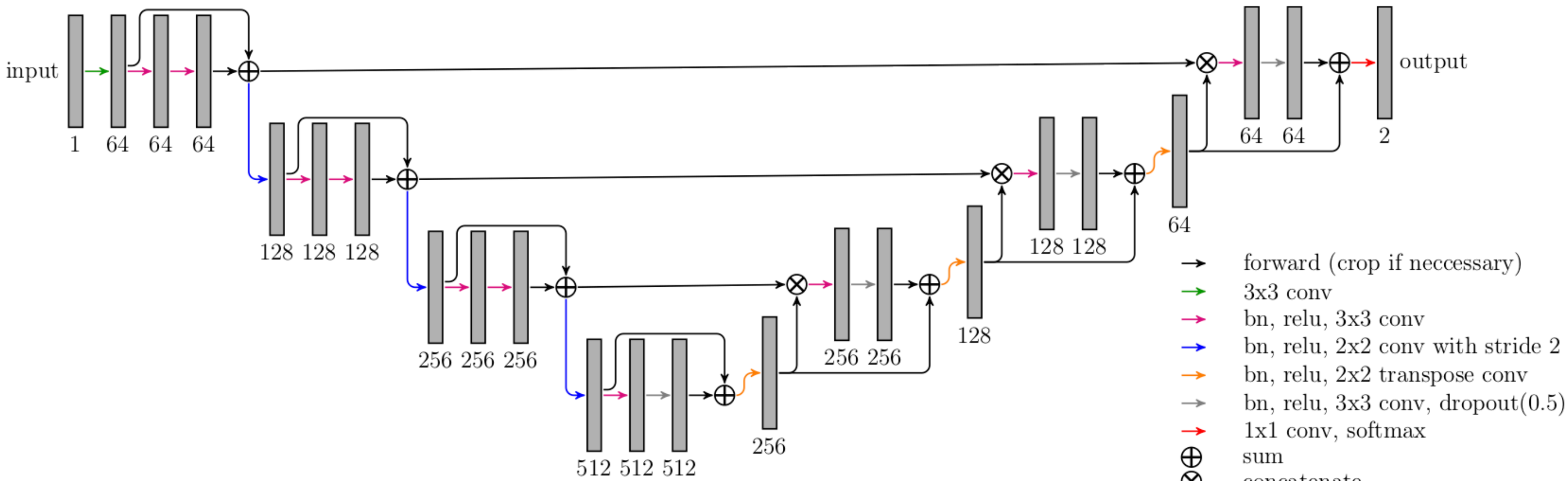
Segmentation Pipelines

- OrthoMean [1]



[1] Prasoon A et al., “Deep feature learning for knee cartilage segmentation using a triplanar convolutional neural network”, MICCAI 2013.

Neural network architecture



- U-net like [1]
- 4 resolution levels
- 9M trainable parameters
- Receptive field 94x94 voxels
- 3x3 convolution kernels
- Short skip connections [2]
- Batch normalization
- Spatial dropout

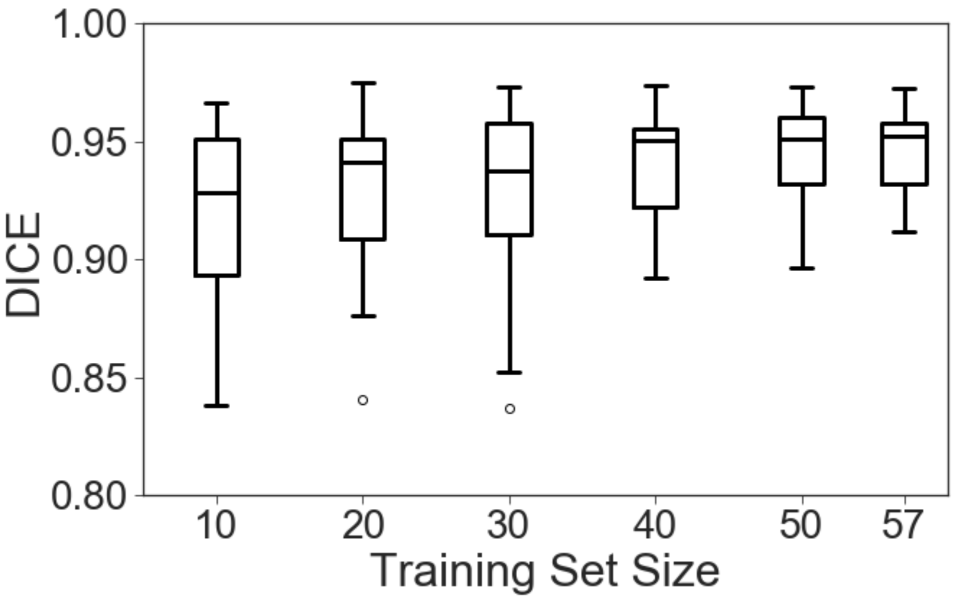
[1] Ronneberger O et al., "Convolutional networks for biomedical image segmentation", MICCAI 2015.
[2] Drozdzal M et al., "The importance of skip connections in biomedical image segmentation", 2016.

Data preprocessing

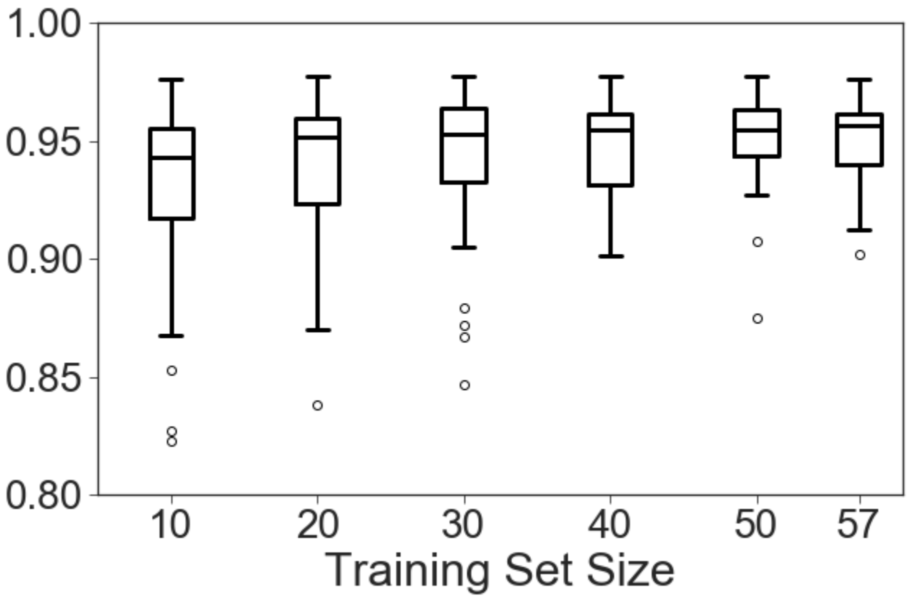
- Normalization
  - 2nd and 98th percentiles mapped to [0, 1] range
- Resampling to a 2mm isotropic voxel size
- Training data augmentation
  - Random rotations
  - Random intensity shifts
- Training/validation/evaluation split
  - 57/5/28 liver
  - 60/5/20 liver tumor

Results: Training Data Size

- Liver segmentation quality

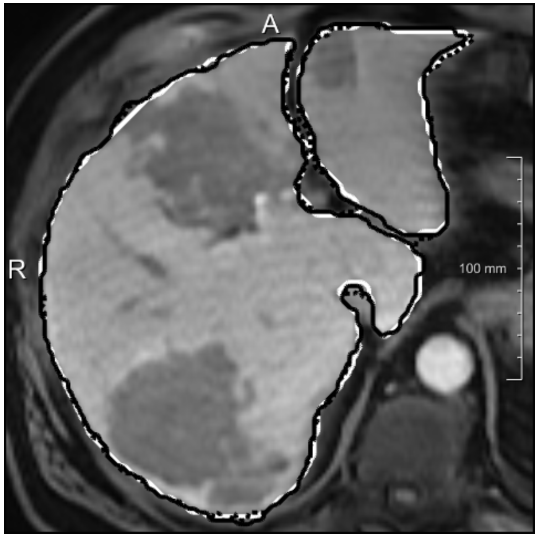


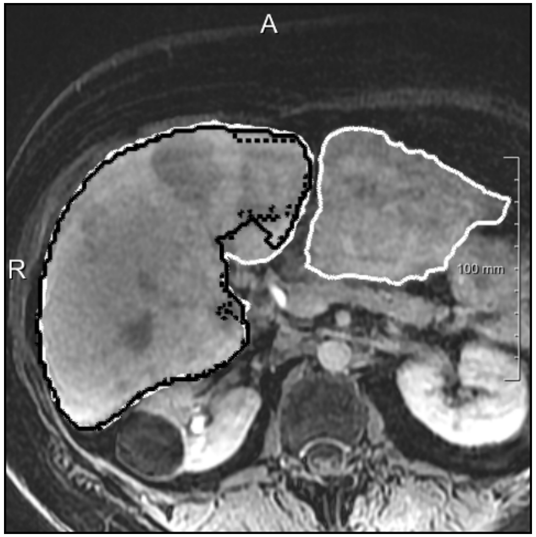
Axial



OrthoMean

Examples: Liver



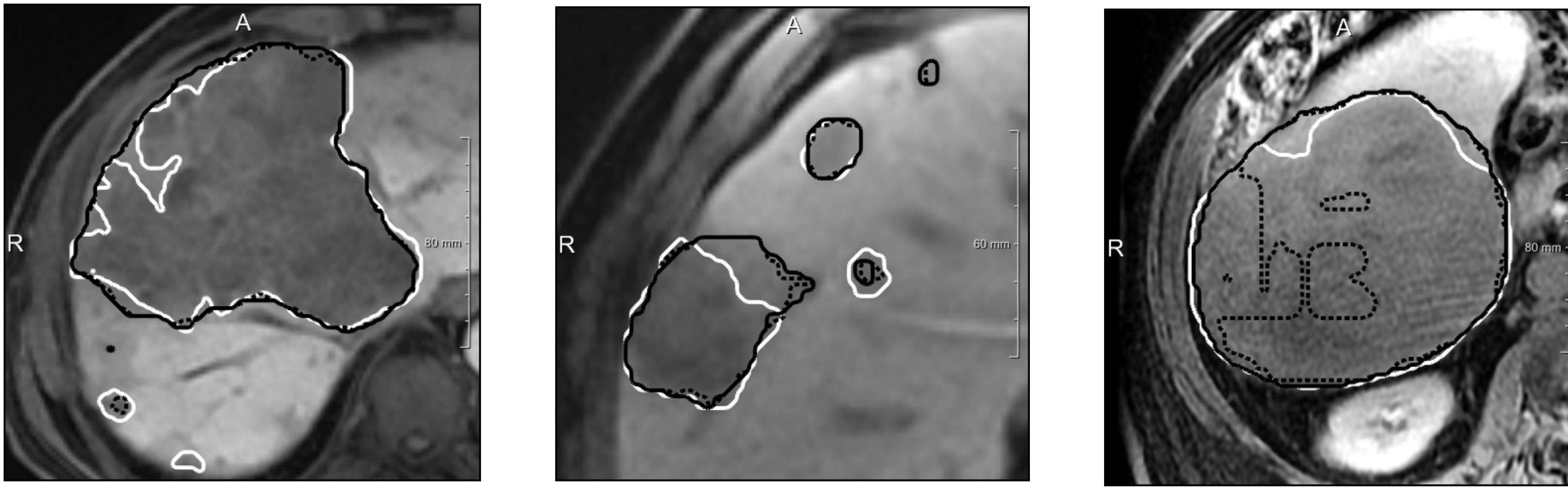


White – Reference

Solid black – Axial

Dashed black – OrthoMean

Examples: Liver tumors



White – Reference

Solid black – Axial

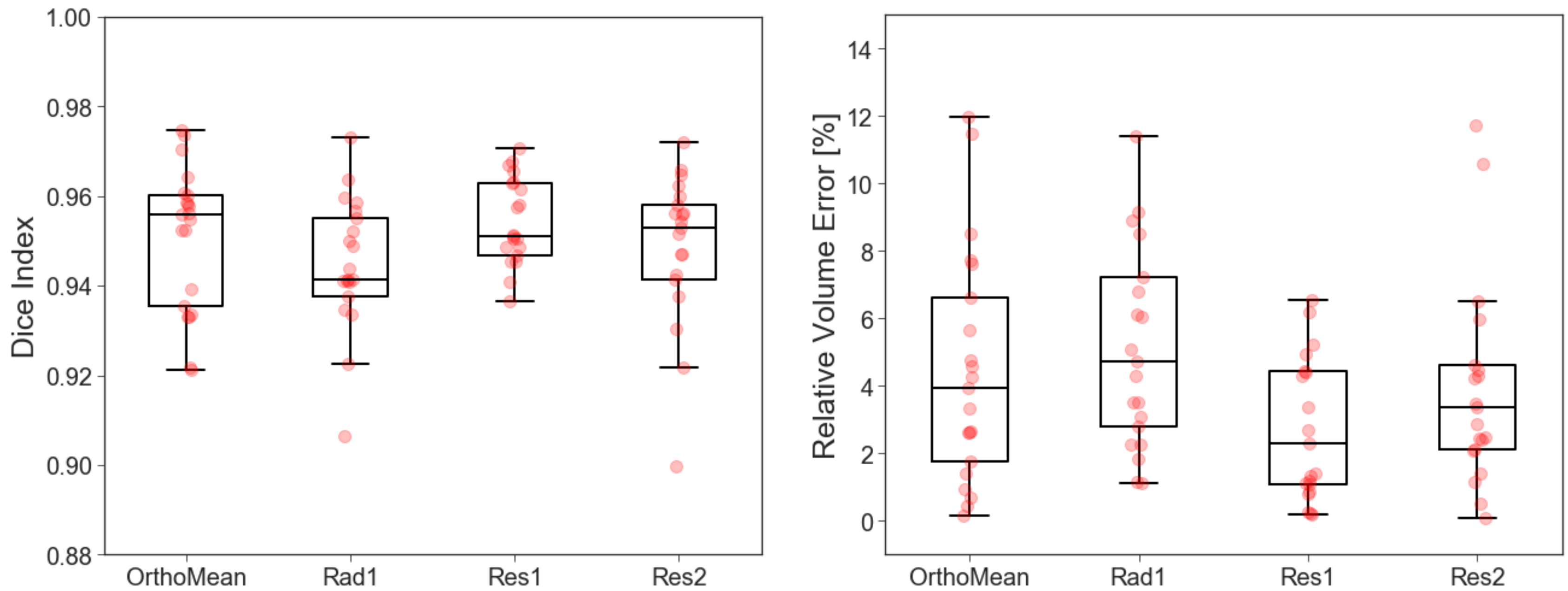
Dashed black – OrthoMean

Results

- Axial vs OrthoMean

	DICE	RVE[%]	t[s]
Liver			
Axial	0.946 ± 0.018	4.20 ± 3.34	2.05 ± 0.34
OrthoMean	0.951 ± 0.018	4.20 ± 3.65	7.32 ± 0.36
Tumor			
Axial	0.627 ± 0.241	48.9 ± 53.3	1.73 ± 0.73
OrthoMean	0.647 ± 0.210	35.9 ± 28.2	7.63 ± 2.23

Results: Comparison with routine segmentations of the liver



- Manual routine segmentations: 10 ± 4 min
- OrthoMean: 7.3 ± 0.4s

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Comparison with literature

	DICE	#	Dataset Sequence	Scanner	Resolution [mm]	Slice thickness [mm]
Liver						
Axial, OrthoMean	0.946 ± 0.018, 0.951 ± 0.018	90	LAVA	3T Discovery(GE)	0.74-1.76	2.0-5.0
Christ et al. [6]	0.870	31	n/a	1.5T Avanto(Siemens)	n/a	5.0
Suzuki et al. [7]	0.936 ± 0.017*	23	LAVA, THRIVE	1.5T Signa HDx/HDxt(GE), 1.5T Achieva(Philips)	1.17-1.72	4.0-5.0
Le et al. [8]	0.910 ± 0.028	10	VIBE	1.5T Avanto(Siemens)	1.18-1.40	3.5-4.0
Bereciartua et al. [9]	0.902 ± 0.086	18	VIBE	1.5T Avanto(Siemens)	n/a	n/a
Huynh et al. [10]	0.911 ± 0.019	27	VIBE, LAVA, THRIVE	1.5T Signa HDx/HDxt(GE), 1.5T Achieva(Philips), 1.5T Avanto(Siemens)	1.17-1.72	3.5-5.0
Ivashchenko et al. [11]	n/a	5	mDIXON	n/a	1.00	1.5
Tumor						
Axial, OrthoMean	0.627 ± 0.241, 0.647 ± 0.210	85	LAVA	3T Discovery(GE)	0.74-1.76	2.0-5.0
Christ et al. [6]	0.697	31	n/a	1.5T Avanto(Siemens)	n/a	5.0

* Average for CT and MRI dataset.

- Direct comparison not possible due to differences in datasets

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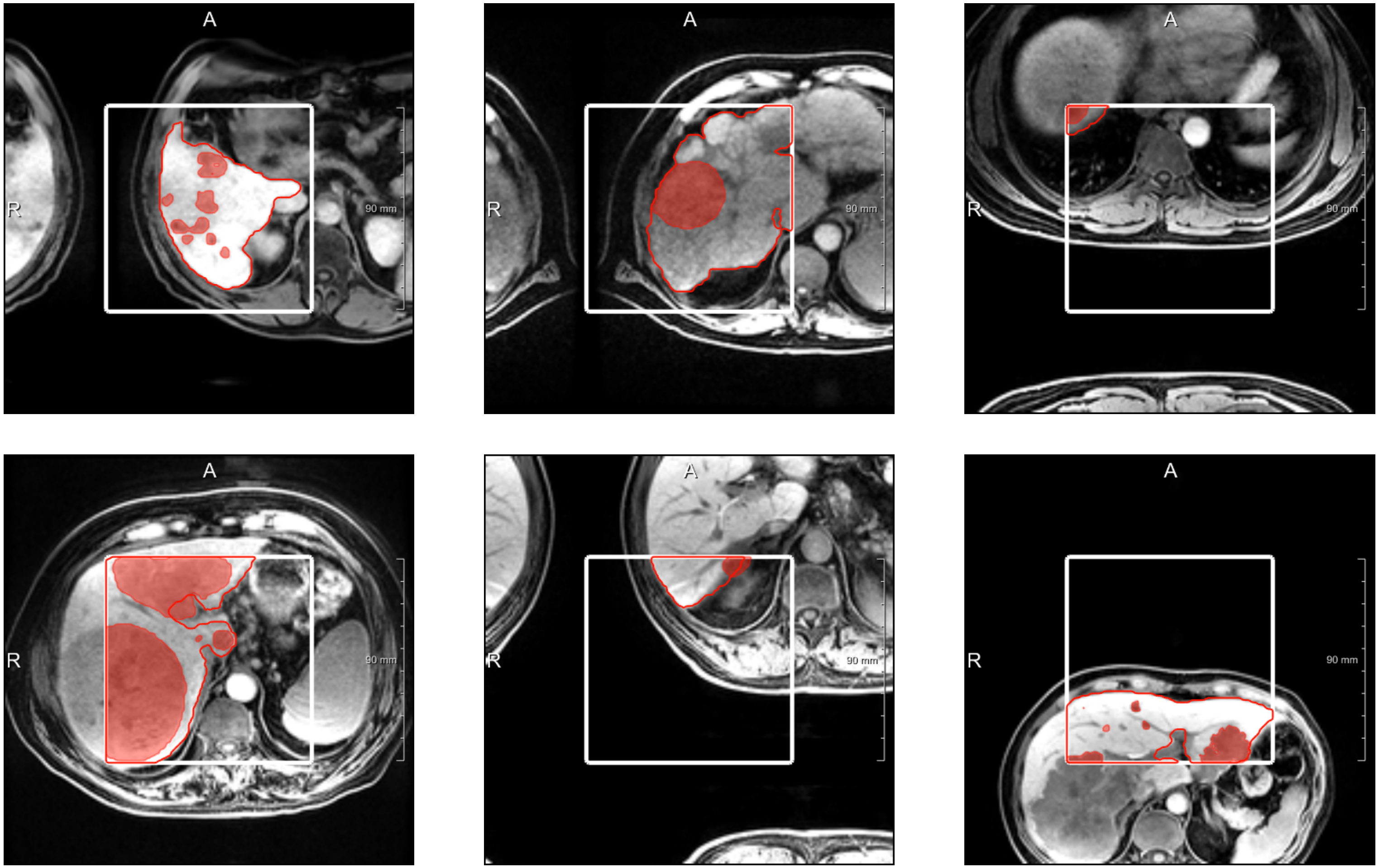
Summary

- Liver segmentation quality of our segmentation approaches was comparable to that of manual routine segmentations
- Tumor segmentation is a more difficult task than liver segmentation
- Acquiring more training data has a positive impact on the model performance
- Direct comparisons with other methods remain difficult due to lack of publicly available data
- Future work
  - More extensive validation
  - Evaluation of 3D architectures

Thank you for your attention ☺

Questions?

What does the neural network see?



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