COMPARISON OF DEEP LEARNING AND SHAPE MODELING FOR AUTOMATIC CT-BASED LIVER SEGMENTATION

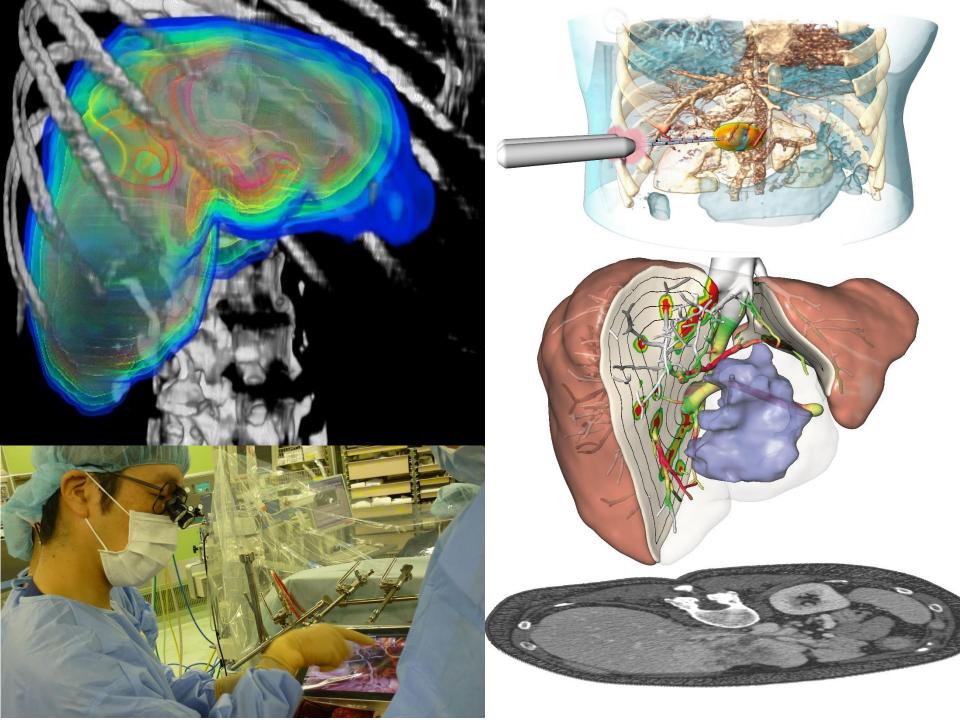
Grzegorz Chlebus¹, Hans Meine¹, Itaru Endo², Andrea Schenk¹

²Yokohama City University Graduate School of Medicine, Yokohama, Japan

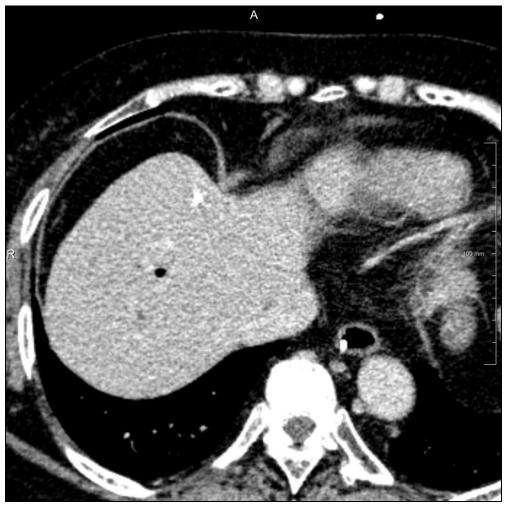




¹Fraunhofer MEVIS, Bremen, Germany



The Challenge



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The Challenge



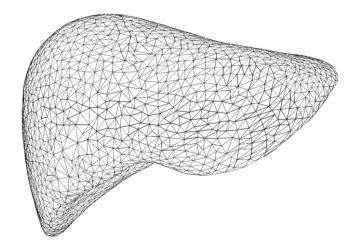


The Challenge



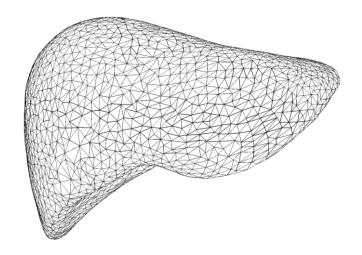
Statistical Shape Model (SSM)

- SSM captures:
 - Mean shape
 - Shape variation modes



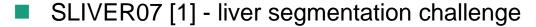
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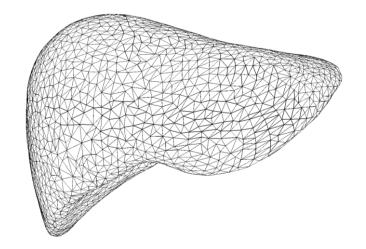
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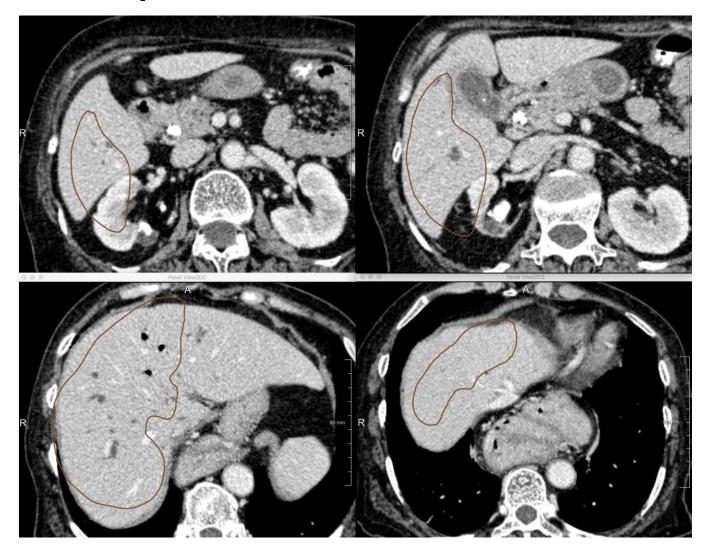
Best automatic methods employ SSM [2]

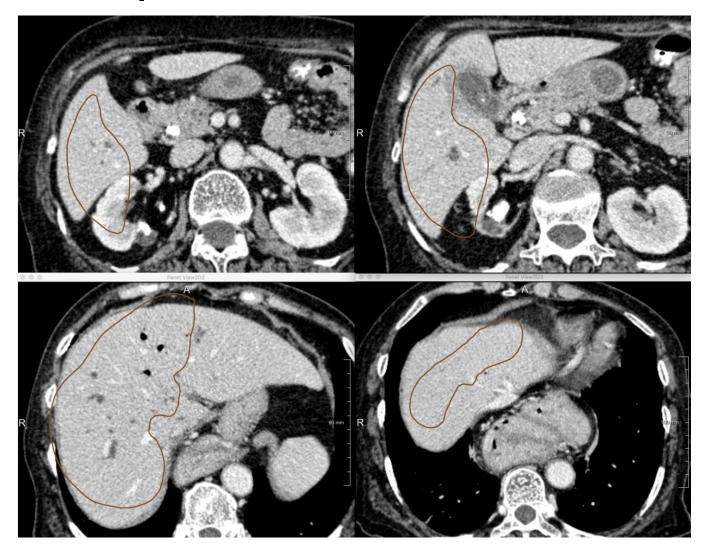
[1] SLIVER07 - Segmentation of the Liver 2007 Challenge, www.sliver07.org

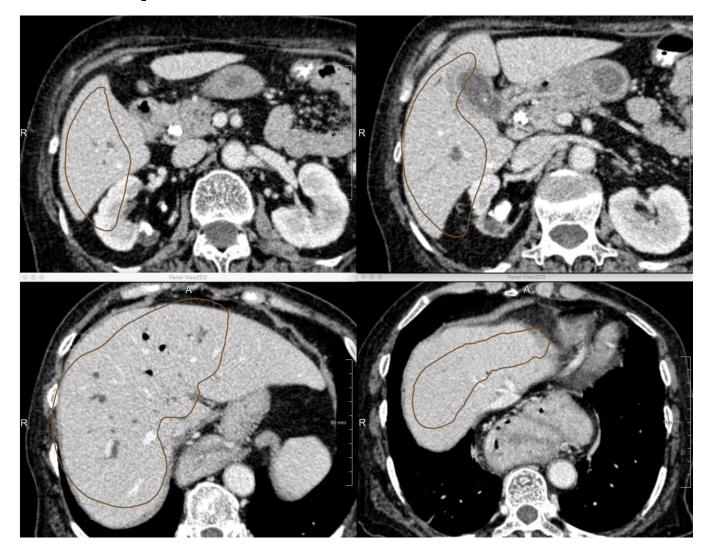
[2] T. Heimann et al., Comparison and Evaluation of Methods for Liver Segmentation From CT Datasets, 2009.

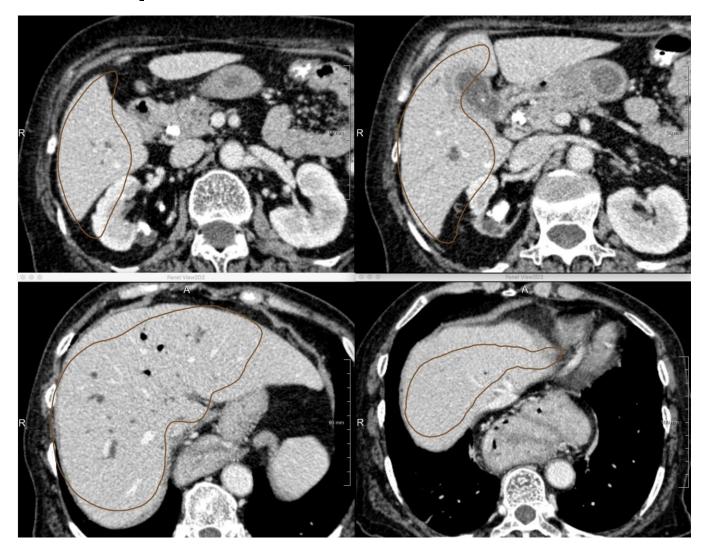


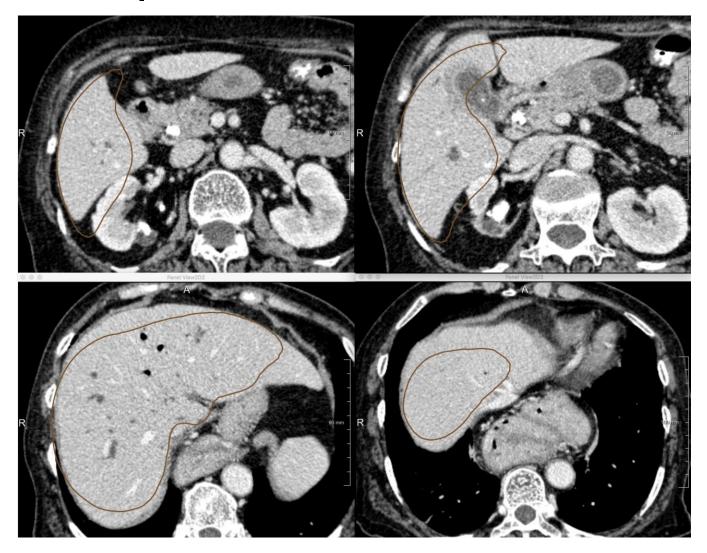




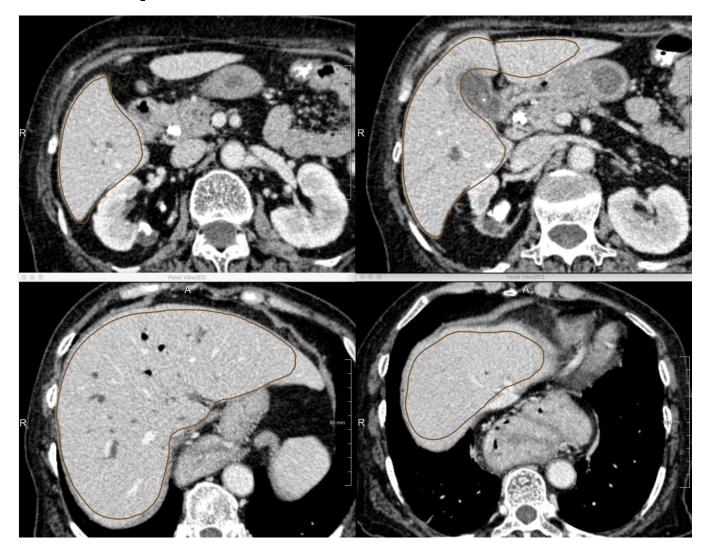




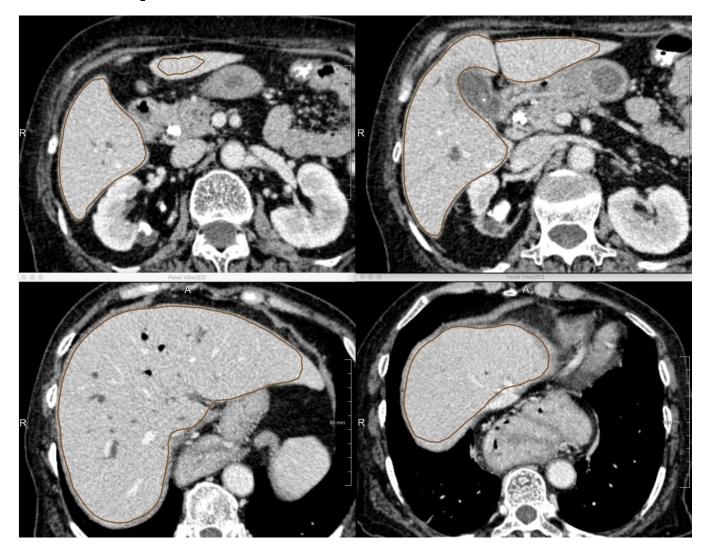






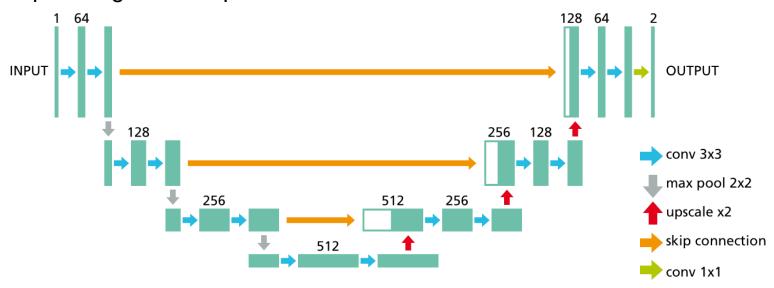






Fully Convolutional Neural Network (FCNN)

- FCNN based on the U-Net [1] architecture
 - 4 resolution levels
 - Input images resampled to 2 mm

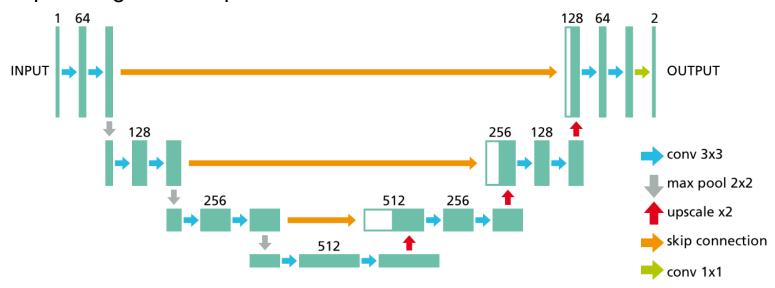


[1] O. Ronneberger et al., U-Net: Convolutional Networks for Biomedical Image Segmentation, 2015.



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■ LiTS: Liver Tumor Segmentation Challenge 2017 [2]

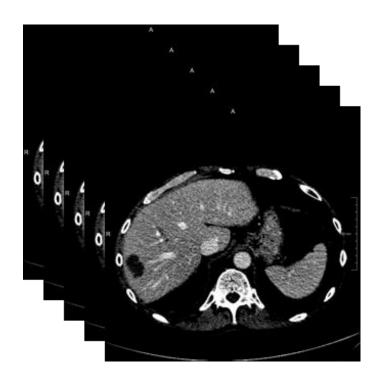
[1] O. Ronneberger et al., U-Net: Convolutional Networks for Biomedical Image Segmentation, 2015.

[2] Liver Tumor Segmentation Challenge: www.lits-challenge.com Medical Knowledge Through Research



Dataset

- 219 CTs from liver surgery planning
- ~0.6 mm in plane-resolution
- ~0.8 mm slice thickness
- Livers segmented by radiological experts with a semi-automatic tool [1]
- Case partitioning
 - 147 training
 - 32 validation
 - 40 evaluation



[1] A. Schenk et al., Efficient Semiautomatic Segmentation of 3D objects in Medical Images, 2000.



Evaluation

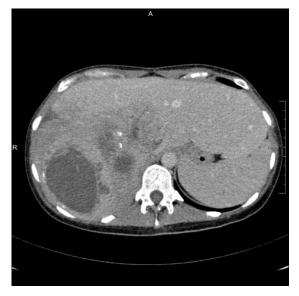
- Metrics
 - Relative volume error
 - Elapsed time

Evaluation

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 - Relative volume error
 - Elapsed time (FCNN ~3 s, SMM ~39s)

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 - Elapsed time (FCNN ~3 s, SSM ~39s)
- 3 cases left out due to SSM failure

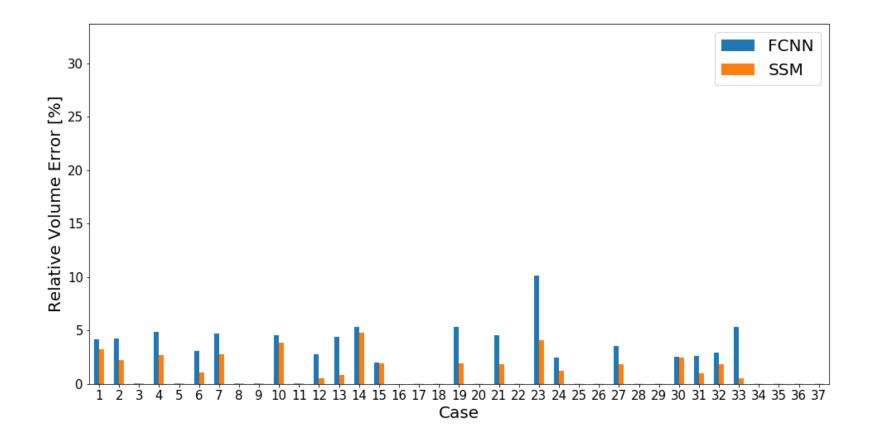


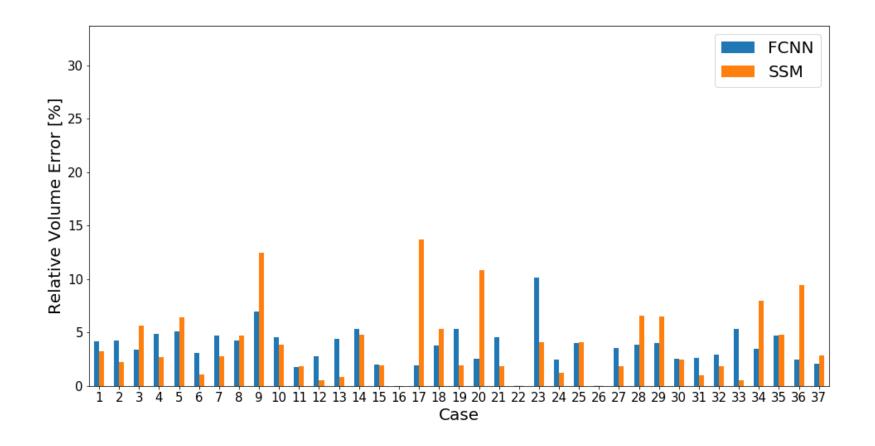


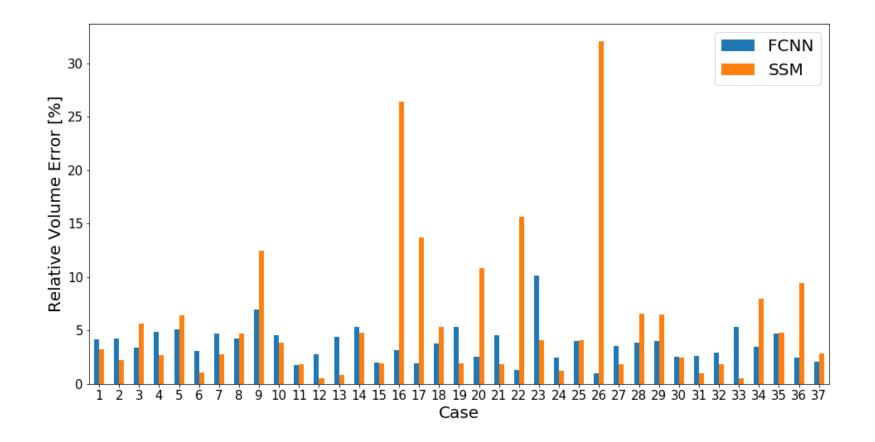


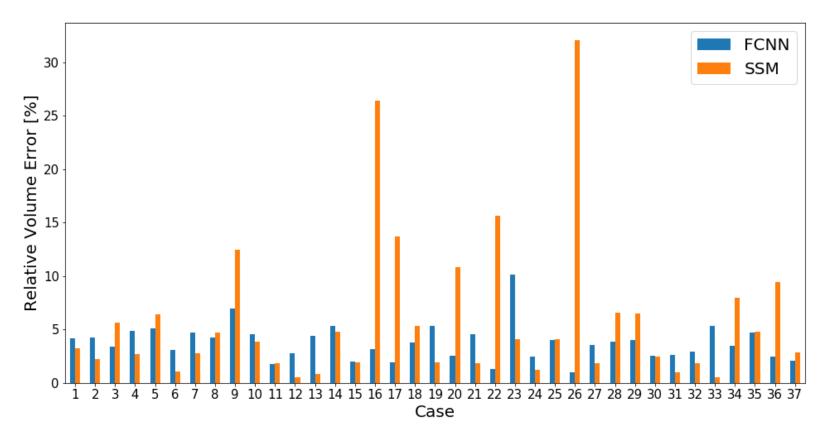
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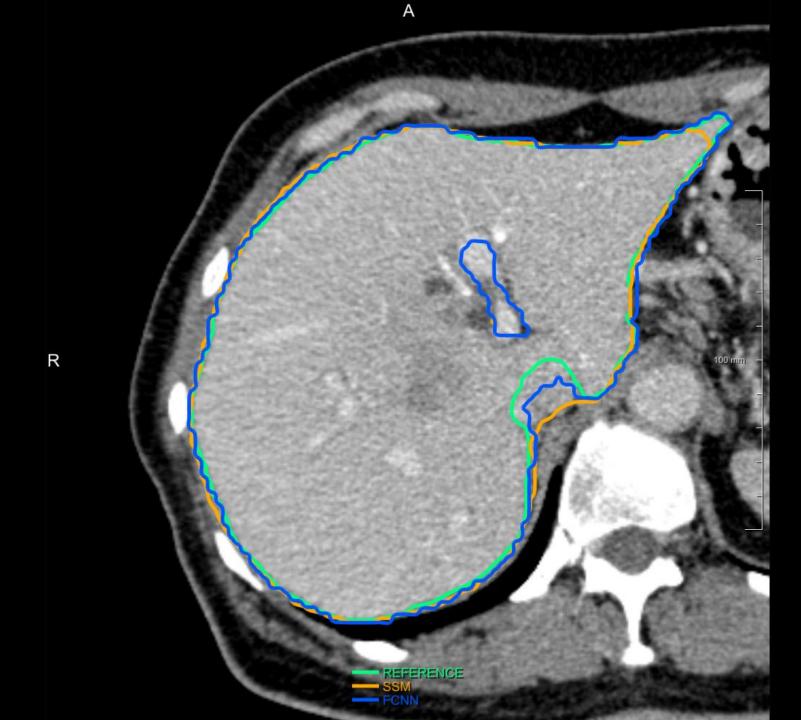




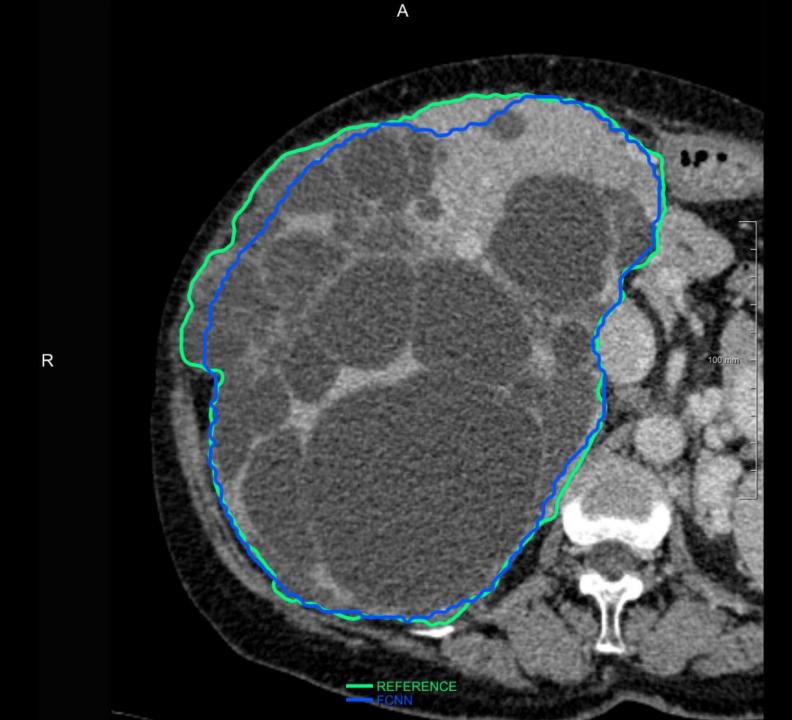


Rel. volume error: FCNN ~4%, SSM ~6%





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- Neural network explainability/uncertainty
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Thank you for your attention © Questions?



