Automatic Liver and Lesion Segmentation in CT using Cascaded Fully Convolutional Neural Networks and 3D Conditional Random Fields

Patrick Christ, Mohamed Ezzeldin A. Elshaer, Florian Ettlinger, Sunil Tatavarty, Marc Bickel, Patrick Bilic, Markus Rempfler, Marco Armbruster, Felix Hofmann, Melvin D'Anastasi, Wieland H. Sommer, Seyed-A. Ahmadi and Bjoern Menze

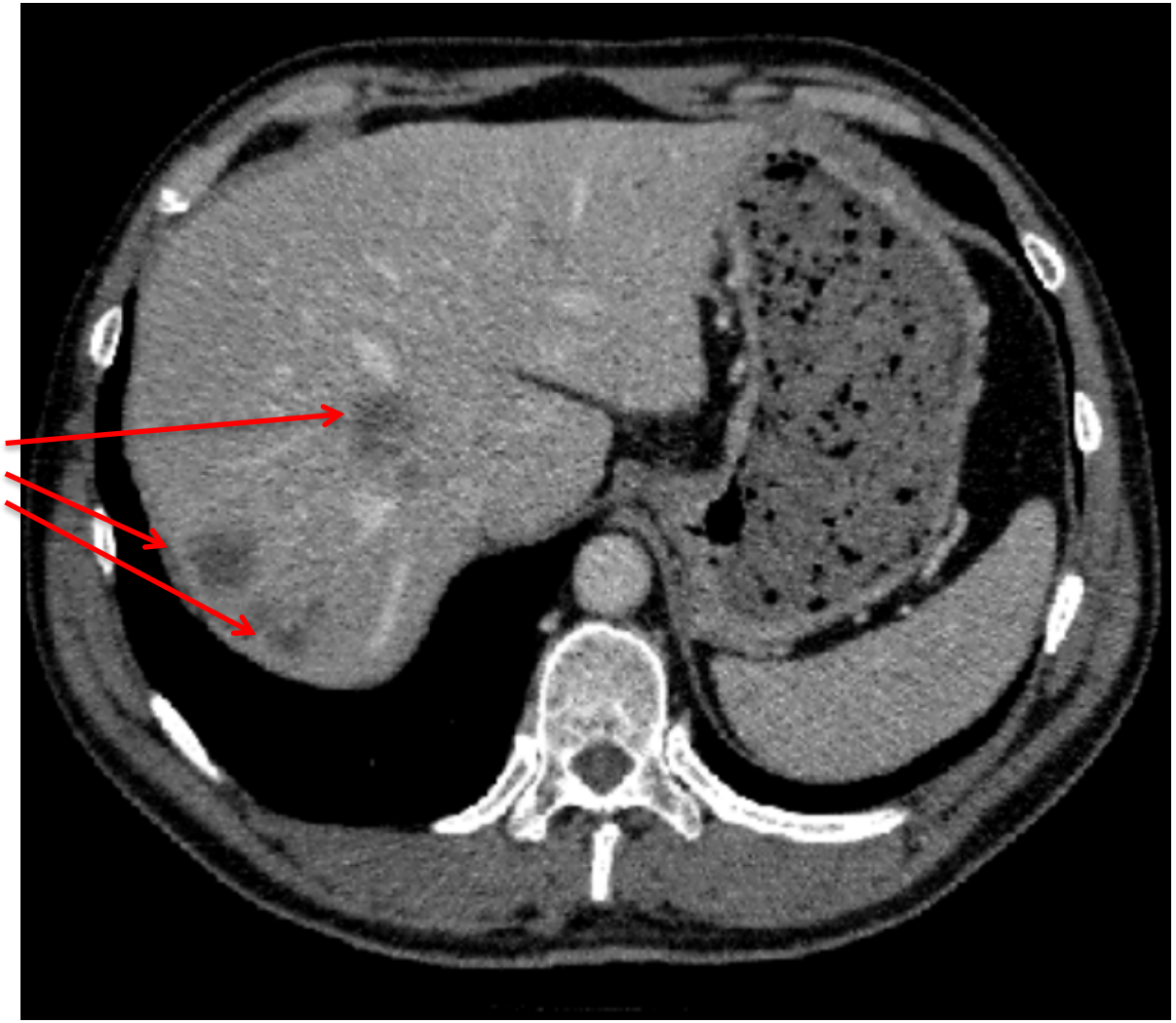
IMETUM Seminar Garching, 12.05.2016

Agenda

- Motivation
- Dataset
- Related Work
- Methods
  - Preprocessing
  - Fully Convolutional Neural Network
  - 3D Conditional Random Field
- Results
- Discussion and Future Work

Motivation

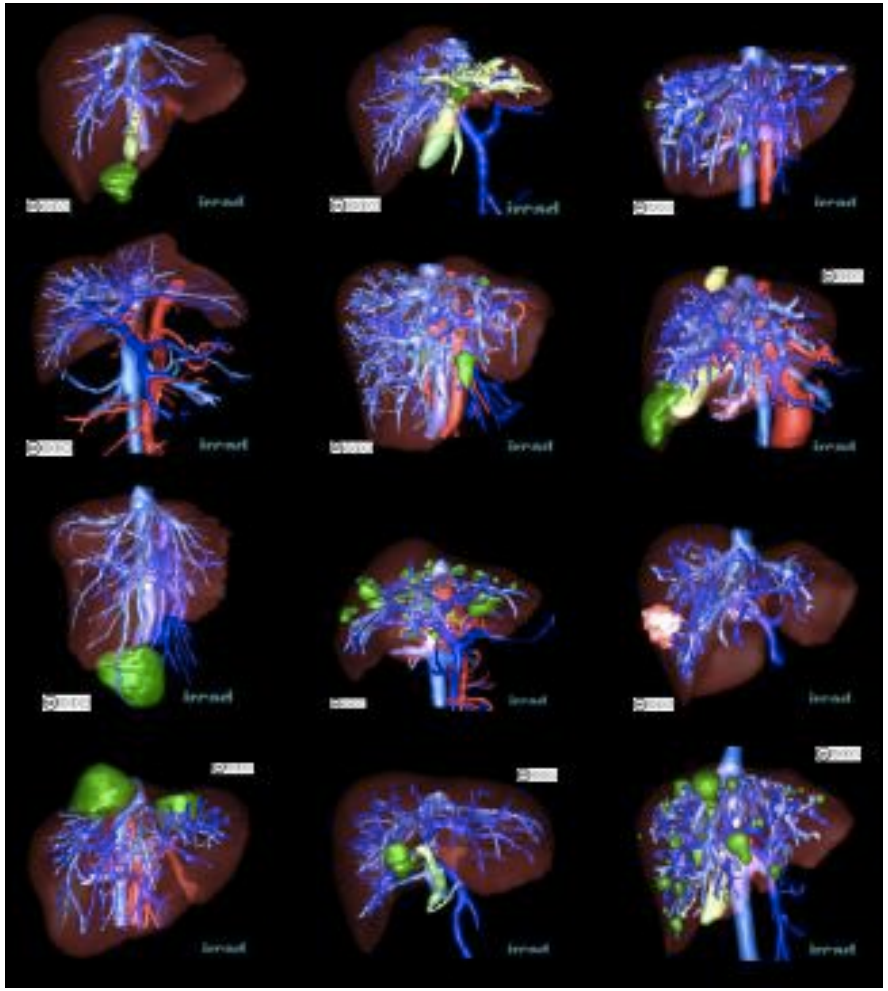
Find and analyse
HCC tumors



Data and Dataset

- 15 CT abdomen volumes with hepatocelluar carcinoma HCC tumors
- Data was acquired with different CT Scanner models at different clinical sites
- All organs and tumors have been segmented manually by radiologists

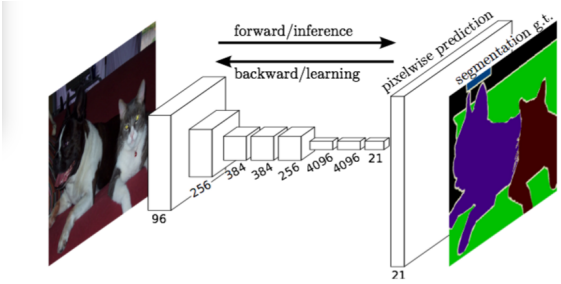
- Data is publically available at http://www.ircad.fr/research/3d-ircadb-01/

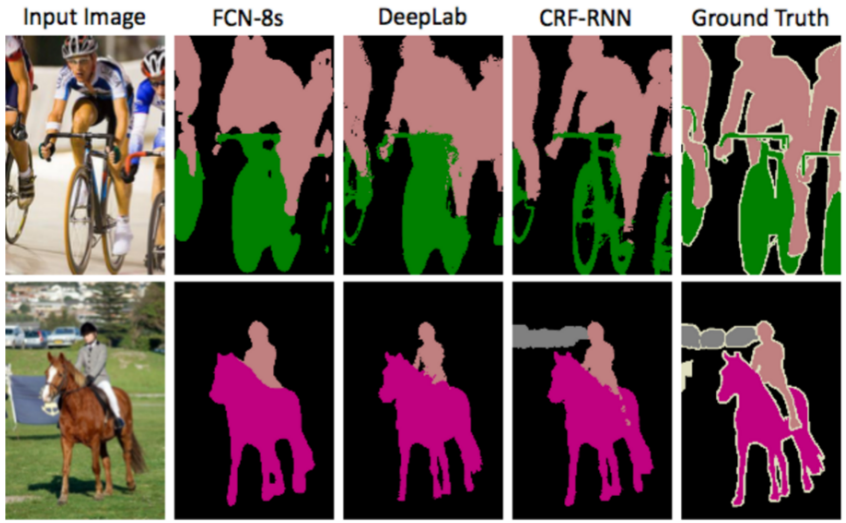


Related Work

Fully Convolutional Networks for Semantic Segmentation

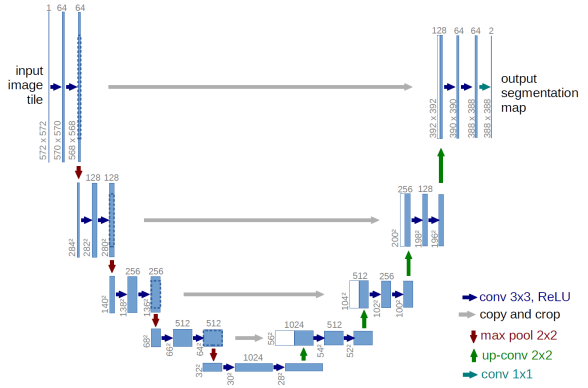
Jon Long, Evan Shelhamer, Trevor Darrell





U-Net: Convolutional Networks for Biomedical Image Segmentation

Olaf Ronneberger, Philipp Fischer, Thomas Brox



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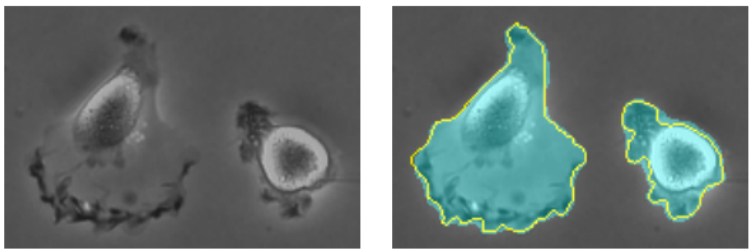
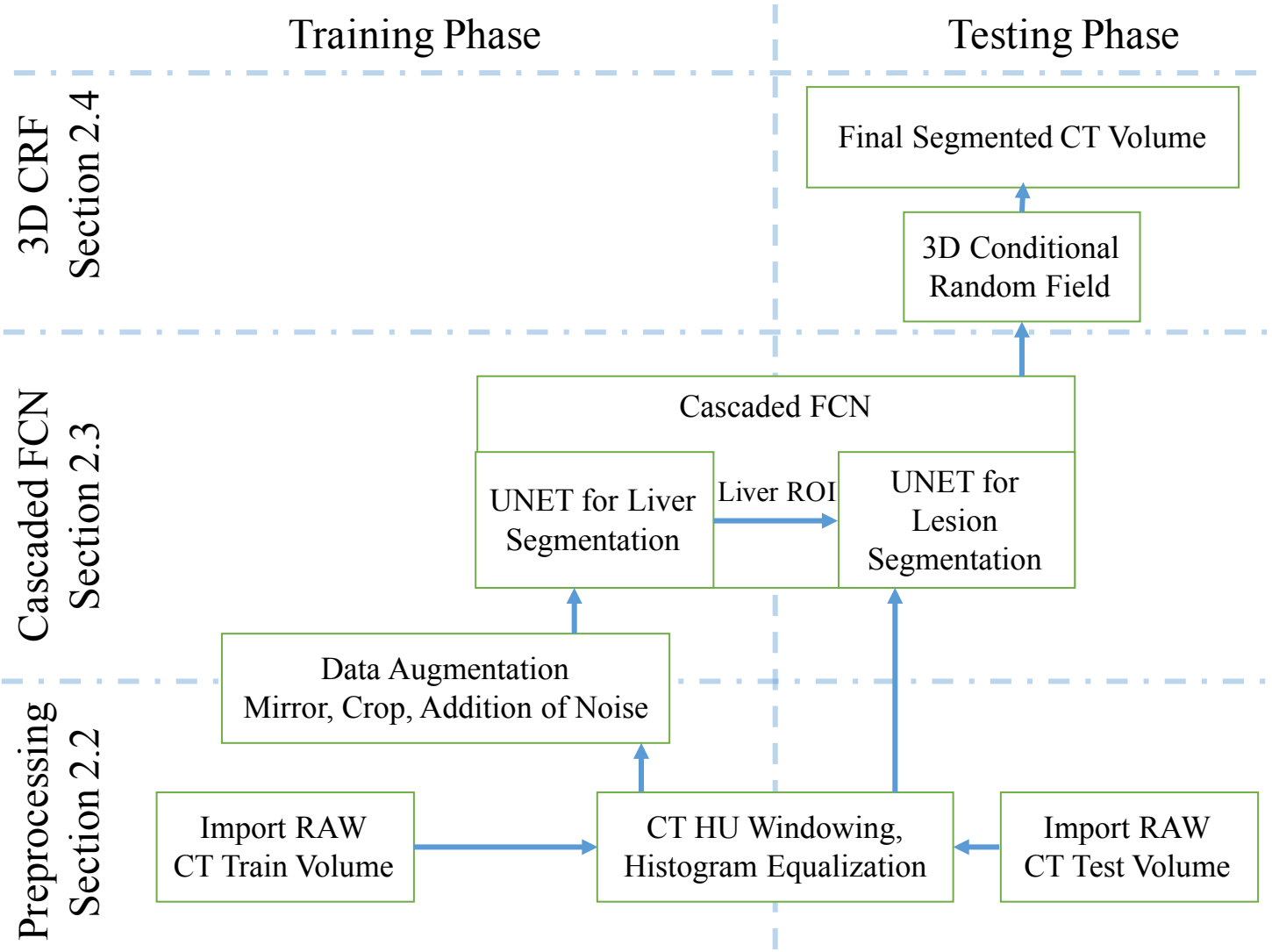


Our approach



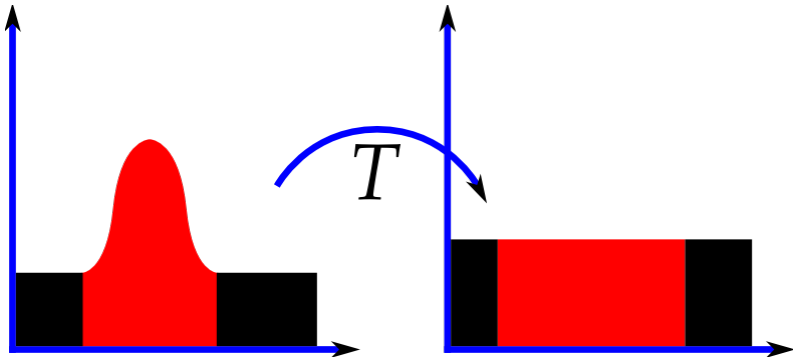
Preprocessing

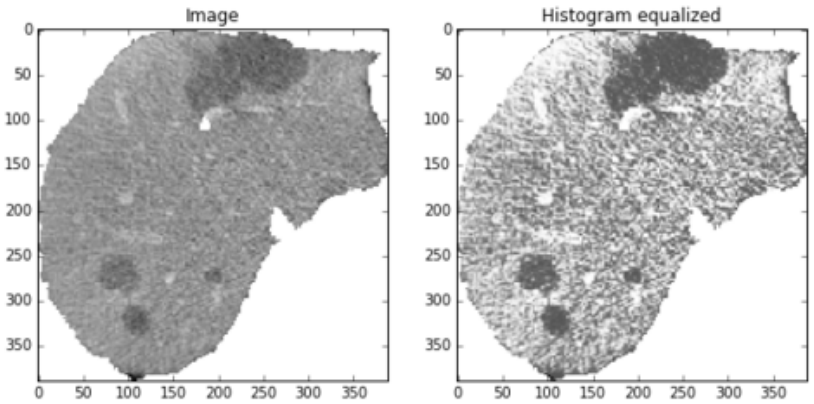
1. CT Windowing

Windowing of the CT Hounsfield Units to a range between -100 and 200 HU for a high soft-tissue contrast

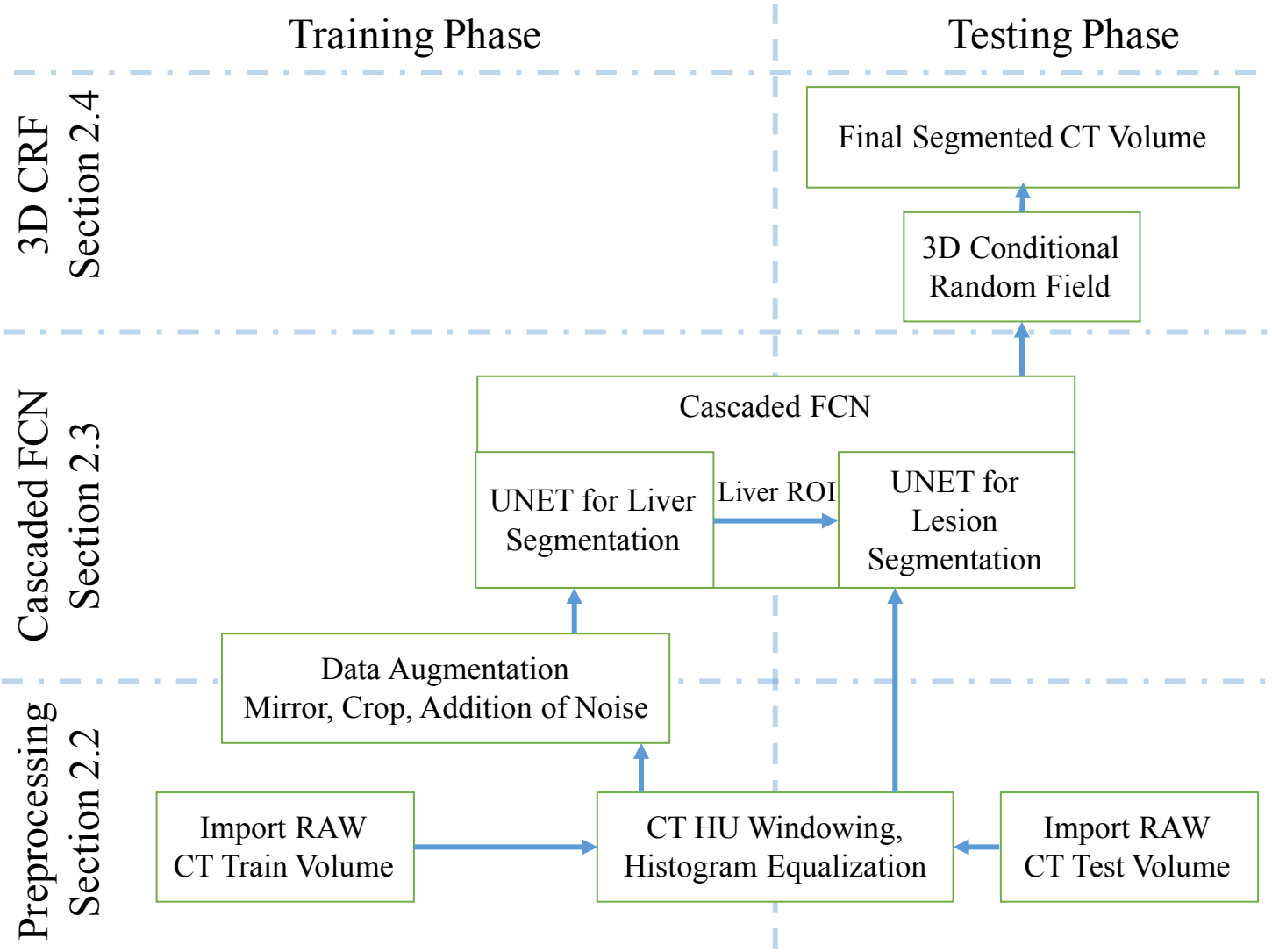
2. Histogram Equilization

Increasing the contrast of low contrasted regions by splitting the histogram uniformely

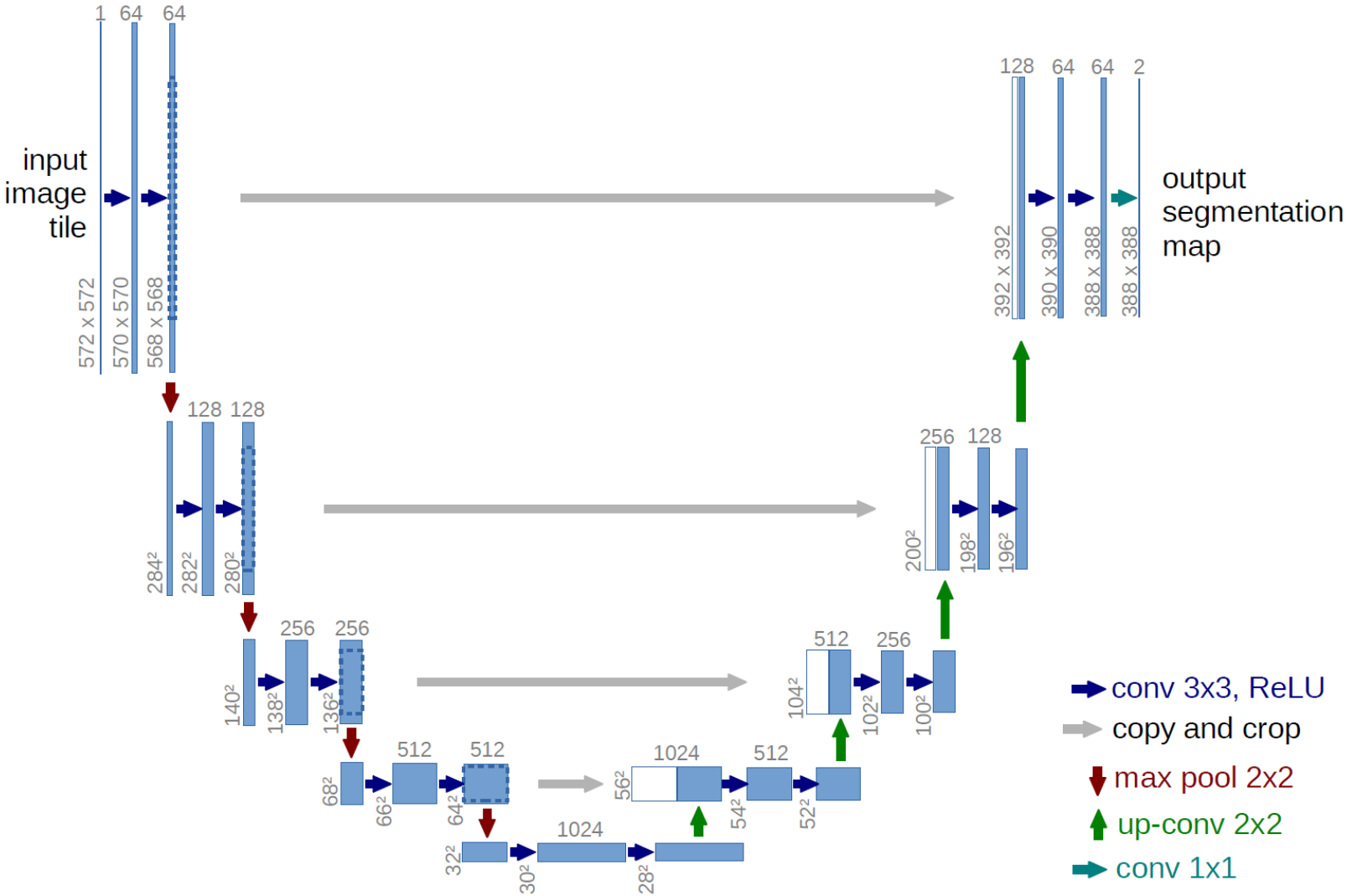




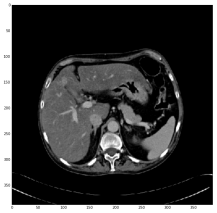
Our approach

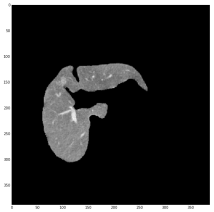


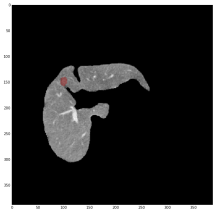
The UNET Architecture by Ronneberg et al. 2015

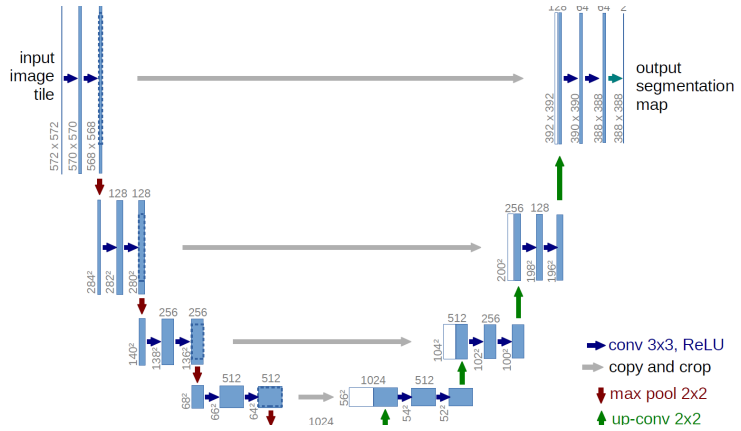


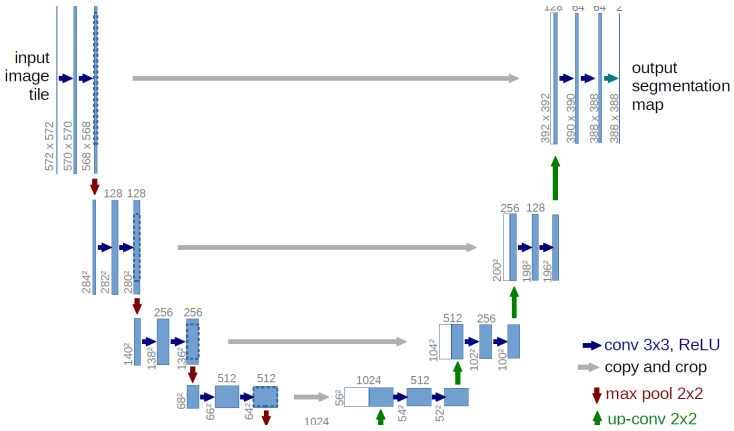
Cascaded Fully Convolutional Neural Networks

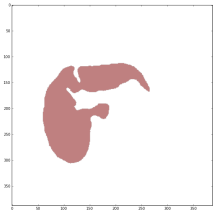


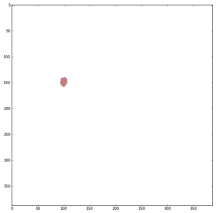




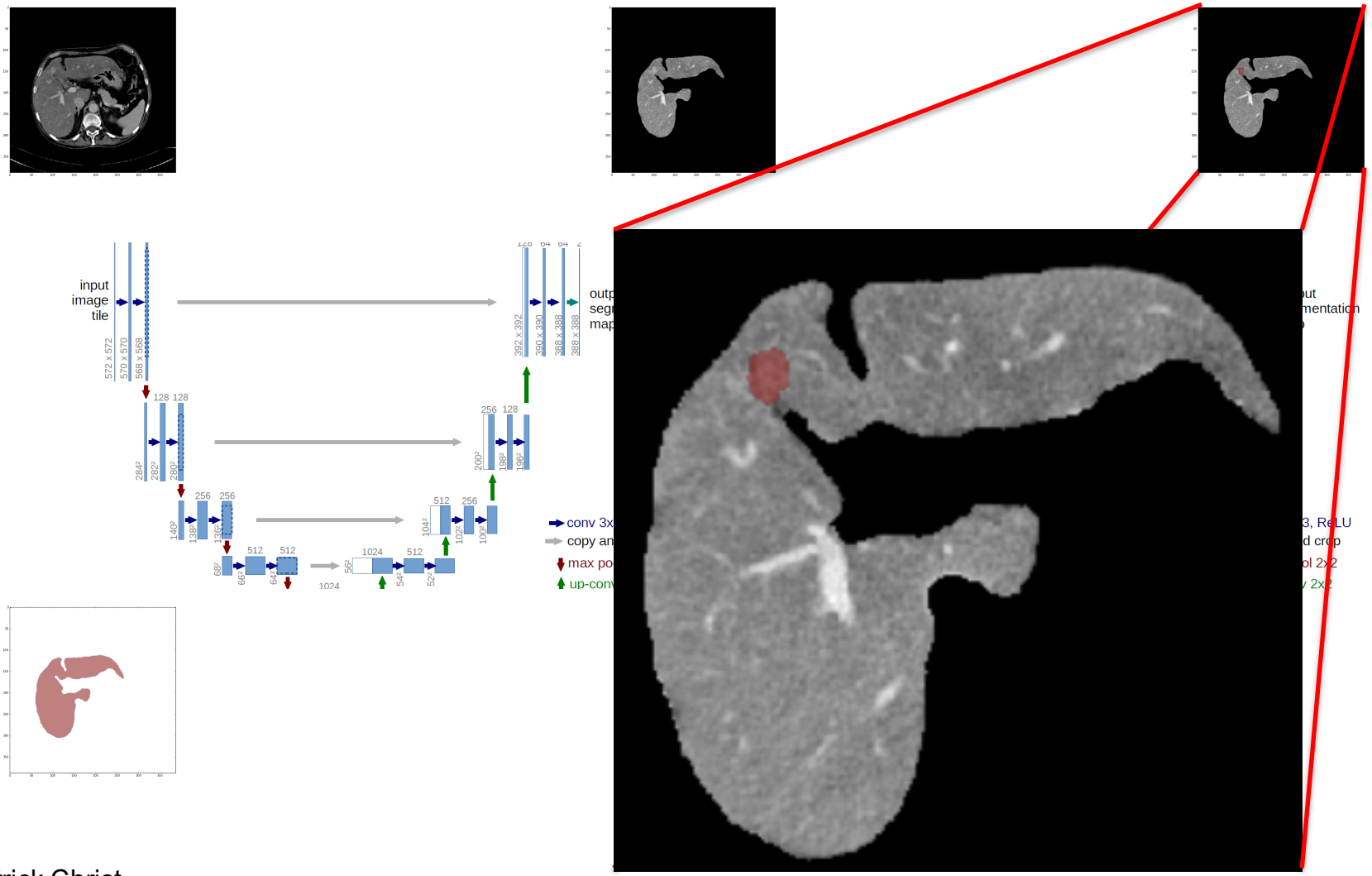




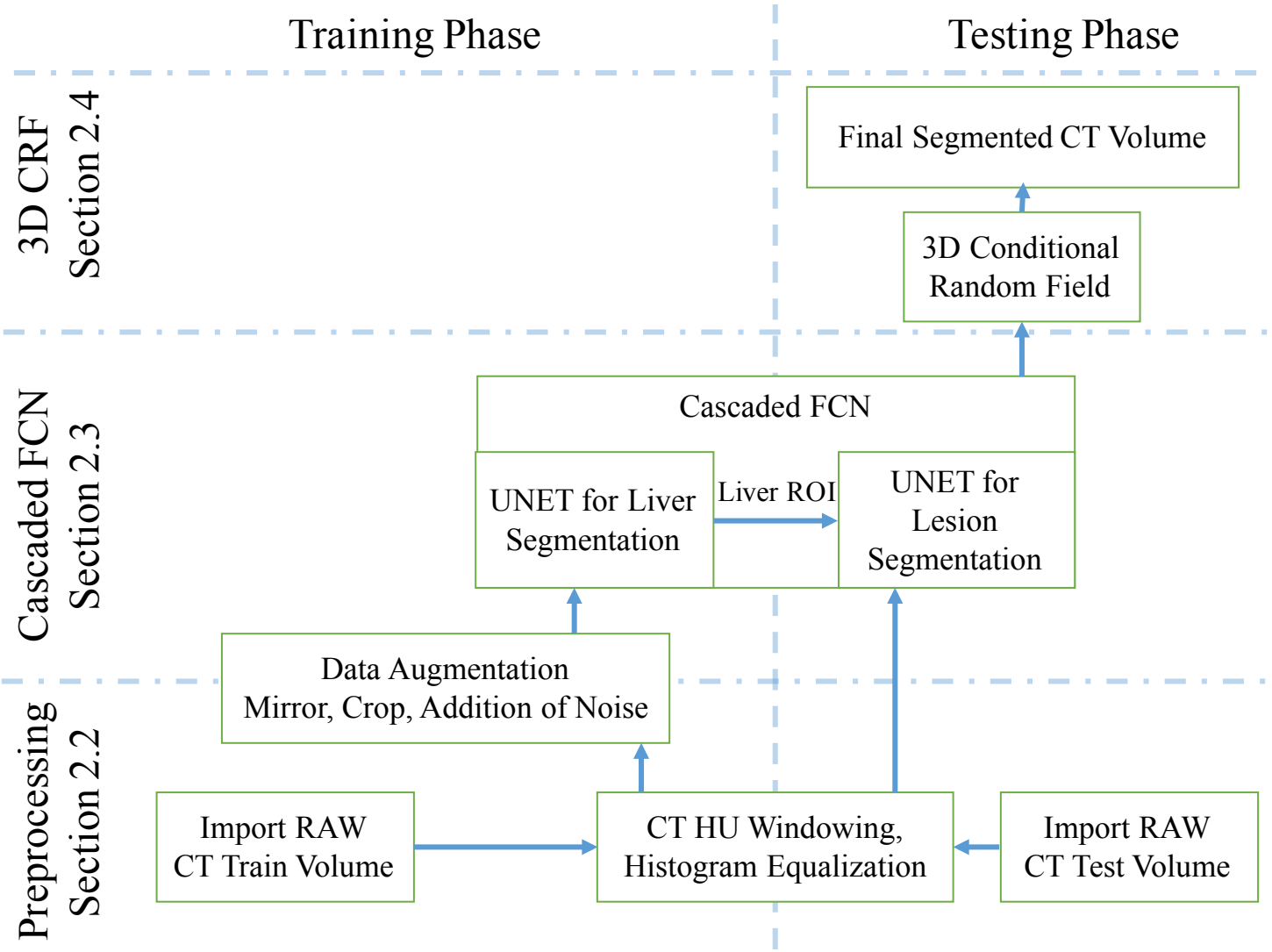




Cascaded Fully Convolutional Neural Networks



Our approach

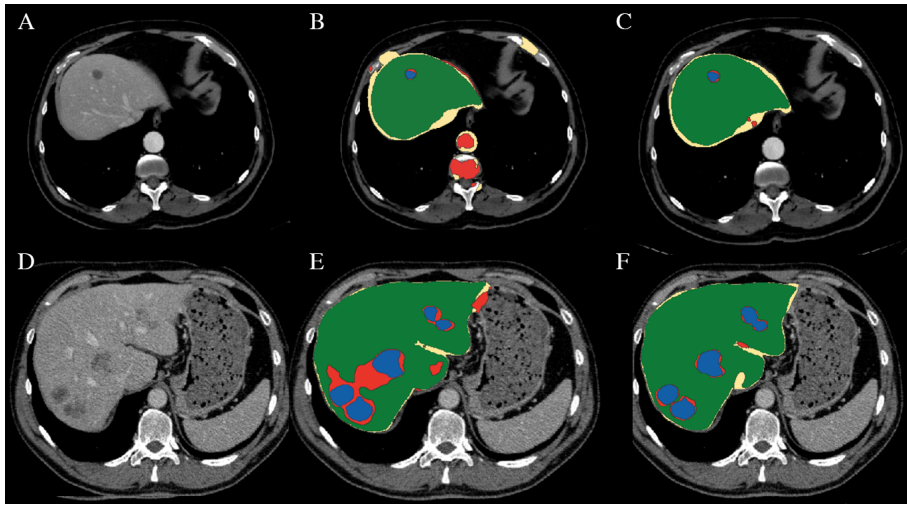


3D Conditional Random Field 3DCRF

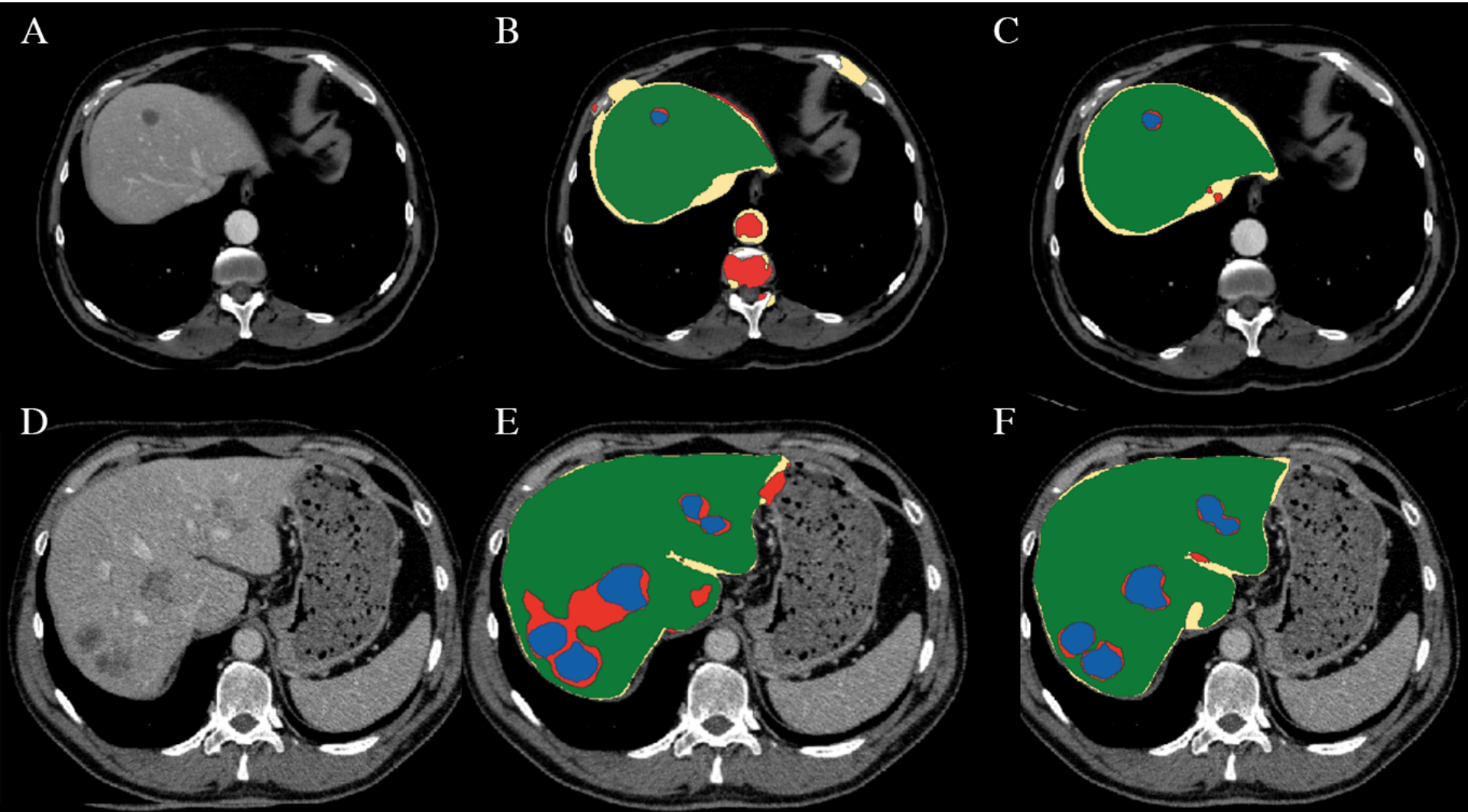
Application of a 3D Conditional Random Field to refine the segmentation by accounting for spatial appearance and coherence.

$$E(\mathbf{x}) = \sum_{i \in \mathcal{V}} \phi_i(x_i) + \sum_{(i,j) \in \mathcal{E}} \phi_{ij}(x_i, x_j)$$

$$\phi_{ij}(x_i, x_j) = \mu(x_i, x_j) \left(w_{\text{pos}} \exp\left(-\frac{|p_i - p_j|^2}{2\sigma_{\text{pos}}^2} \right) + w_{\text{bil}} \exp\left(-\frac{|p_i - p_j|^2}{2\sigma_{\text{bil}}^2} - \frac{|I_i - I_j|^2}{2\sigma_{\text{int}}^2} \right) \right)$$



3D Conditional Random Field 3DCRF



Qualitative Results

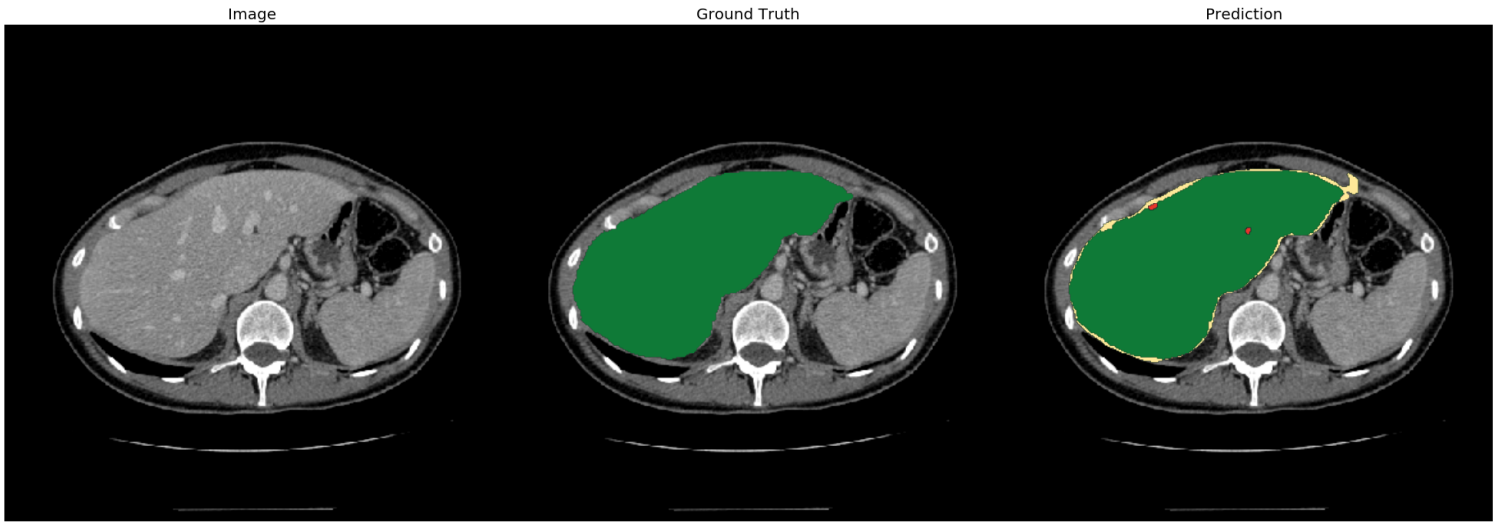


image12.nii slc181
Liver 0.97

Qualitative Results

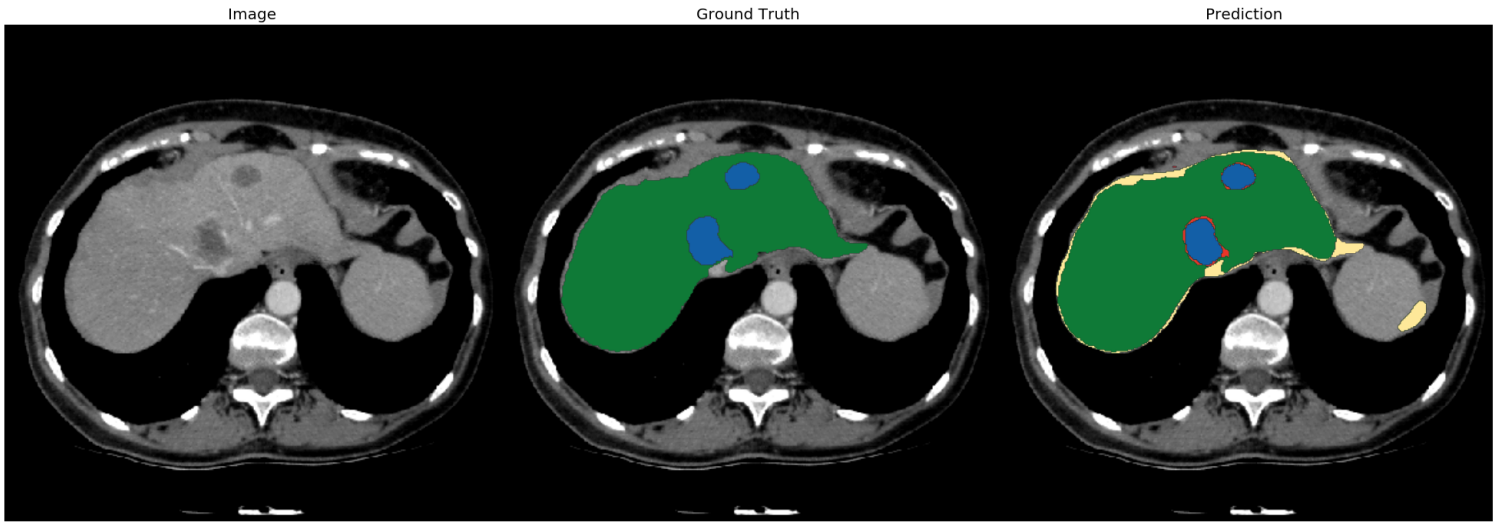


image01.nii slc114
Liver 0.92
Lesion 0.92

Quantitative Results

We could achieve an improvement over UNET by Ronneberg et al. (2015) using Cascaded Fully Convolutional Neural Networks CFCNs.

Applying the 3D CRF as a postprocessing step increased the segmentation performance further.

Our approach competes with state-of-the art methods such as Li et al. (2014).

Our proposed method has a run-time per volume below 100s.

	Approach	VOE [%]	RVD [%]	ASD [%]	MSD [mm]	DICE [%]
Liver	UNET	39	87	19.4	119	72.9
	Cascaded UNET	12.8	-3.3	2.3	46.7	93.1
	Cascaded UNET + 3D CRF	10.7	-1.4	1.5	24.0	94.3
	Li et al. [14]	9.2	−11.2	1.6	28.2	

Discussion and future work

Further improvements could be achieved by augmenting small livers.

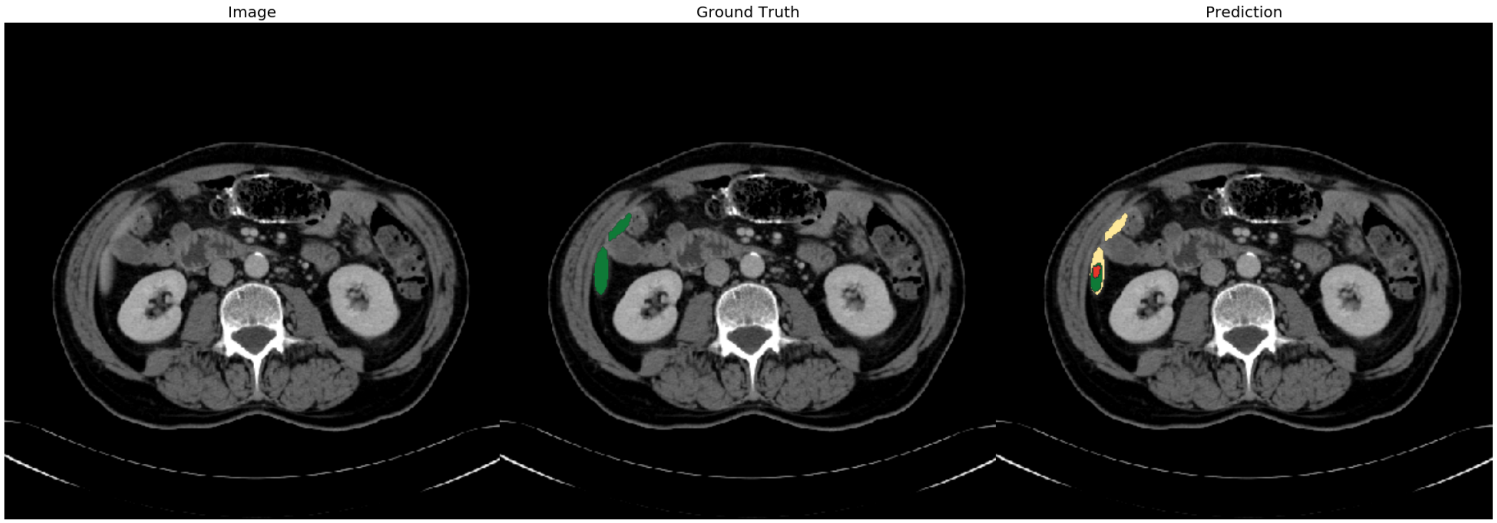


image04.nii slc20
Liver 0.5

Discussion and future work

Further improvements could be achieved by employing 3D convolution architectures

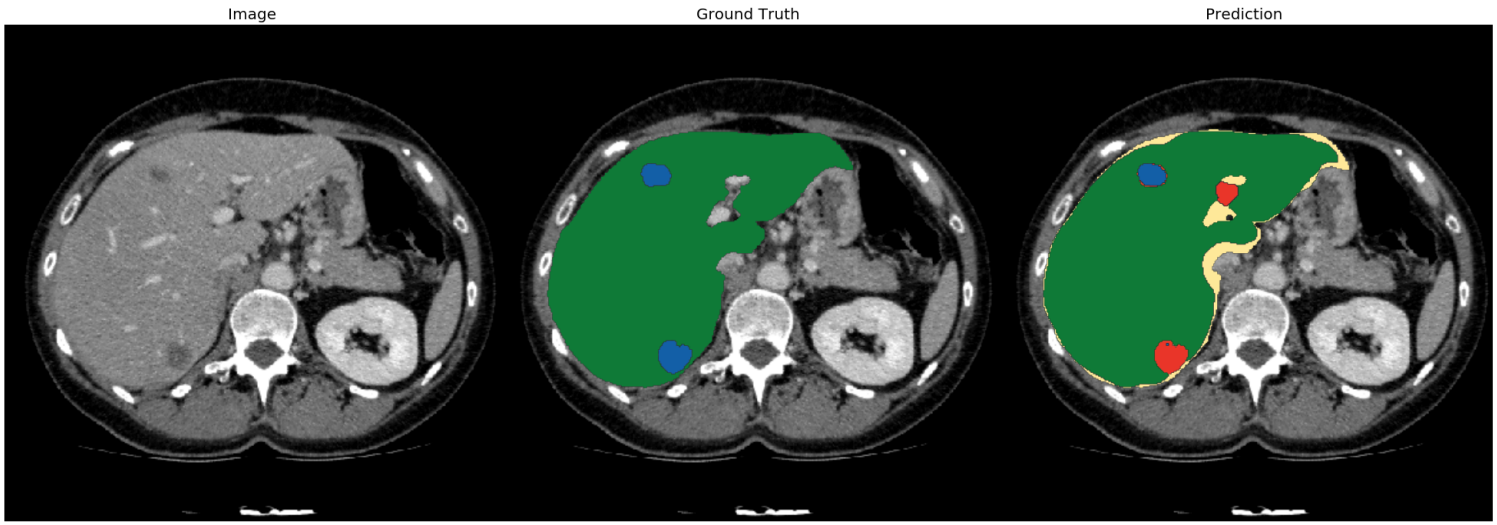


image01.nii slc82
Liver 0.95
Lesion 0.45

Contact us at Patrick.Christ@tum.de