

# Organ segmentation using U-Net like models

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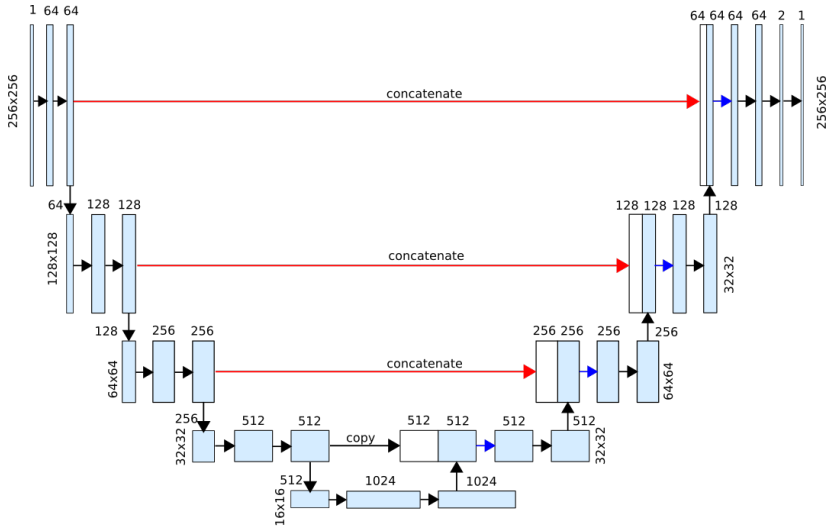
# Semantic segmentation

- ◆ input:  $x \in [0, 1]^{D \times H \times W}$  image
- ◆ output:  $\hat{y} \in [0, 1]^{C \times H \times W}$  prediction
- ◆ target:  $y \in \{0, 1\}^{C \times H \times W}$  mask

# Metrics

- ◆ accuracy:  $\frac{|y \cap \hat{y}|}{HW}$
- ◆ Dice similarity coefficient:  $\frac{2|y \cap \hat{y}|}{|y| + |\hat{y}|}$
- ◆ IoU score:  $\frac{|y \cap \hat{y}|}{|y \cup \hat{y}|}$
- ◆ average modified (95<sup>th</sup> percentile) Hausdorff distance
- ◆ area under ROC, PR curves

# U-Net



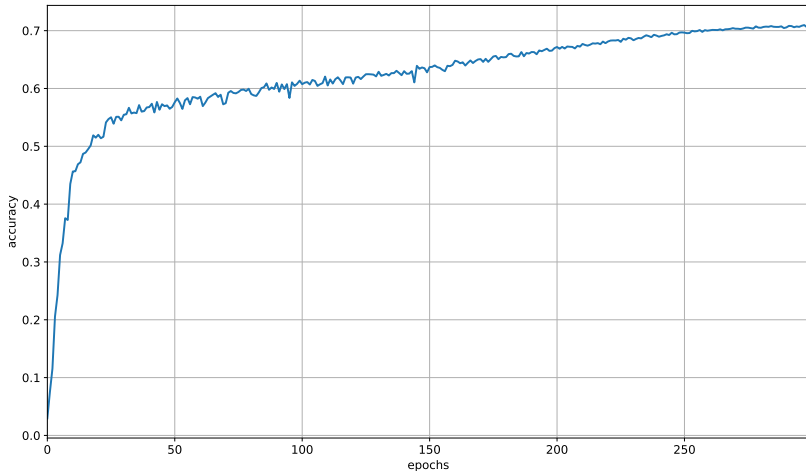
# Synapse

- ◆ multi-organ CT dataset
- ◆ segmentation mask for eight organs
- ◆ 2D slices of 3D CT images
- ◆ train: 12 samples, 1800 slices
- ◆ validation: 4 samples, 300 slices

# Experiments with weight initialisation

| weight init        | acc   | AUC   | AP    | DSC   | IoU   | HD95  |
|--------------------|-------|-------|-------|-------|-------|-------|
| He (fan out)       | 0.990 | 0.969 | 0.785 | 0.735 | 0.619 | 0.003 |
| He (fan in)        | 0.990 | 0.979 | 0.776 | 0.731 | 0.612 | 0.003 |
| Glorot             | 0.990 | 0.976 | 0.762 | 0.718 | 0.601 | 0.003 |
| orthogonal         | 0.991 | 0.976 | 0.789 | 0.737 | 0.614 | 0.003 |
| pretrained encoder | 0.990 | 0.983 | 0.817 | 0.750 | 0.626 | 0.004 |

# Training on Imagenet

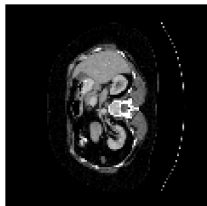


# Experiments with downsampling methods

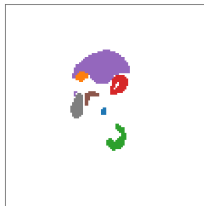
| downsampling             | acc   | AUC   | AP    | DSC   | IoU   | HD95  |
|--------------------------|-------|-------|-------|-------|-------|-------|
| maxpool                  | 0.989 | 0.981 | 0.796 | 0.773 | 0.659 | 0.004 |
| conv (channel change)    | 0.989 | 0.945 | 0.710 | 0.709 | 0.595 | 0.005 |
| conv (no channel change) | 0.988 | 0.945 | 0.710 | 0.709 | 0.599 | 0.004 |



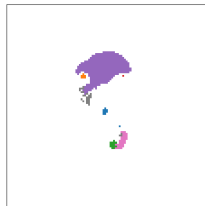
# Example prediction



original image

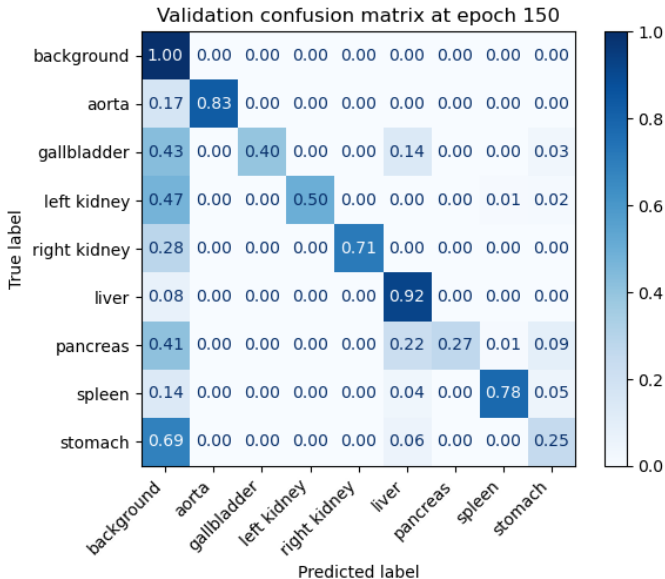


ground truth



prediction

- aorta
- gallbladder
- left kidney
- right kidney
- liver
- pancreas
- spleen
- stomach



# References

- [1] O. Ronneberger, P. Fischer, T. Brox. U-Net: Convolutional networks for biomedical image segmentation. *Medical Image Computing and Computer-Assisted Intervention*, November 2015, pp. 234–241.
- [2] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.
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- [4] O. Russakovsky et al. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision* **115**, 2015, pp. 211–252.
- [5] O. Oktay et al. Attention U-Net: Learning where to look for the pancreas. arXiv preprint, April 2018. arXiv:1804.03999v3 [cs.CV]