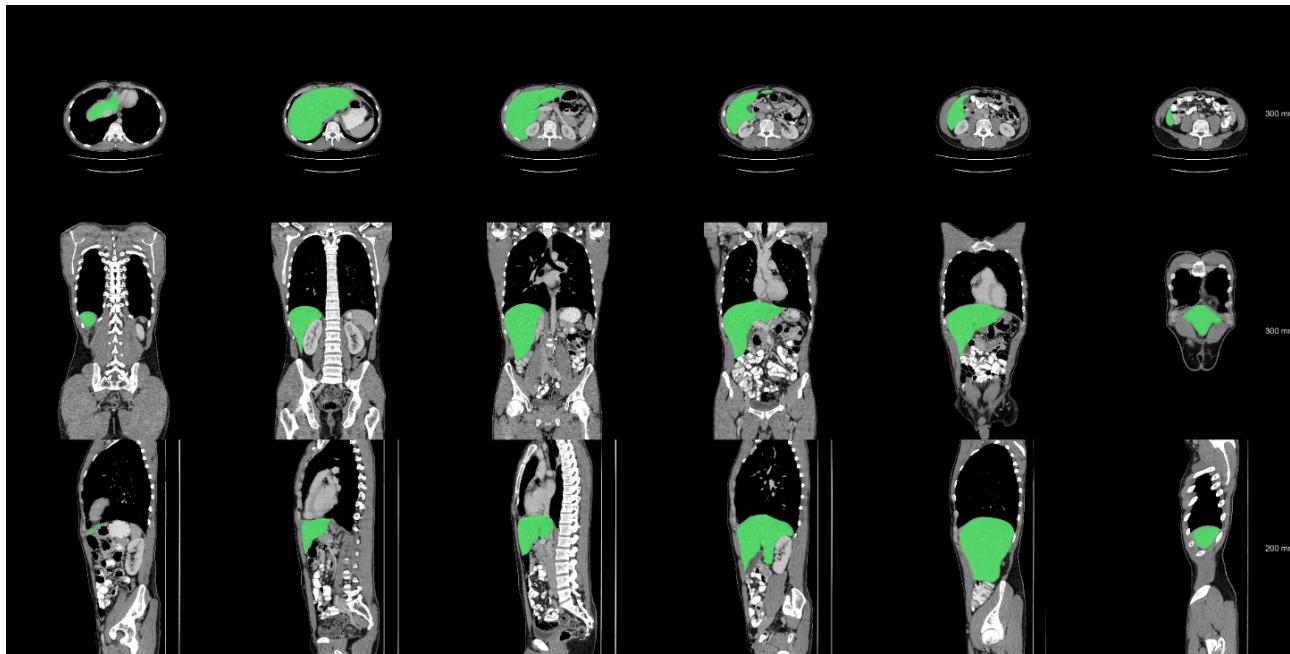


MIMICKING RADIOLOGISTS TO IMPROVE THE ROBUSTNESS OF DEEP-LEARNING BASED AUTOMATIC LIVER SEGMENTATION

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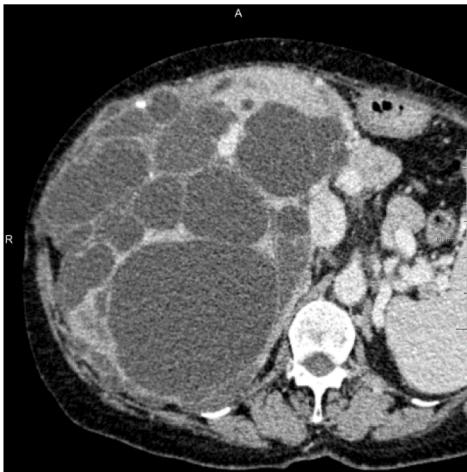
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Medical Knowledge Through Research

Motivation

- Develop segmentation algorithms working robustly on large, heterogeneous datasets
- Develop concepts for a big-scale error analysis to identify prevailing shortcomings of an algorithm



Polycystic liver



Resected liver

Data

Training data

- Yokohama City University Hospital, Japan
 - 80 cases
 - Contrast-enhanced CT, late phase
- Radboudumc, The Netherlands
 - 80 cases
 - Contrast-enhanced CT, late phase

Evaluation data

- Radboudumc, The Netherlands
 - 826 cases
 - Various protocols



Baseline model

- 3D u-net [1]
- 4 771 826 parameters

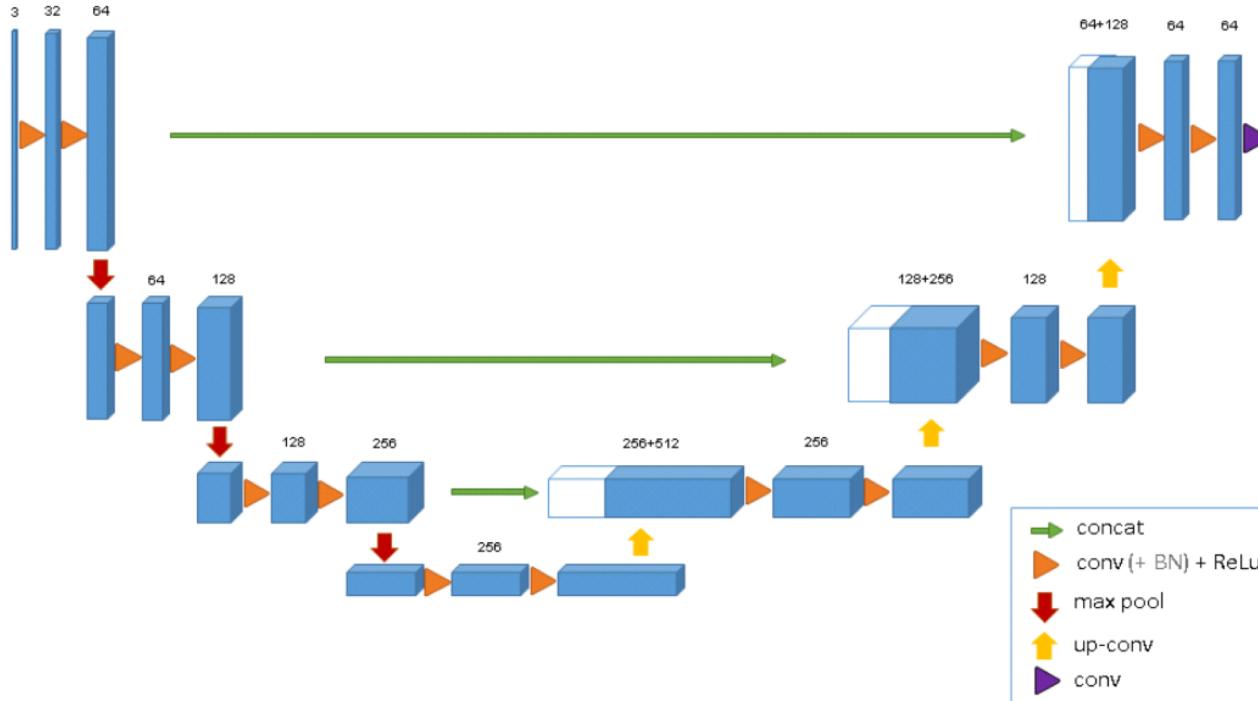


Figure from [1]

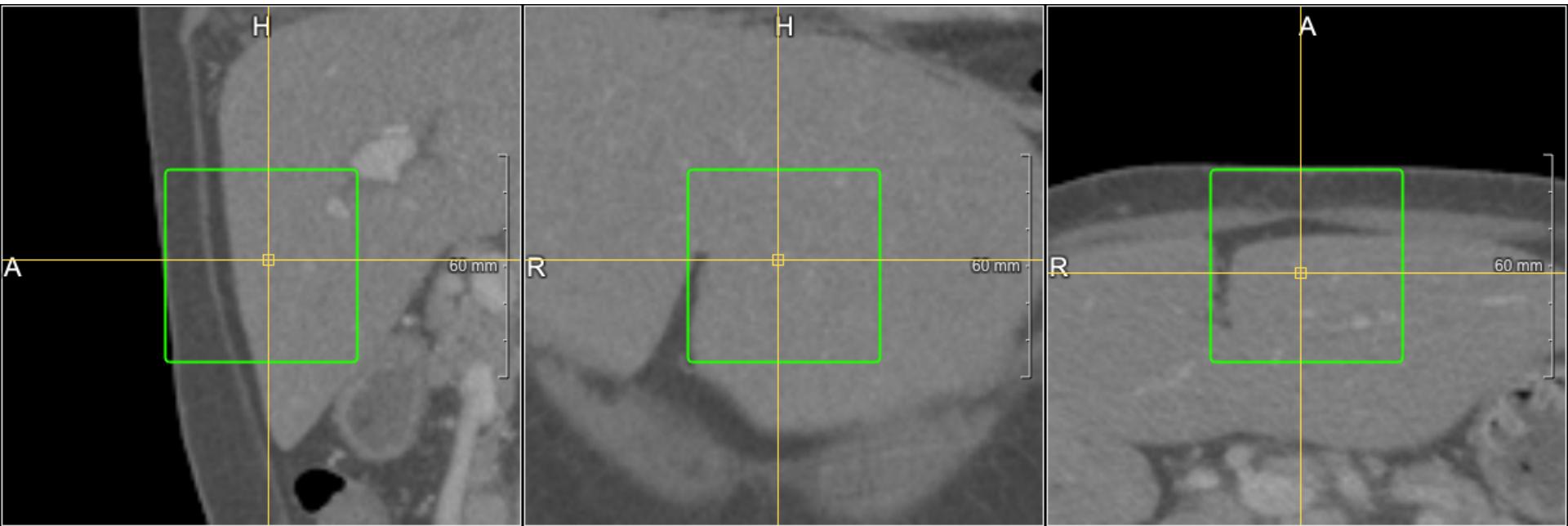
[1] Çiçek, Özgün, et al. "3D U-Net: learning dense volumetric segmentation from sparse annotation." International conference on medical image computing and computer-assisted intervention. Springer, Cham, 2016.

Medical Knowledge Through Research

Baseline model

Receptive field:

- $92 \times 92 \times 92 \text{ mm}^3$

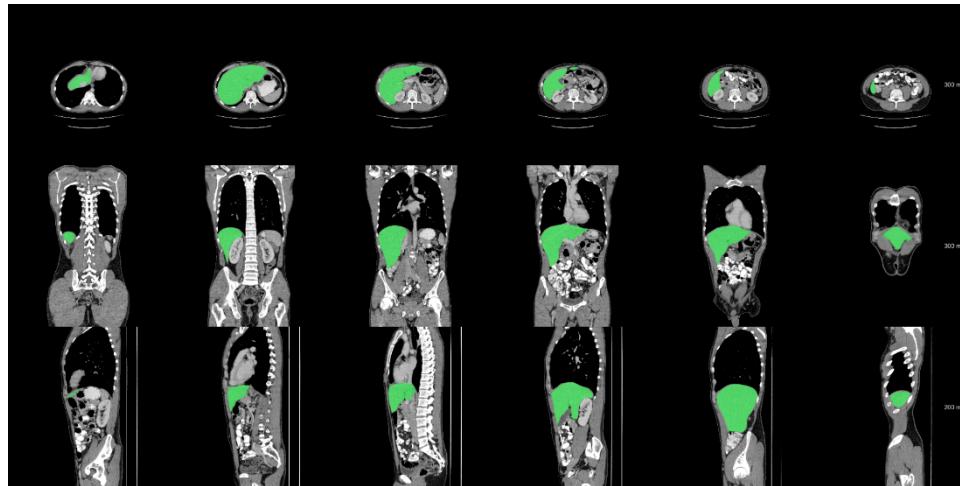


Input image patch in sagittal, coronal and axial orientation required by the baseline model to segment the region within the green box.

Evaluation

Screenshot-based

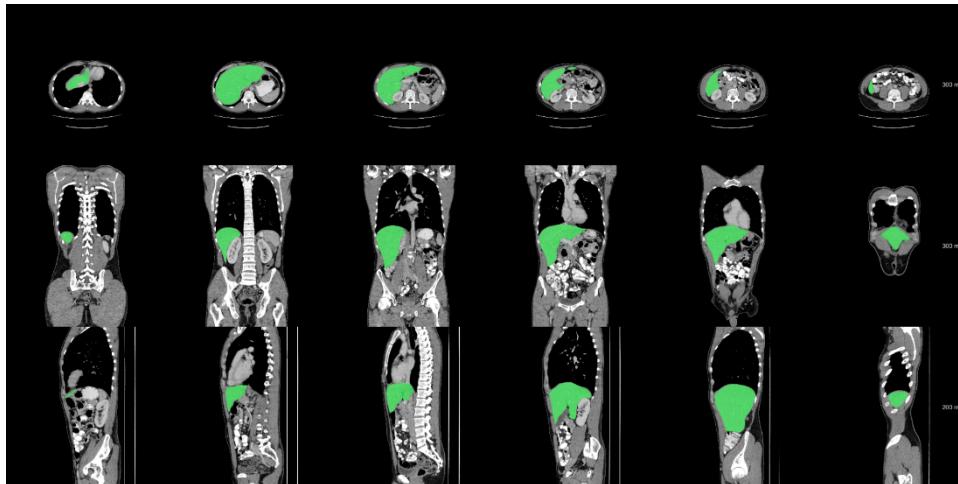
- Visual inspection by a human expert
- Scoring speed ~500 cases / hour



Evaluation

Screenshot-based

- Visual inspection by a human expert
- Scoring speed ~500 cases / hour

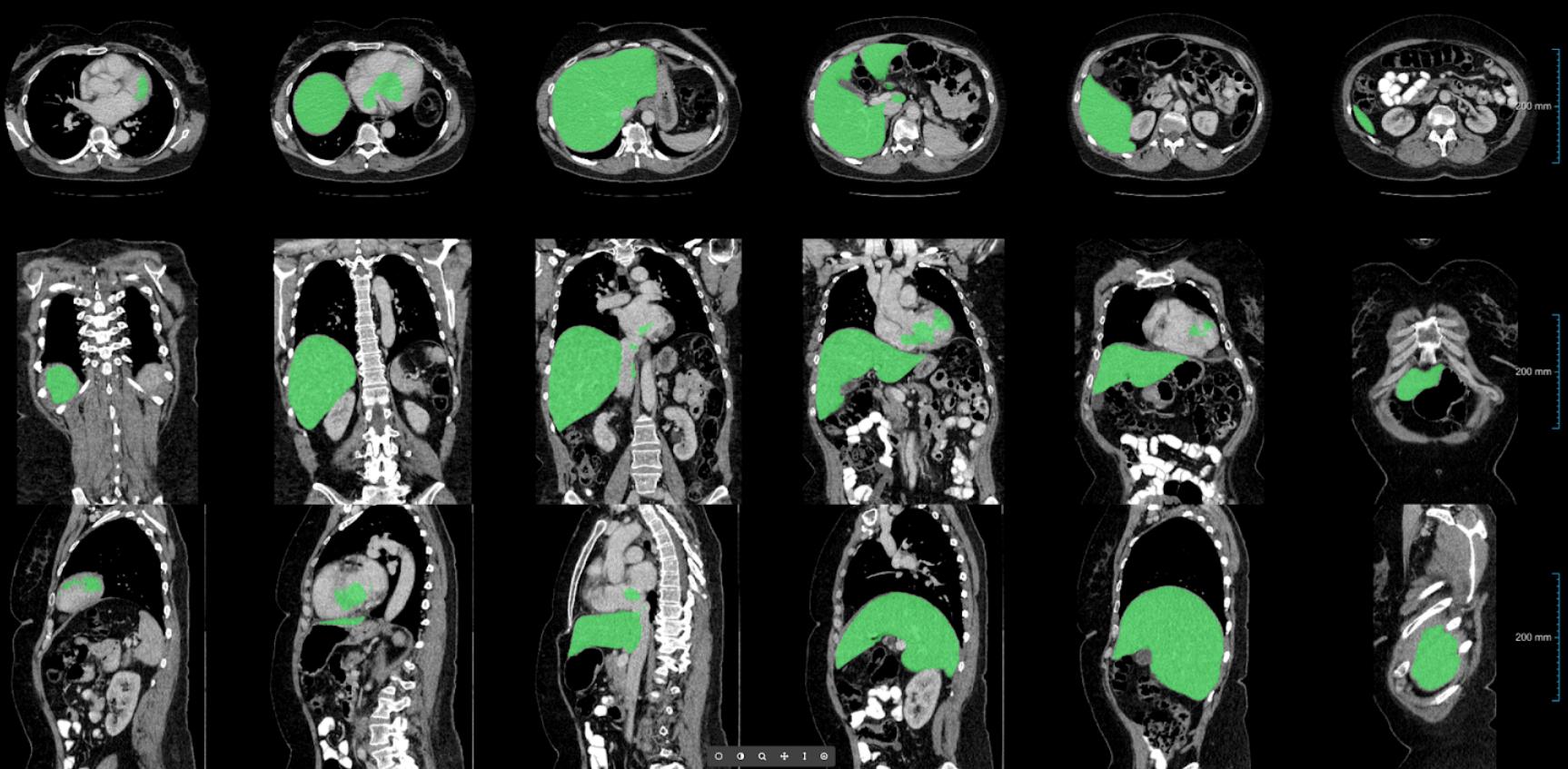


Baseline model results

- 1 - no corrections required – 516 cases (62%)
- 2 - minor corrections required – 123 cases (15%)
- 3 - major corrections required – 187 cases (23%)

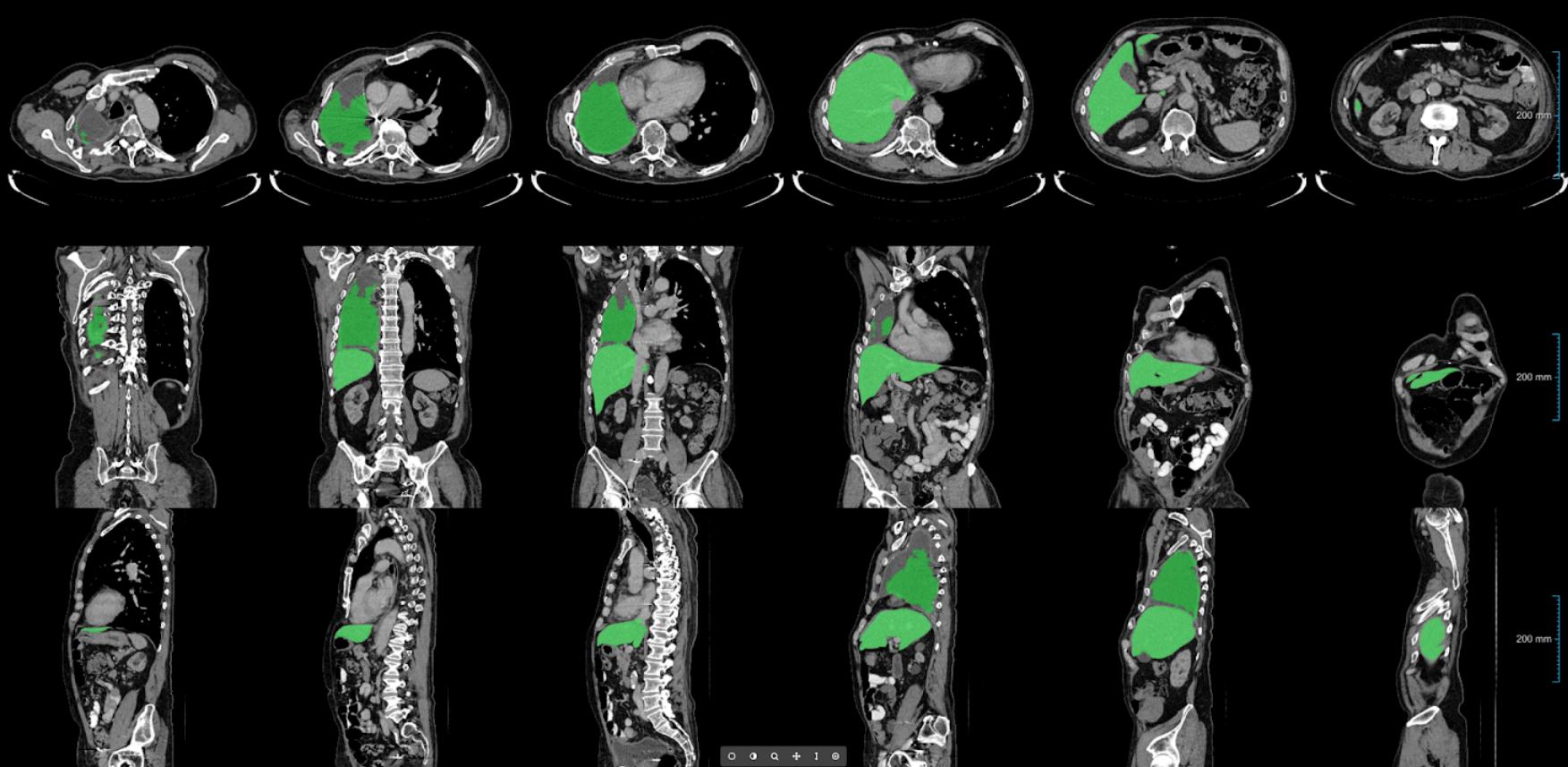
Baseline model evaluation: error analysis

- Leakage into surrounding structures



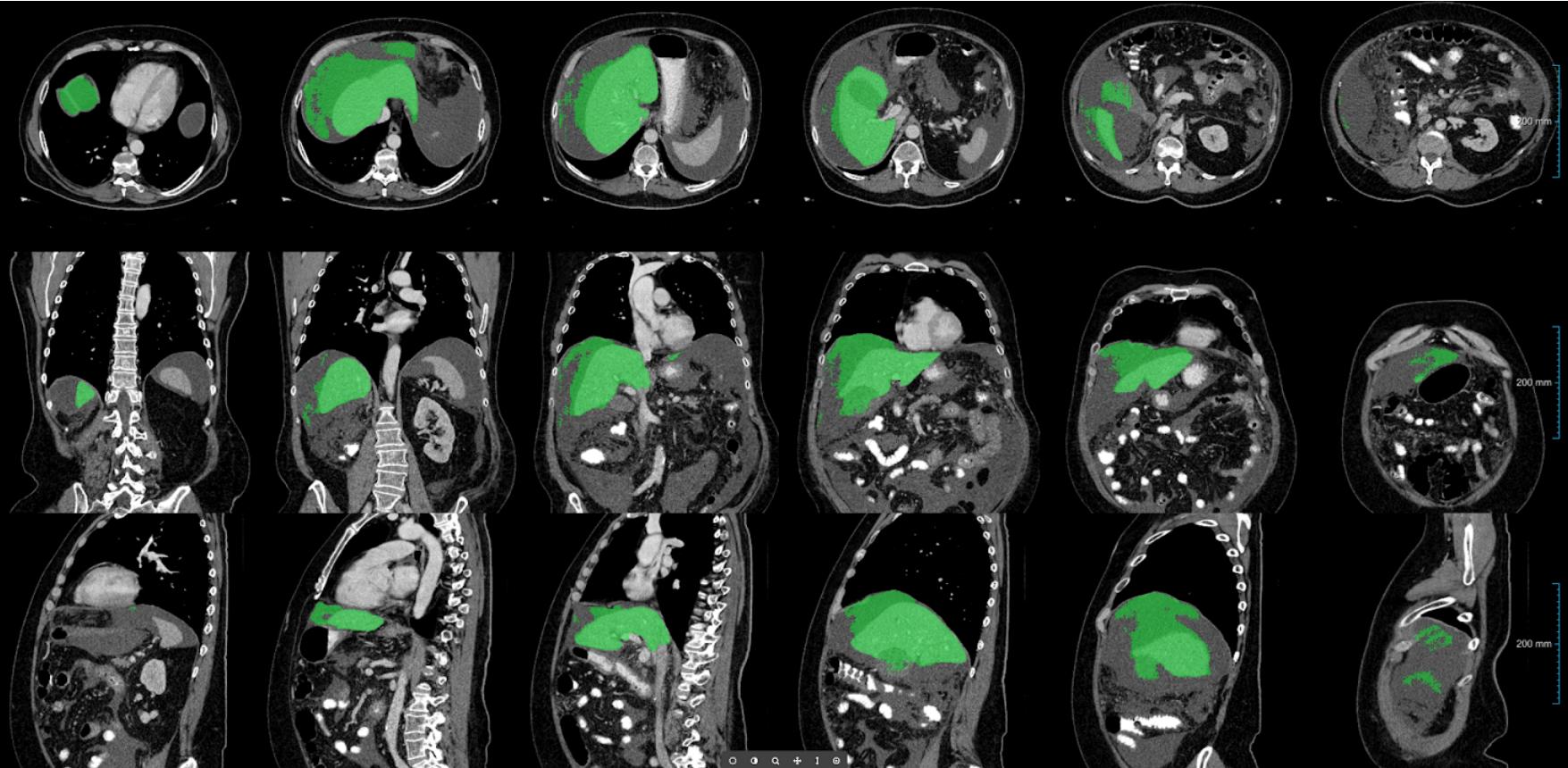
Baseline model evaluation: error analysis

- Segmentation of surrounding pathologies



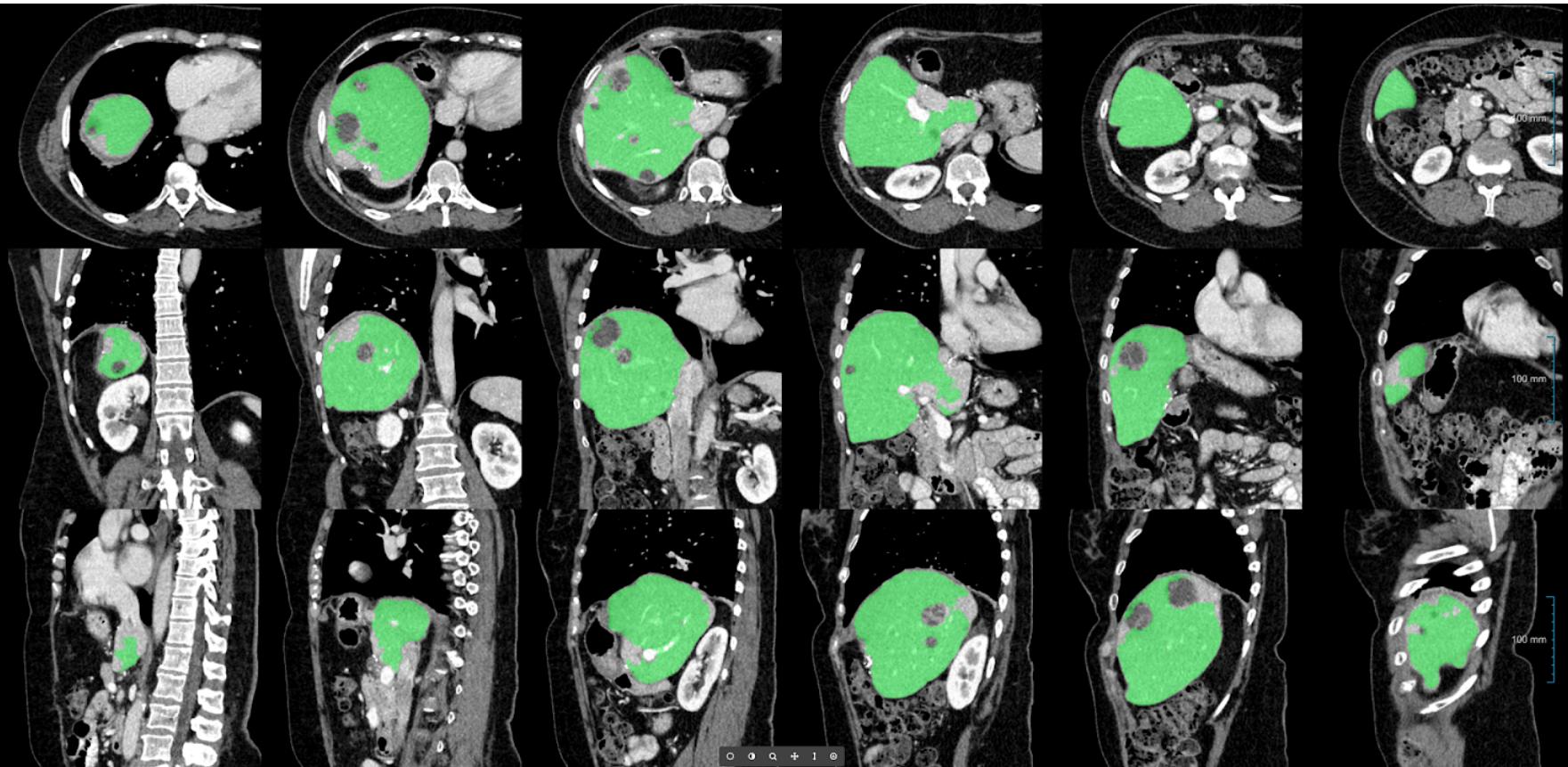
Baseline model evaluation: error analysis

- Segmentation of surrounding pathologies



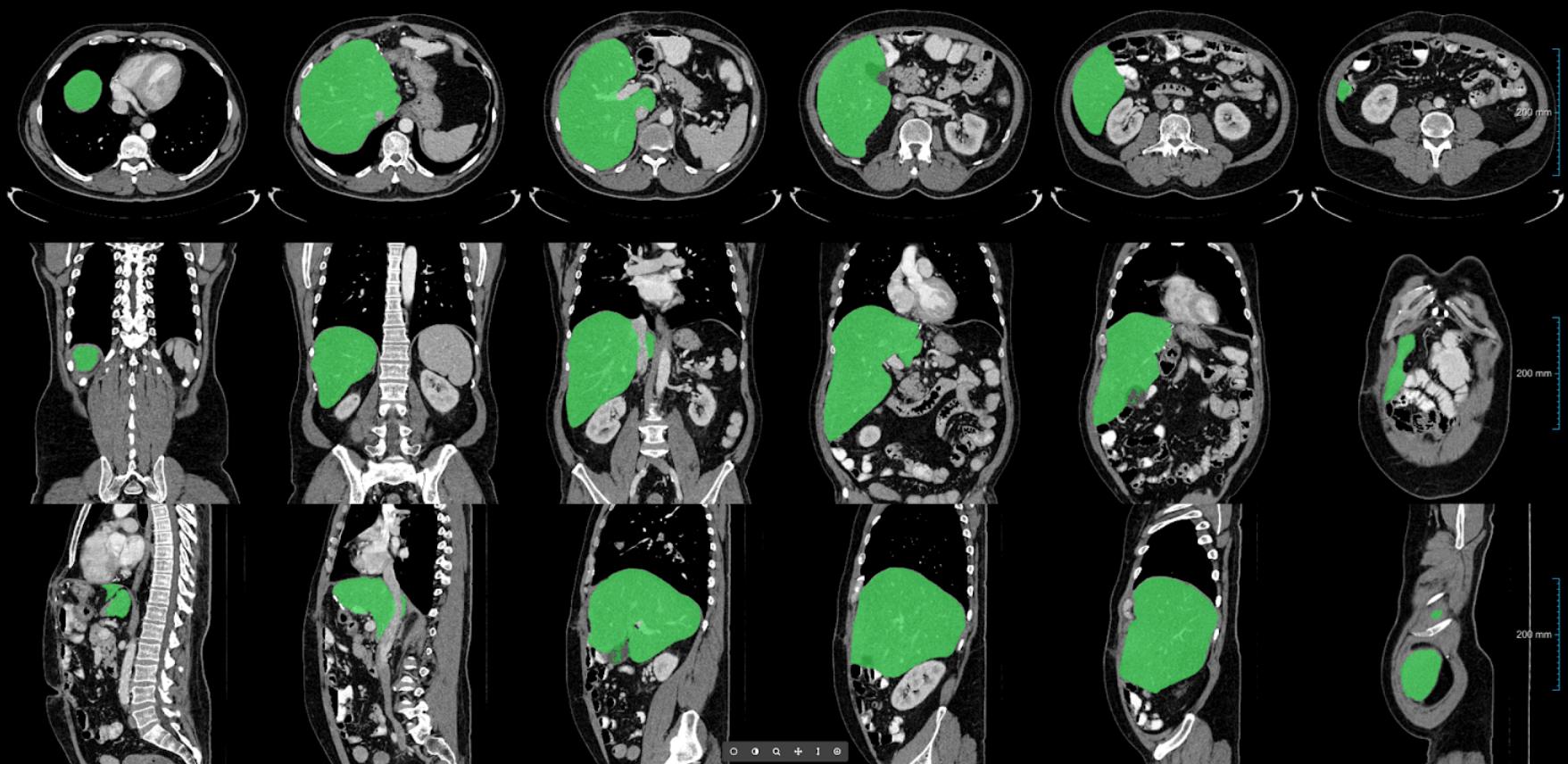
Baseline model evaluation: error analysis

- Hypodense lesions excluded from the liver mask



Baseline model evaluation: error analysis

- Gallbladder partly included in the liver mask



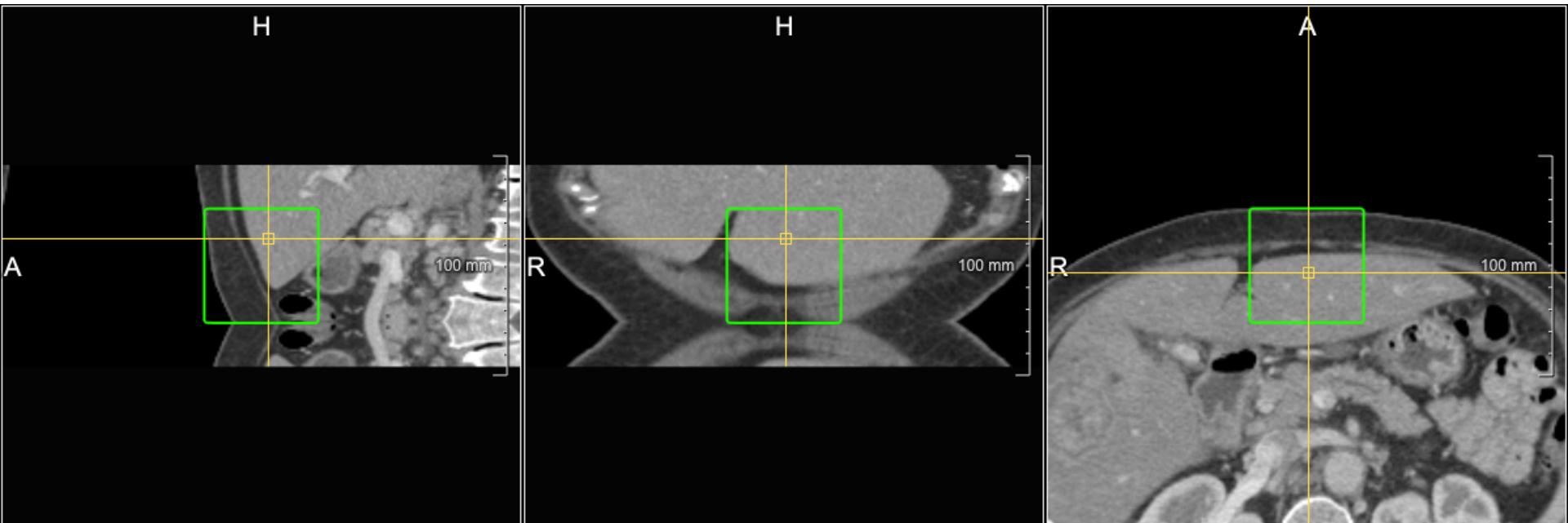
Anisotropic-net

Intuition

Radiologists segmenting organs typically consider a couple of neighboring slices while taking into account the whole in-plane context

3D CNN with an anisotropic receptive field (4 985 906 parameters)

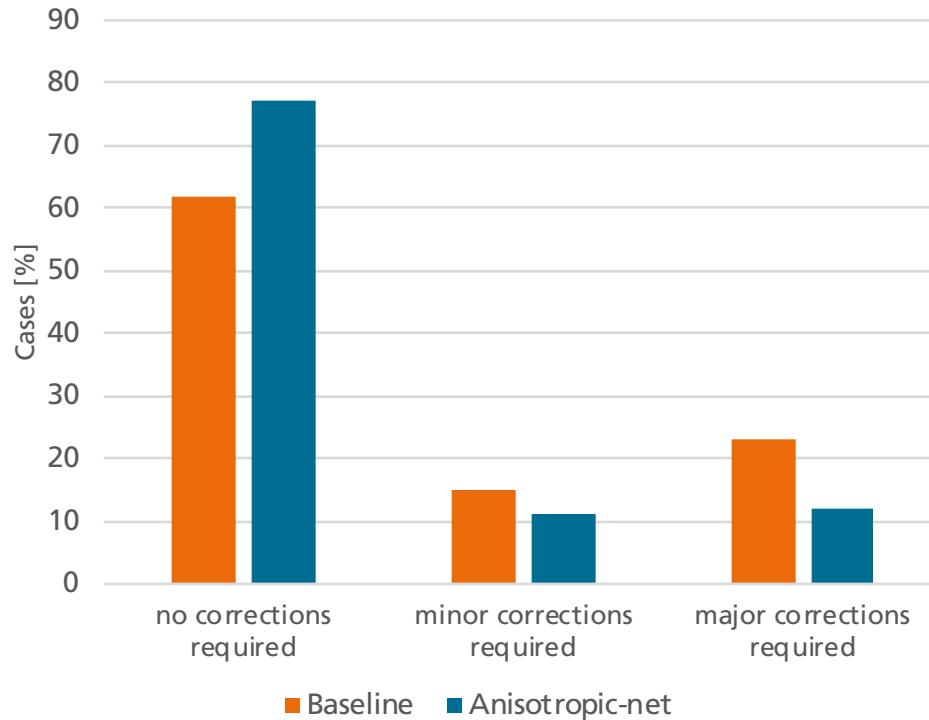
- 188 x 188 x 66 mm³



Evaluation results

Anisotropic-net

- 1 - no corrections required – 634 cases (77%, change **+15%**)
- 2 - minor corrections required – 93 cases (11%, change **-4%**)
- 3 - major corrections required – 99 cases (12%, change **-11%**)



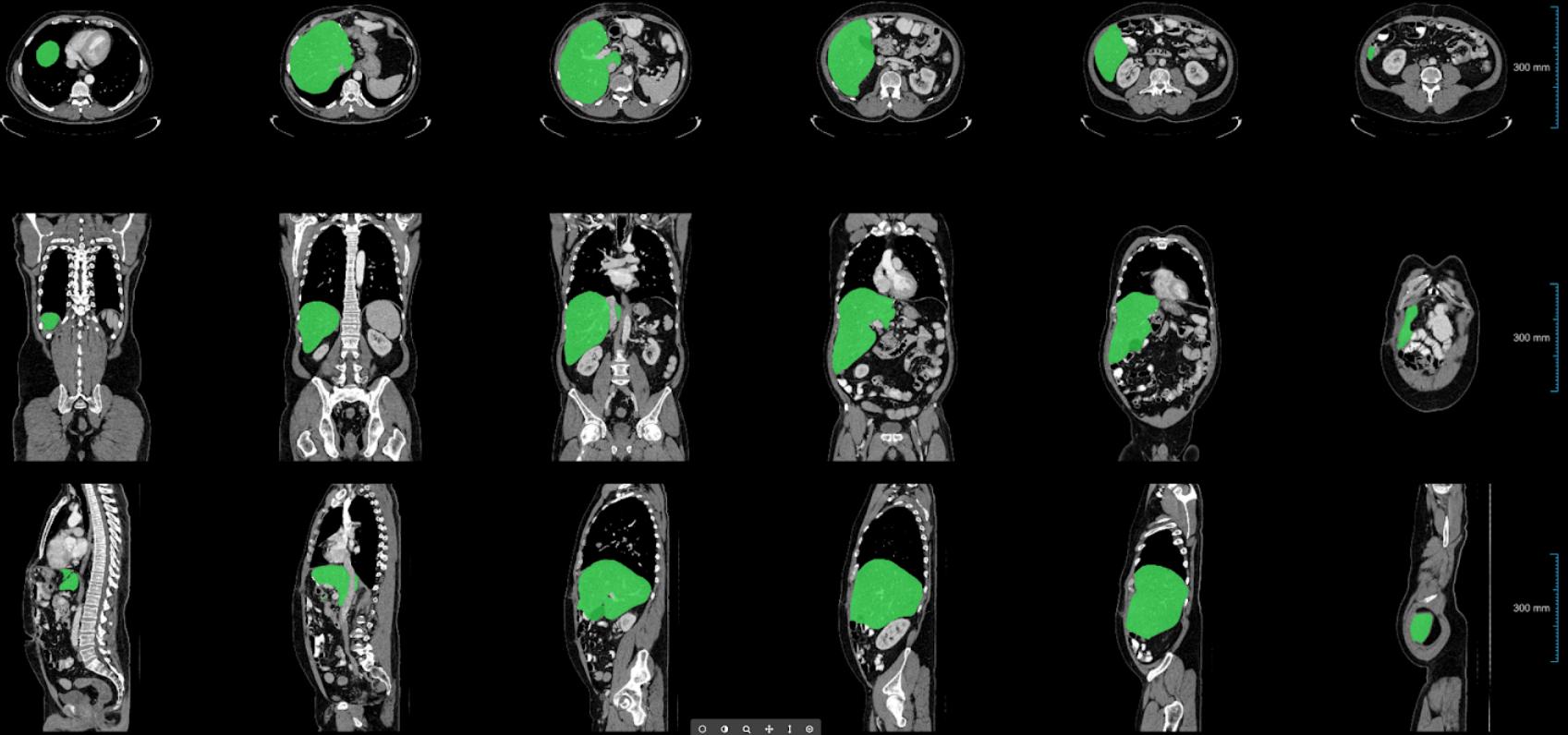
Evaluation results

3D u-net score	Anisotropic-net score	Case count
2	1	87
3	1	94
3	2	22
1	1	453
2	2	23
3	3	71
1	2	48
1	3	15
2	3	13

- 1 - no corrections required
- 2 - minor corrections required
- 3 - major corrections required

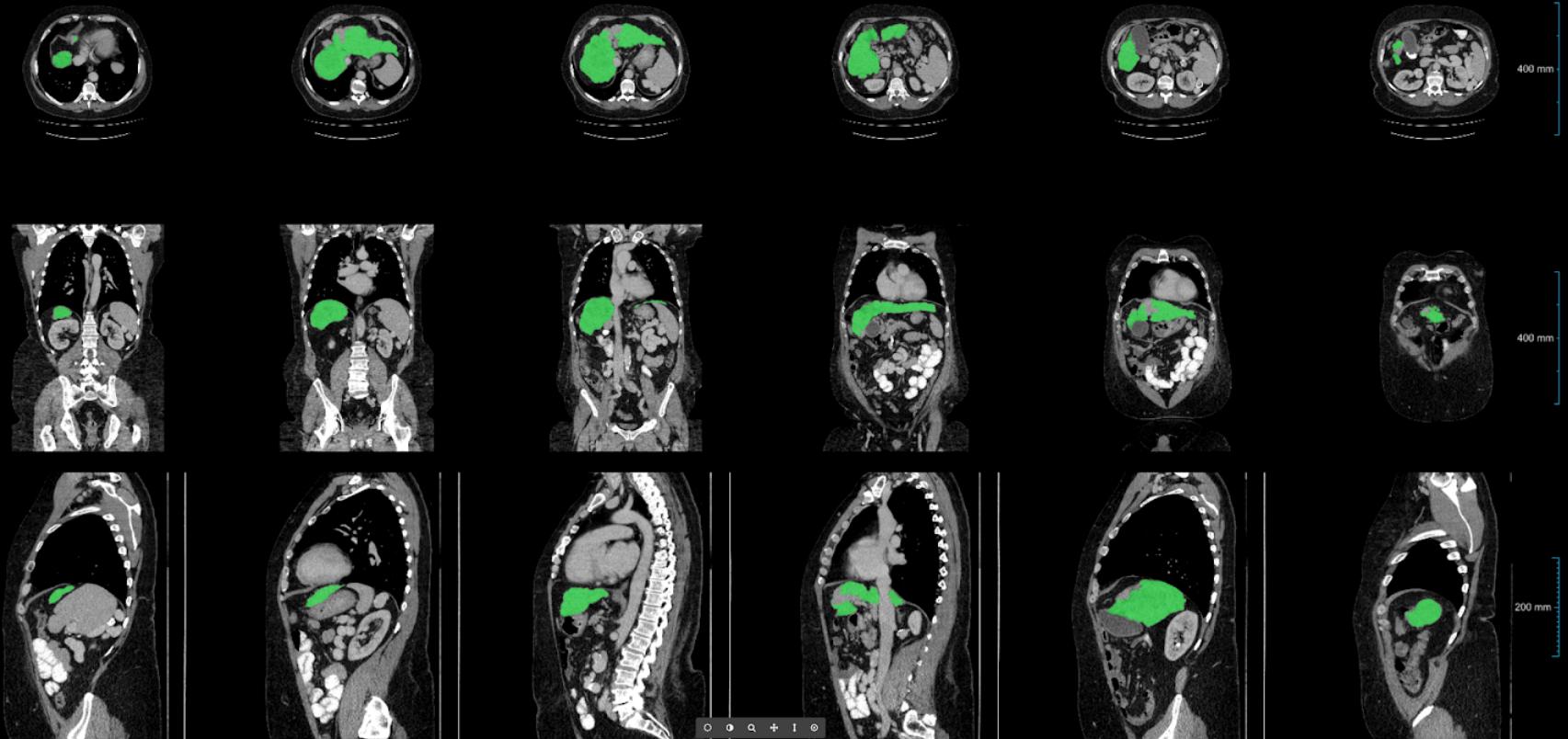
Anisotropic-net evaluation: error analysis

- Leakage into the gallbladder



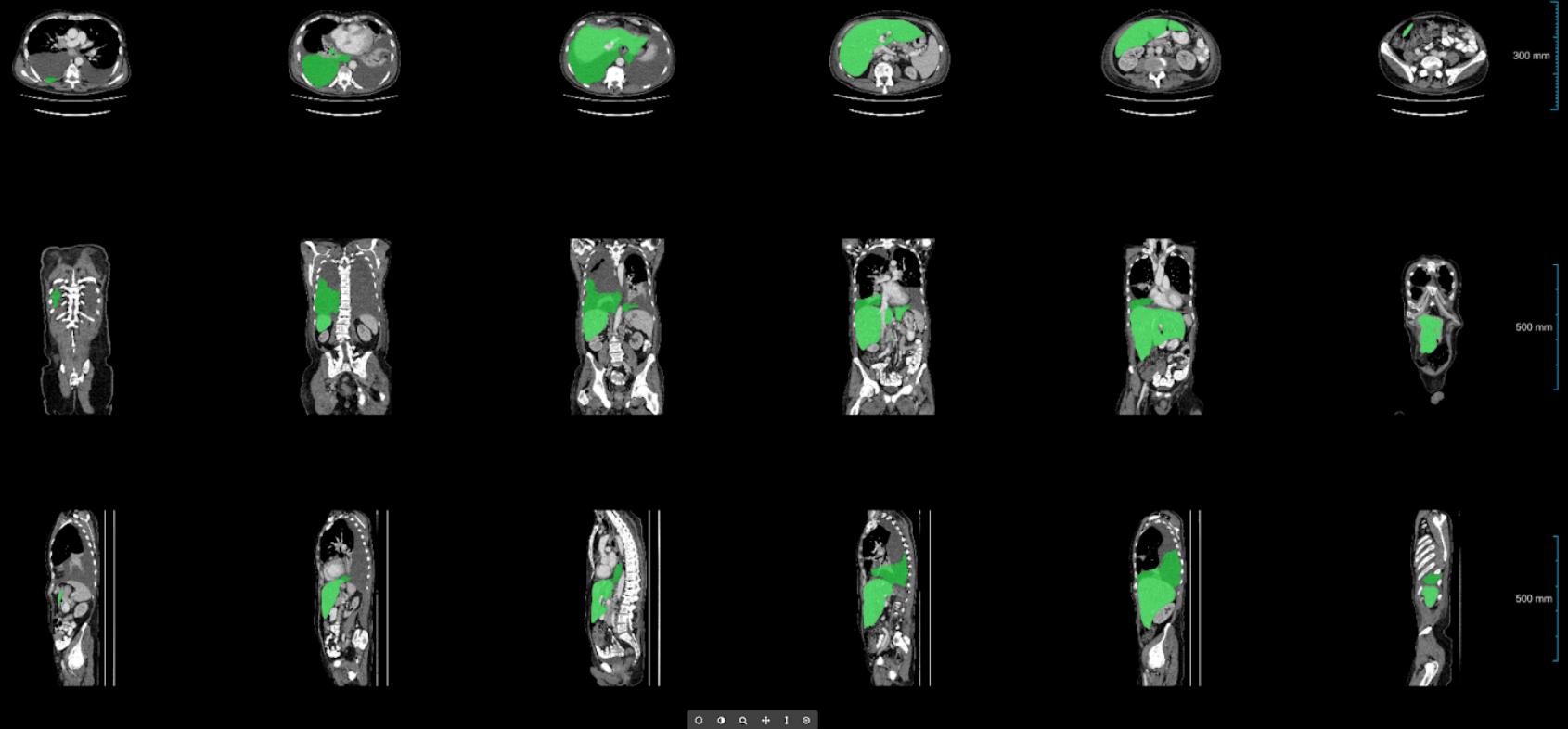
Anisotropic-net evaluation: error analysis

- Underestimation of the liver parenchyma



Anisotropic-net evaluation: error analysis

- Segmentation of surrounding pathologies



Summary

Conclusions

- 3D anisotropic-net produces less segmentations requiring corrections than the baseline model (3D u-net)
- Screenshot-based evaluation is an efficient way to score large amount of cases

Future work

- More extensive validation of the 3D anisotropic-net
- Active-learning to address remaining segmentation errors