Robust Deep Learning-based Semantic Organ Segmentation in Hyperspectral Images

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Introduction

Aim

To explore the use of hyperspectral images for semantic segmentation.

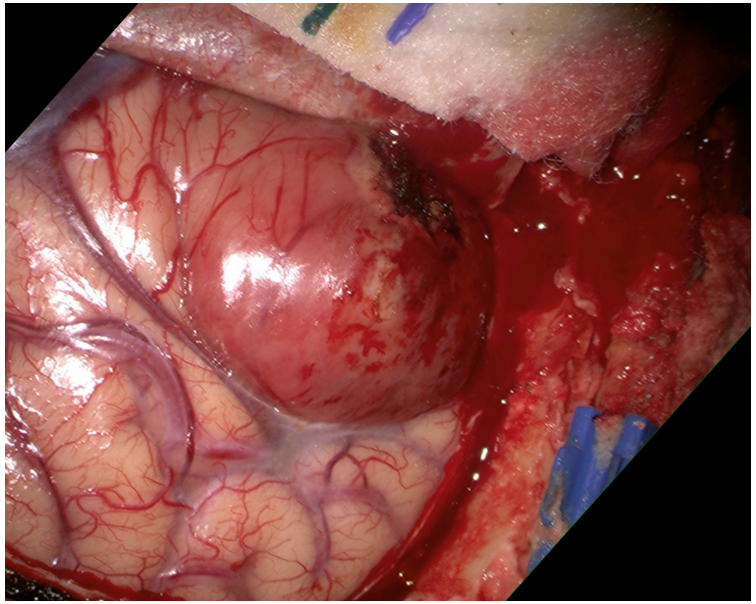
Questions

1) What is an adequate representation of HSI data for neural network-based fully automated organ segmentation?
2) Is there a benefit of using HSI data compared to other modalities, namely RGB data and processed HSI data (e.g. tissue parameters like oxygenation), when performing semantic organ segmentation?

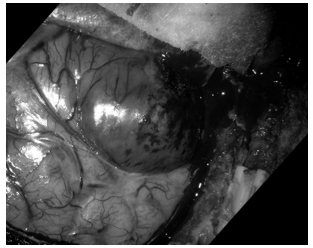
Hyperpectral/Multispectral Images (H/MSI)

What is it?

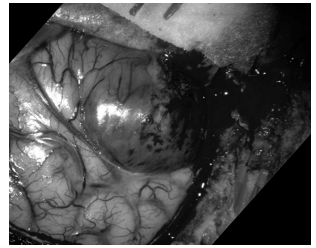
HSI is a stack of images with spatial information on the first two axes (row-column) and spectral information on the third axis (image at wavelength n).



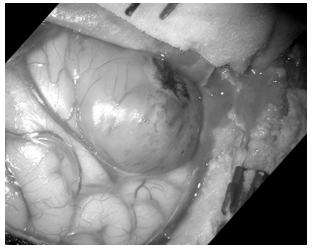
Colour Image



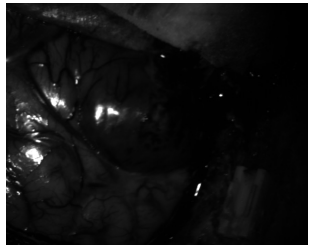
Blue Channel



Green Channel

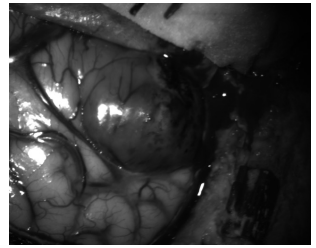


Red Channel



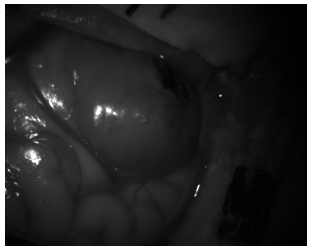
500nm

. . .



600nm

. . .



700nm

Background

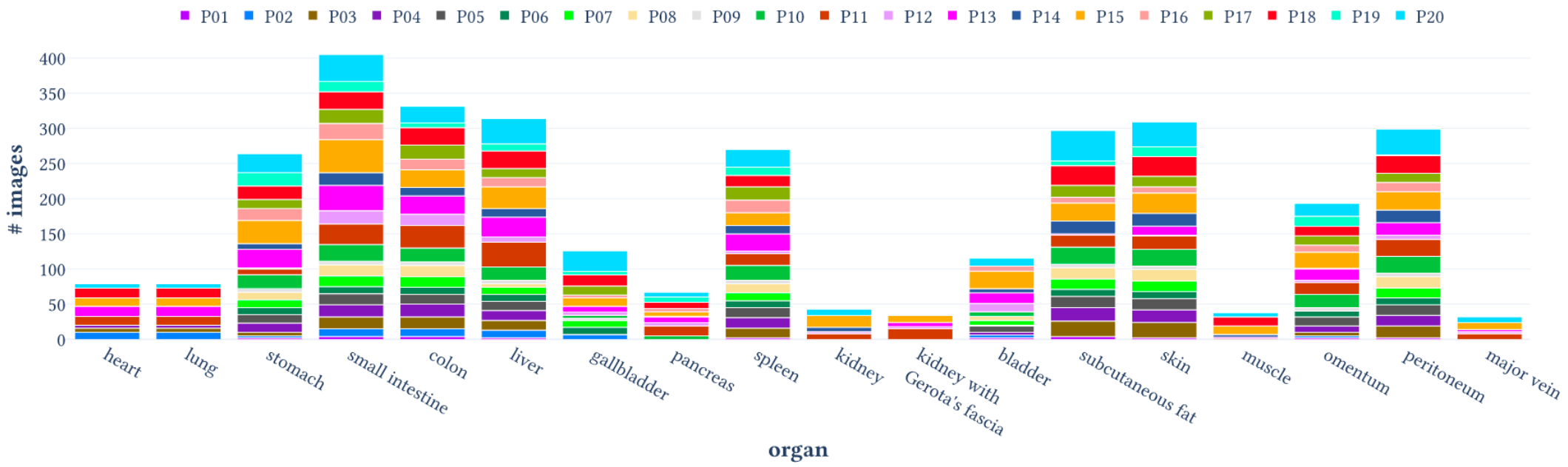
Deep learning-based organ segmentation

There have been many organ segmentation models over the last few years acquired during open and minimally-invasive surgery.

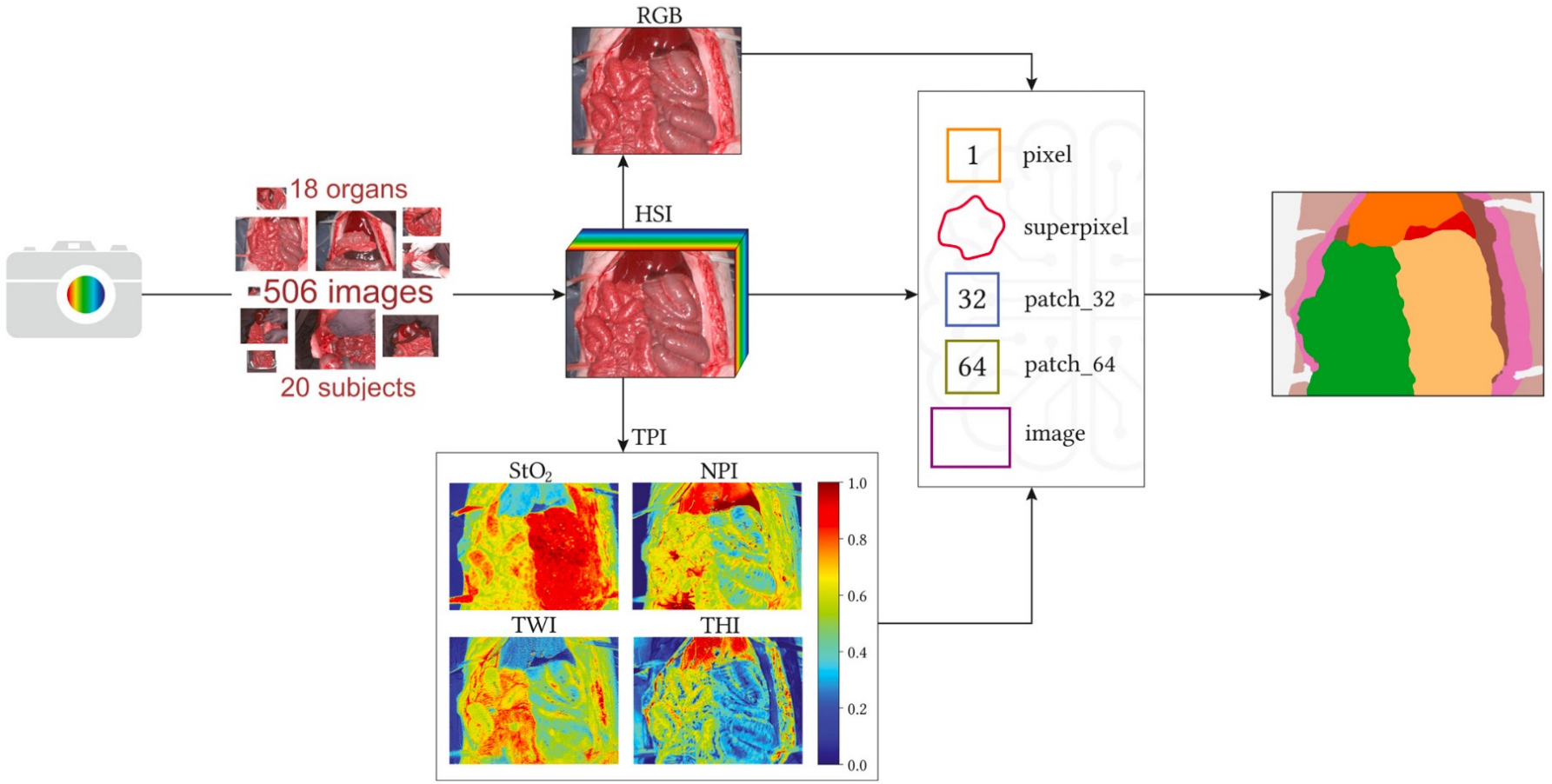
HSI and MSI segmentation

Some papers have shown great results, but there is still only a little discussion on: a) how it performs against other image types and b) the standard of acquiring and handling HSI and MSI data.

Dataset


P01 P02 P03 P04 P05 P06 P07 P08 P09 P10 P11 P12 P13 P14 P15 P16 P17 P18 P19 P20
images
400
350
300
250
200
150
100
50
0
heart
lung
stomach
small intestine
colon
liver
gallbladder
pancreas
spleen
kidney
kidney with Gerota's fascia
bladder
subcutaneous fat
skin
muscle
omentum
peritoneum
major vein
organ

Methodology

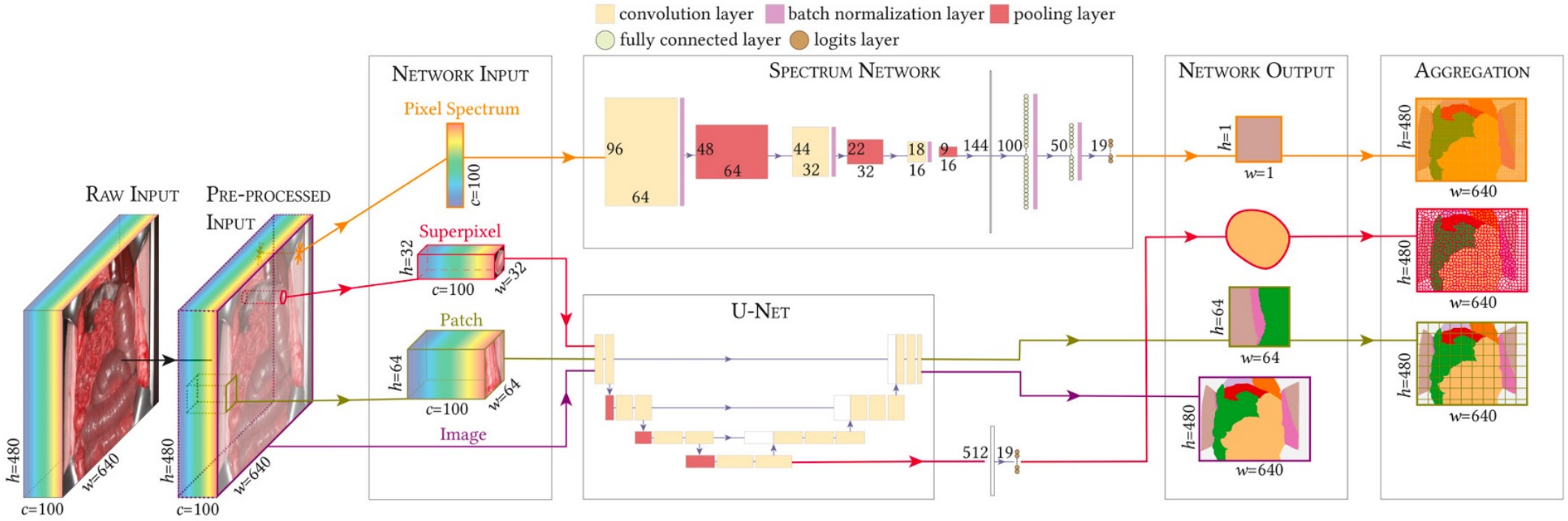


Acquisition

Preprocessing and Annotation

Training and Evaluation

Model


convolution layer
batch normalization layer
pooling layer
fully connected layer
logits layer
Raw Input
Pre-processed Input
h=480
w=640
c=100
Network Input
Pixel Spectrum
Superpixel
Patch
Image
h=32
w=32
h=64
w=64
Spectrum Network
96
64
48
64
44
32
22
32
18
16
9
16
144
100
50
19
U-Net
512
19
Network Output
h=1
w=1
h=64
w=64
Aggregation

Experimental Setup

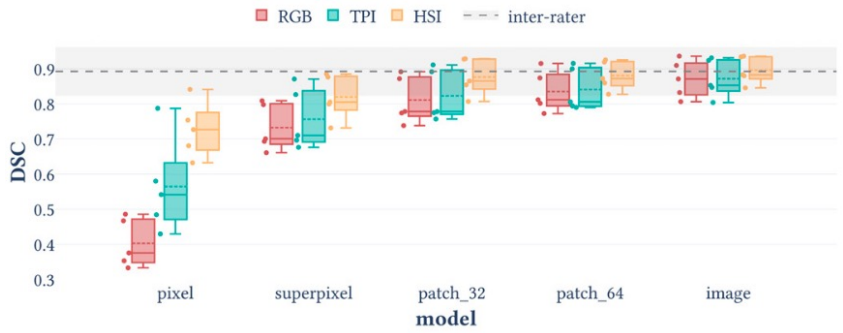
Train-test-split

Images of 20 pigs were divided into 15 pigs for the training data and 5 pigs for the test data (75-25).

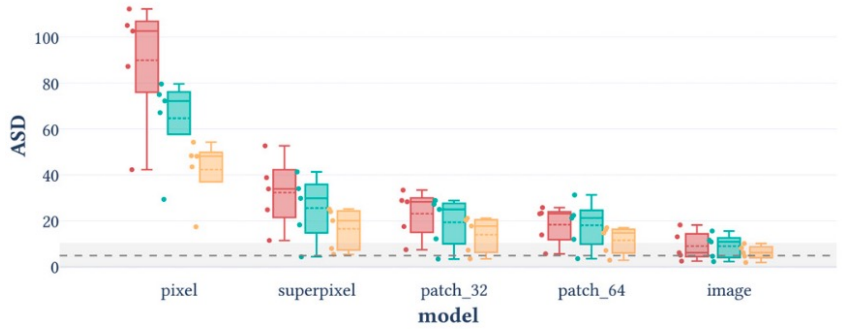
Validation Metrics

- Dice similarity coefficient
- Average surface distance
- Normalised surface dice

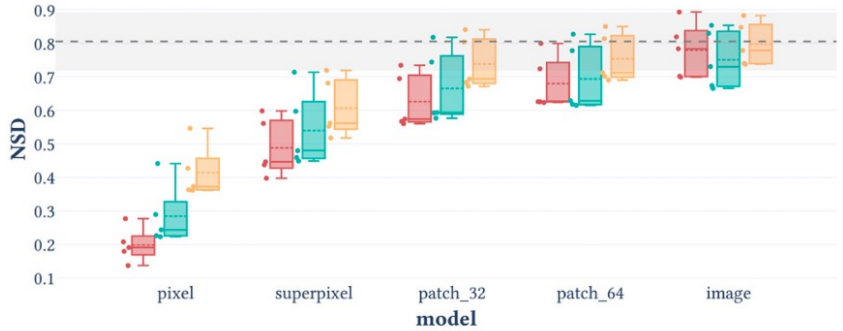
Results



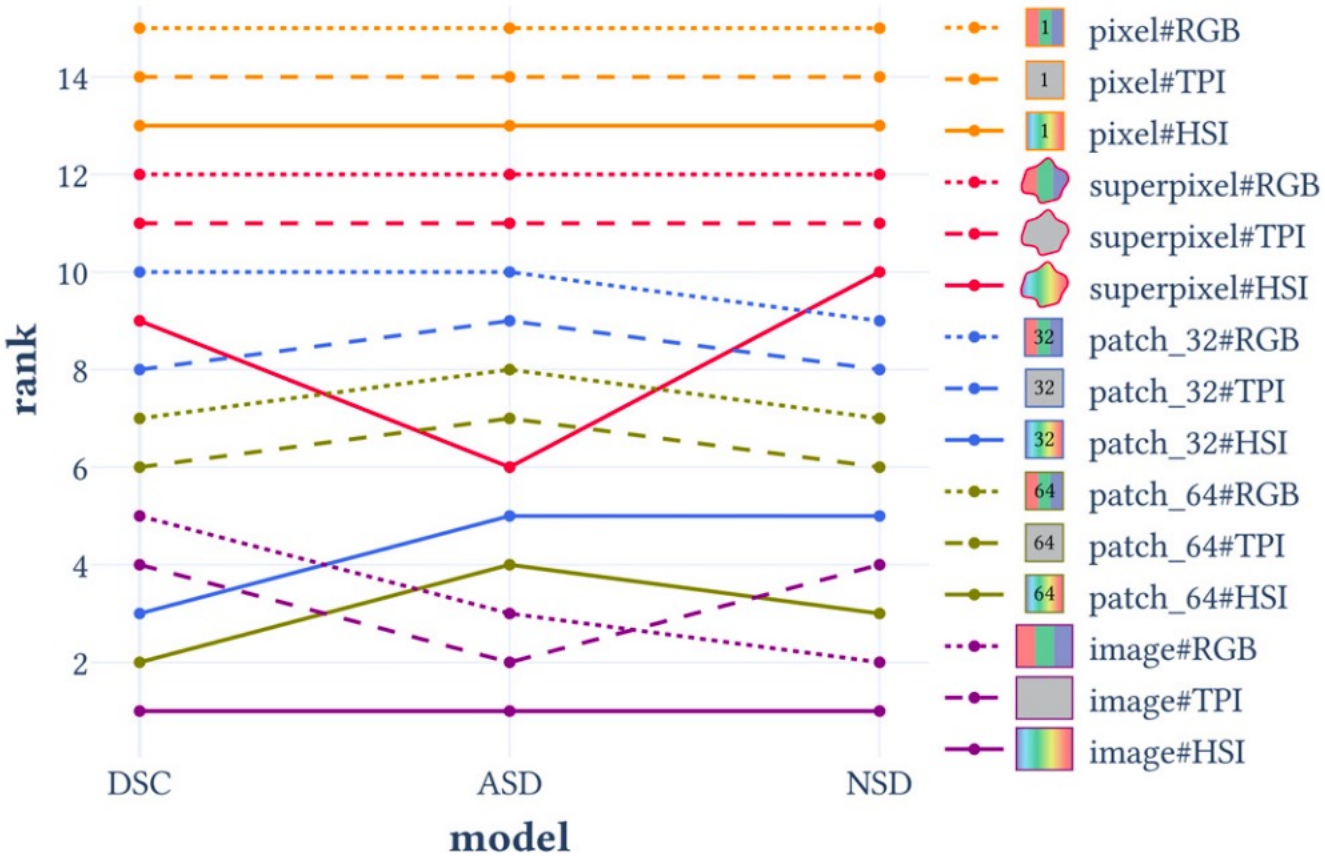
(a) Dice similarity coefficient (DSC)



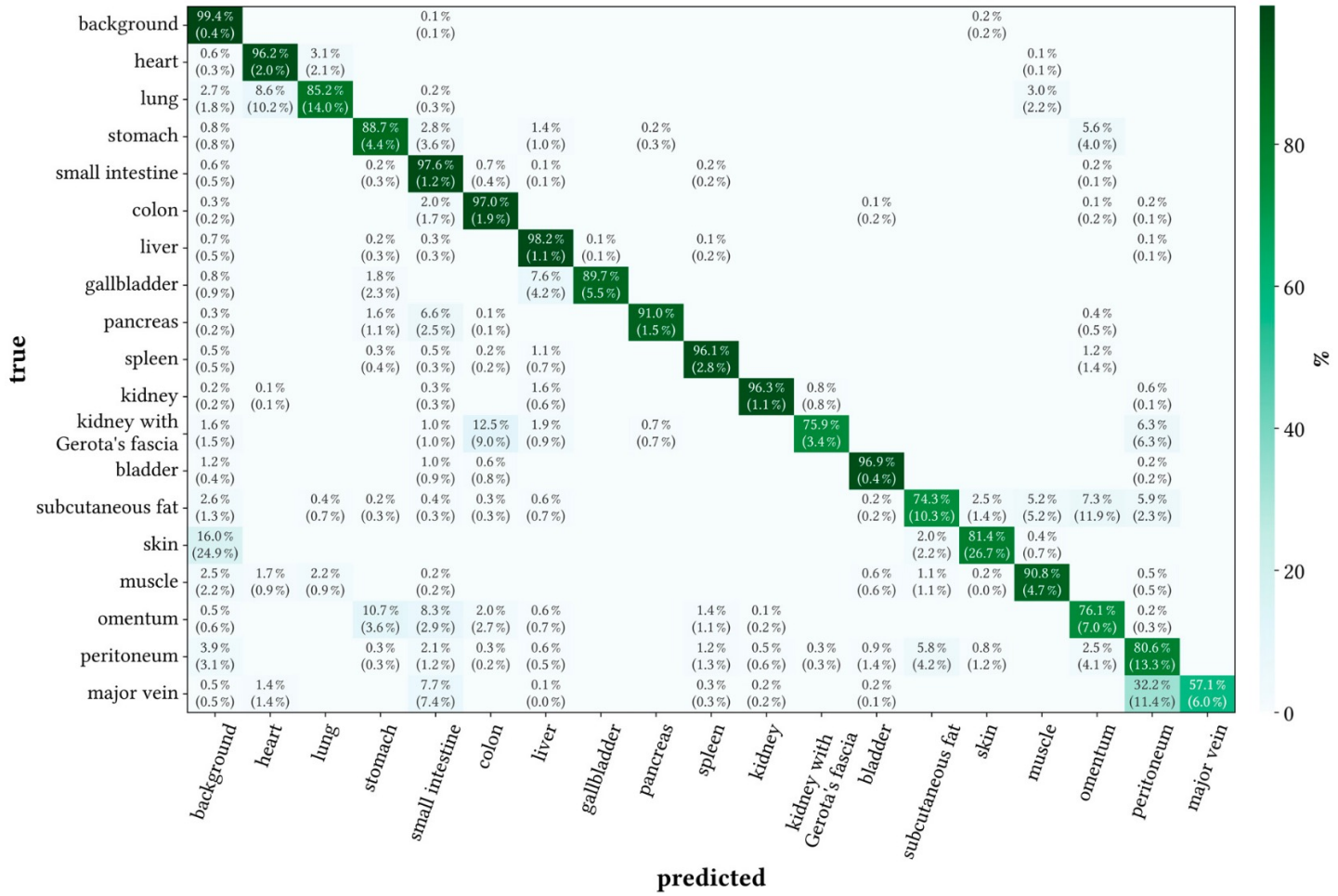
(b) Average surface distance (ASD)

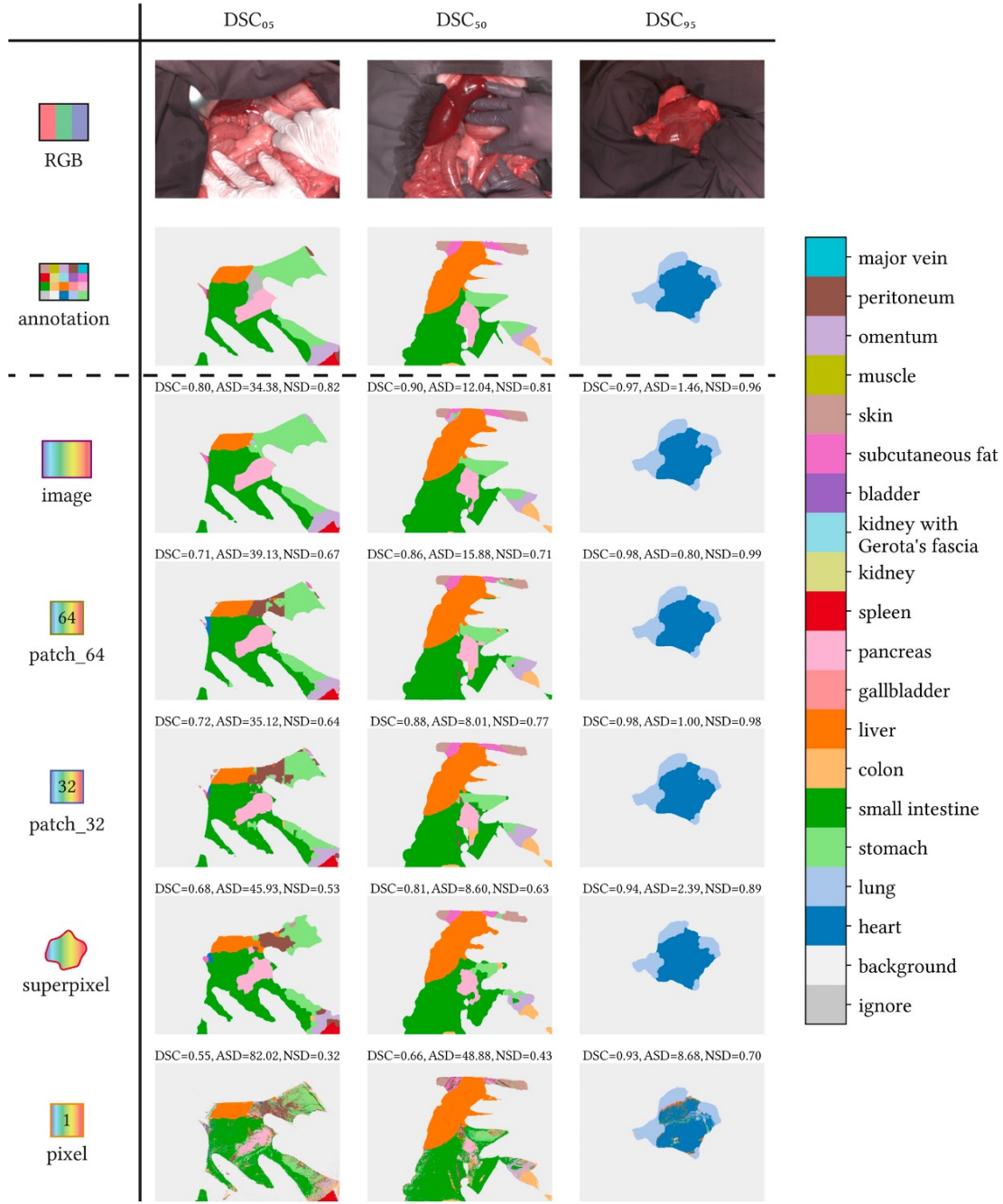


(c) Normalized surface dice (NSD)

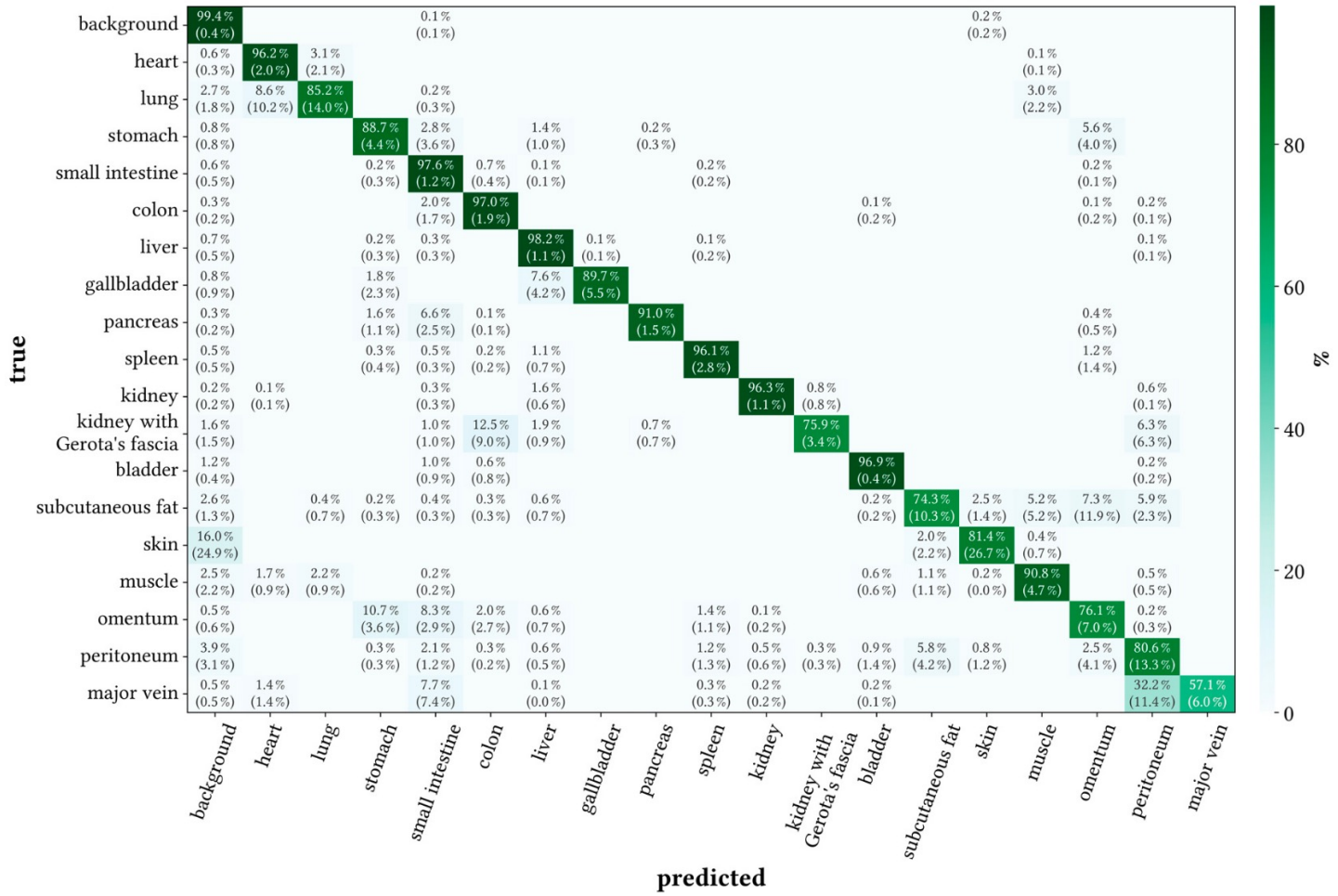


Confusion Matrix




DSC05
DSC50
DSC95
RGB
annotation
DSC=0.80, ASD=34.38, NSD=0.82
DSC=0.90, ASD=12.04, NSD=0.81
DSC=0.97, ASD=1.46, NSD=0.96
image
DSC=0.71, ASD=39.13, NSD=0.67
DSC=0.86, ASD=15.88, NSD=0.71
DSC=0.98, ASD=0.80, NSD=0.99
64
patch_64
DSC=0.72, ASD=35.12, NSD=0.64
DSC=0.88, ASD=8.01, NSD=0.77
DSC=0.98, ASD=1.00, NSD=0.98
32
patch_32
DSC=0.68, ASD=45.93, NSD=0.53
DSC=0.81, ASD=8.60, NSD=0.63
DSC=0.94, ASD=2.39, NSD=0.89
superpixel
DSC=0.55, ASD=82.02, NSD=0.32
DSC=0.66, ASD=48.88, NSD=0.43
DSC=0.93, ASD=8.68, NSD=0.70
1
pixel
major vein
peritoneum
omentum
muscle
skin
subcutaneous fat
bladder
kidney with Gerota's fascia
kidney
spleen
pancreas
gallbladder
liver
colon
small intestine
stomach
lung
heart
background
ignore

Confusion Matrix



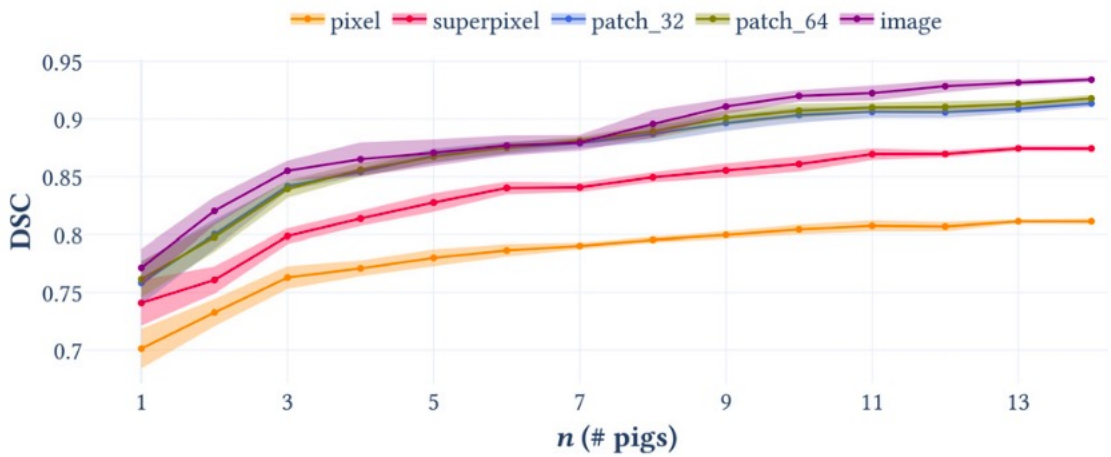
Discussion

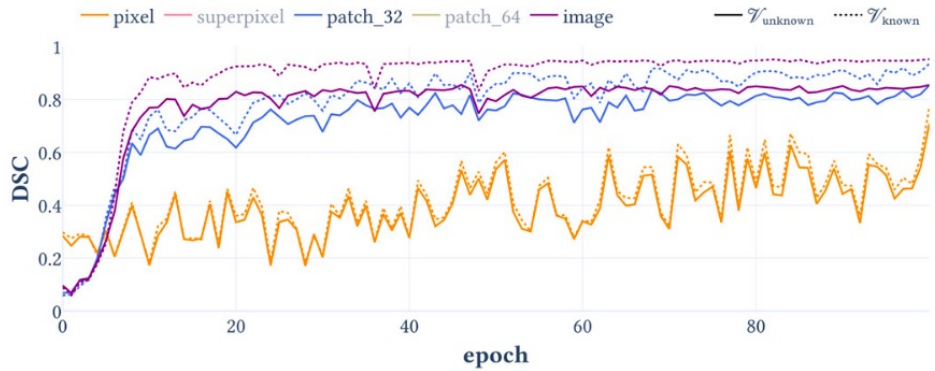
Spatial granularity

Segmentation on the whole image performs better than smaller regions of patches or pixels.

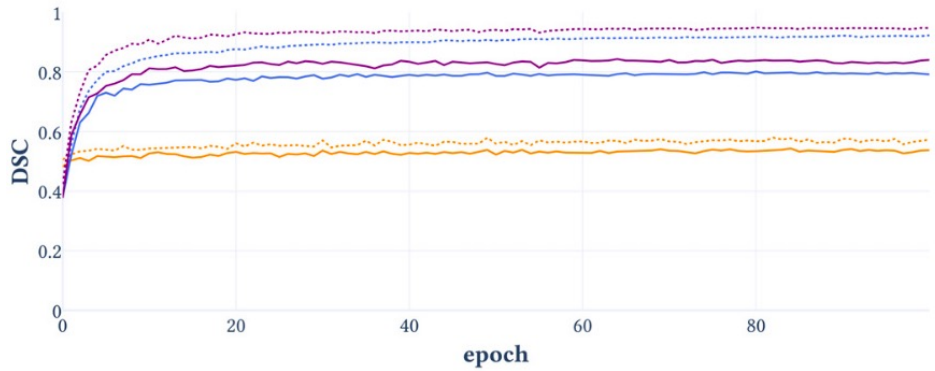
Data size

In all data size, whole image-based segmentation performs close or better than image sizes.

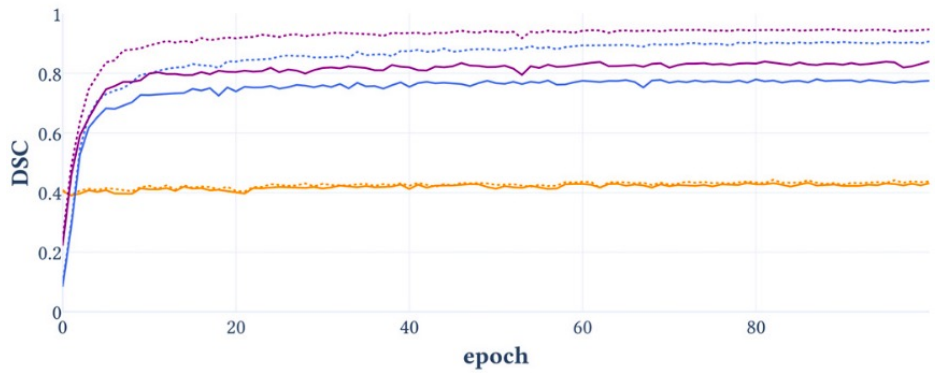




(a) Hyperspectral imaging (HSI)



(b) Tissue parameter images (TPI)



(c) RGB

Conclusion

Overall

Segmentation on HSI gives more benefit than RGB or TPI.

Future works

- Expanding segmentation to larger scope, such as medical instruments.
- Optimum HSI environment
- Generalisation to human
- Annotation improvement
- Number of spectral channels

Thank You

Questions?