Learning Multi-Class Segmentations From Single-Class Datasets: Supplementary Material

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Base model

Below are the details on the architecture of the base model.

	Input
Encoder	Conv 2
Encoder	DenseBlock 16x3 + MaxPooling
Encoder	DenseBlock 32x3 + MaxPooling
Encoder	DenseBlock 64x3 + MaxPooling
Encoder	DenseBlock 128x3 + MaxPooling
Encoder	DenseBlock 256x3 + MaxPooling
Encoder	DenseBlock 512x3 + MaxPooling
Decoder	TransConv 512 + DenseBlock 256x3
Decoder	TransConv 256 + DenseBlock 128x3
Decoder	TransConv 128 + DenseBlock 64x3
Decoder	TransConv 64 + DenseBlock 32x3
Decoder	TransConv 32 + DenseBlock 16x3
Decoder	TransConv 16 + DenseBlock 8x3
Decoder	Conv 32
Decoder	Conv 1
	Output

Table 1. Architecture details of the base model. We utilize 2D or 3D convolutional and transposed convolutional ($TransConv$) layers, depending on the experiment. Each $DenseBlock\ X \times N$ contained N densely connected convolutional layers with X filters each.

References

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[2] Roth Holger, Farag Amal, Turkbey Evrim, Lu Le, Liu Jiamin, and Summers Ronald. Data from pancreas – CT. *Cancer Imaging Archive*, 2016.