DUALTAIL-NET for Liver Segmentation on Abdominal CT Images

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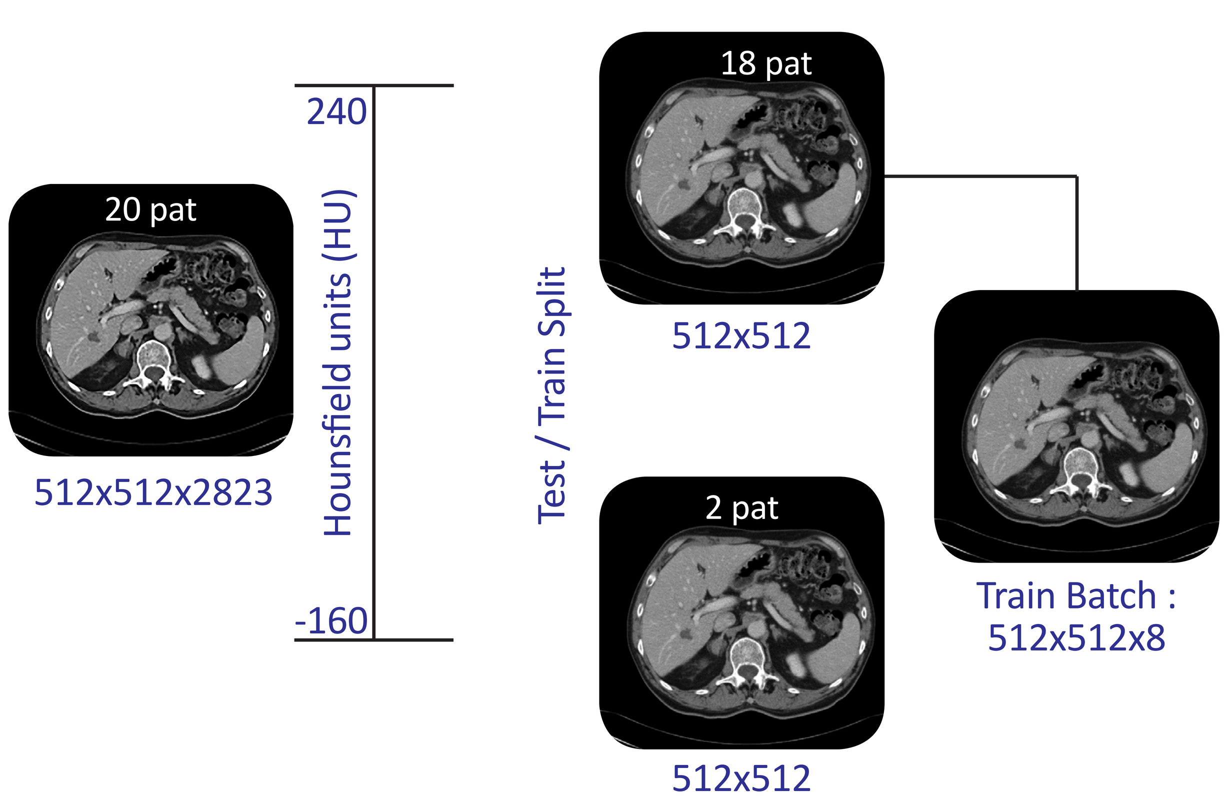
Background

In clinical trials, the evaluation of CT/MRI images is usually done manually or with the use of semi-automatic segmentation techniques. Liver segmentation, as well as segmentations of other organs such as prostate, lung, is a crucial step in computer-aided systems for cancer detection. In order to improve the quality and performance of diagnosis computer-aided systems became popular, where deep learning approach demonstrates its potential and strengths as robust and powerful tool in particular for medical image segmentation [1]. This work presents a novel deep convolutional neural network architecture DualTail-Net in application for automatic liver segmentation on abdominal CT images.

Our Approach



Dataset

- DualTail-Net was trained on the private dataset (with the ”train-validation-test” split to prevent overfitting) of 20 axial contrast-enhanced CT volumes at portal venous phase, representing in total 2823 slices + corresponding GT segmentations.
- Initial images were not preprocessed except clipping the Hounsfield units (HU) values below -160 and above 240 due to commonly accepted frame of interest for liver region in order to exclude the artifacts such as outer air / colon gas and stones [2].

DualTail-Net Overview

The DualTail-Net architecture consists of an encoder, central block and 2 dependent decoders as shown on Fig. 1.

The encoder consists of 4 blocks of convolutions, each followed by a exponential linear unit (ELU) and max-pooling operation for downsampling. It is important that at each downsampling step the locations of max-pooling indices are memorized for each feature map. Two dependent decoder tails are processed in parallel, where the corresponding feature maps are concatenated after each max-unpooling step. First decoder tail starts from central block and consists of 4 blocks.

Second decoder tail starts from the last encoder block and consists of 3 blocks. At the final layer a 1x1 convolution and sigmoid activation function are used to obtain the binary liver segmentation output.

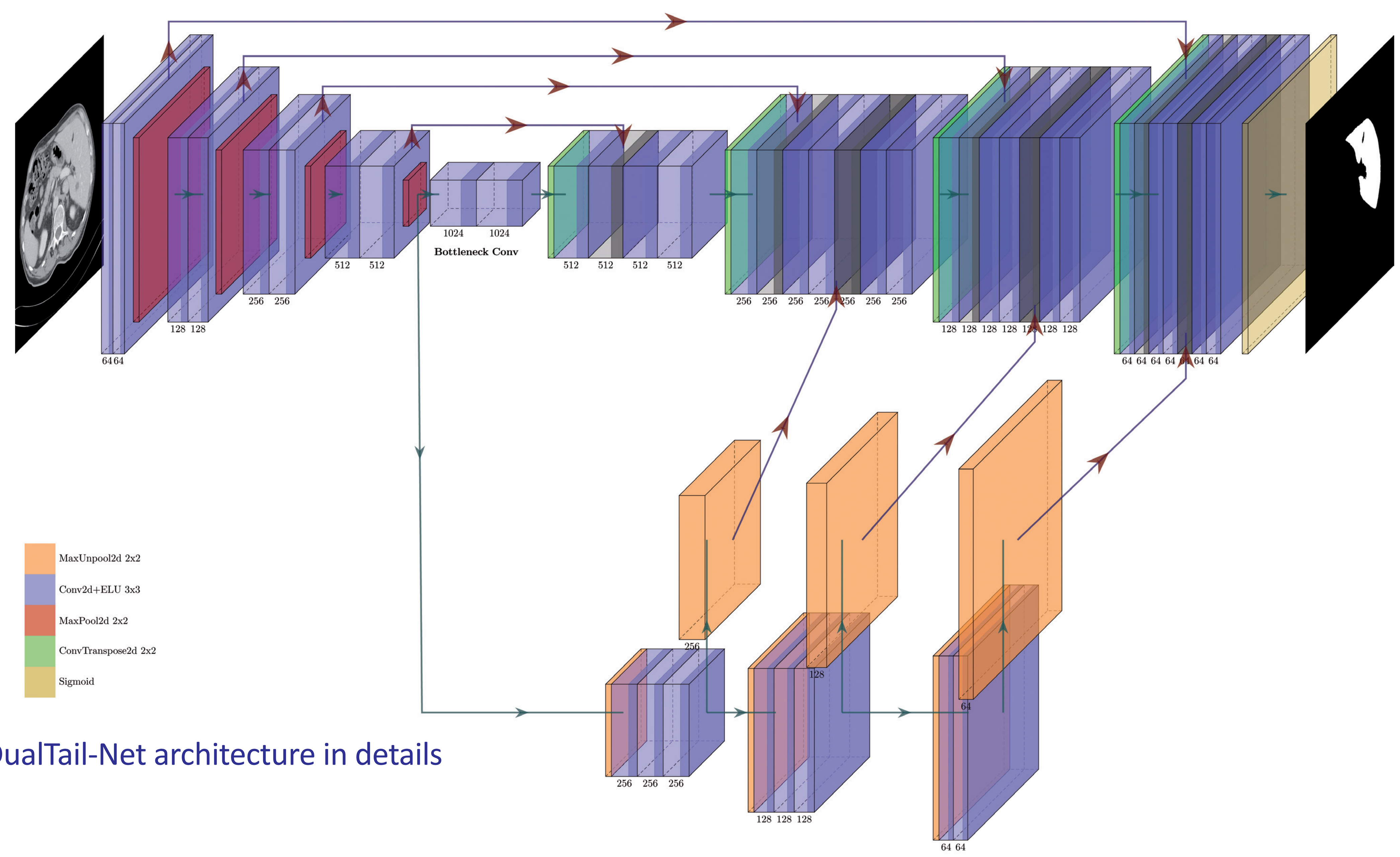
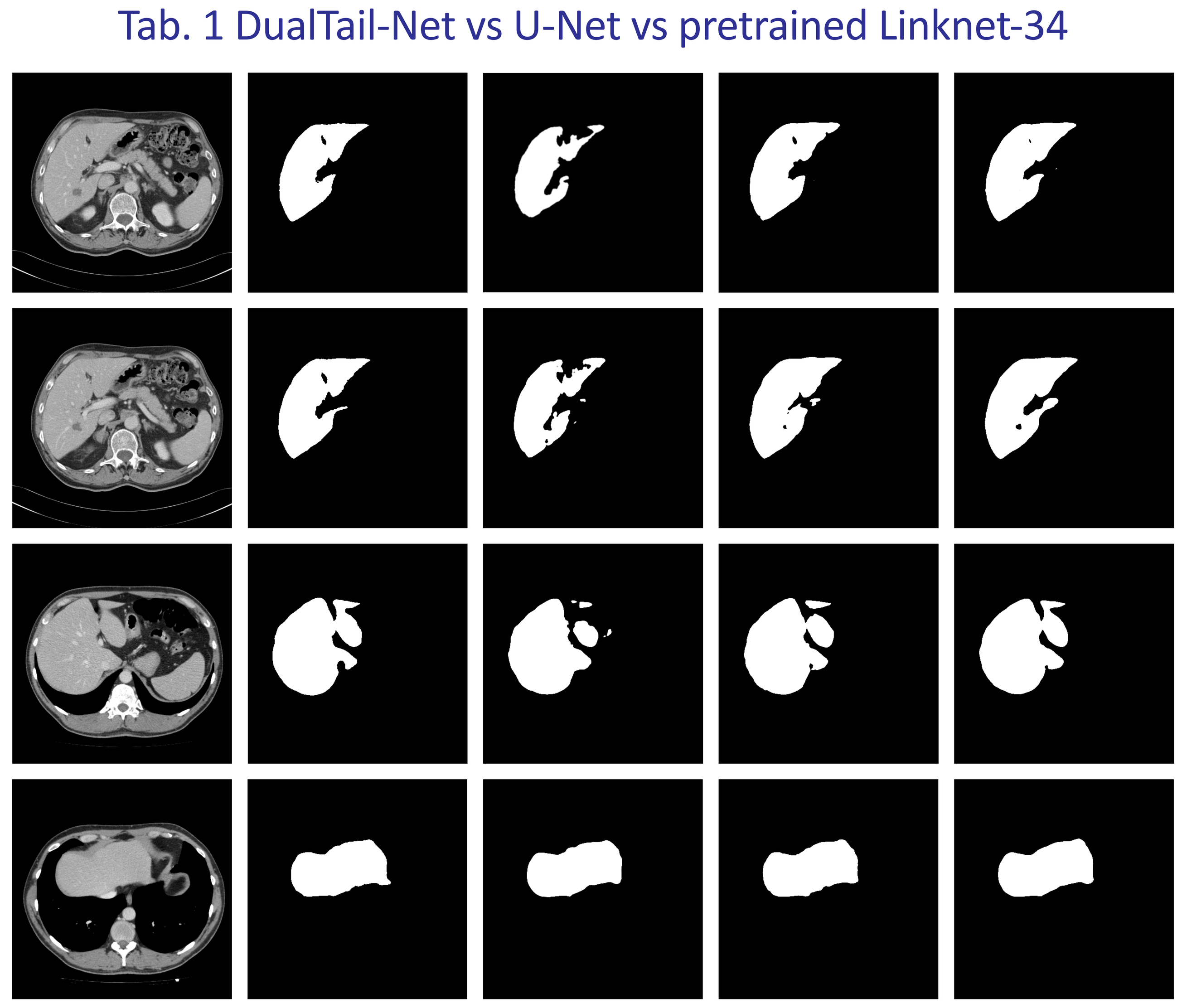


Fig. 1 DualTail-Net architecture in details

Results

	DICE	Recall	Precision
U-Net	0.946	0.959	0.962
DualTail-Net	**0.961**	**0.981**	**0.963**
Linknet-34	0.959	0.973	0.967

Tab. 1 DualTail-Net vs U-Net vs pretrained Linknet-34



(a) Input (b) GT (c) U-Net (d) DualTail-Net (e) Linknet-34

Conclusions

DualTail-Net outperforms the standard U-Net based approach and demonstrates very close performance to the LinkNet-34 [3] with the ResNet34 pretrained on ImageNet as a backbone. Our method shows its significance and the main improvement in providing more consistent and continuous segmentation in the regions where other approaches fail. For a fair comparison, the U-Net (constructed as part of DualTail-Net by removing the second decoder) was also implemented and trained with identical training parameters.

References

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[3] Chaurasia, A., Culurciello, E.: Linknet: *Exploiting encoder representations for efficient semantic segmentation*. arXiv preprint arXiv:1707.03718).