

## [F-06.4]

## LIVER TUMOUR SEGMENTATION WITH CONVOLUTIONAL NEURAL NETWORKS

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The 3D segmentation of the liver can provide doctors with meaningful and reliable quantitative information, which can facilitate the diagnosis of liver abnormalities. However, this segmentation is challenging due to the usually low contrast among liver/lesions/and nearby organs [1]. Convolutional neural networks (CNNs) have become the state of the art in several fields of computational vision. Particularly, CNNs have successfully addressed segmentation problems toward hierarchical representations build from image data. The purpose of this study was to develop a CNN to build 3D liver and tumour shapes from abdominal CT scans. A total of 130 CT scans obtained from the publicly available 2017 MICCAI Lits dataset were used to assess the developed segmentation approach, which aims the identification of the: liver, liver tumor and background. The annotation of the objects was performed in each scan by trained health professionals. We used cascaded CNN architecture, which starts by segmenting the liver in order to establish a target region of interest (ROI), followed by a second step concerning the segmentation of the lesion in the ROI. This segmentation is complemented with a segmentation refinement step performed using a statistical modeling method: 3D Conditional Random Fields (CRF). We designed a variation of the standard U-Net by including a dilated pyramid pooling module as the encoding path. Two CNNs were trained end-to-end, with a He norm weight initialization, and a weight function was integrated into the loss function so as to strengthen the supervision of the tumor boundaries. Our approach was able to successfully extract the liver and tumors in a subset of 30 scans, Figure 1, outperforming two state-of-the-art approaches in terms of the quantitative metrics: Dice coefficient, sensitivity (SE), and specificity (SP), Table 1.

Method	Dice (%)		SE		SP	
	liver	tumor	liver	tumor	liver	tumor
[2]	96.3	65.7	-	-	-	-
[3]	95.9	50.0	-	-	-	-
Ours	94.4	59.6	90.5	50.7	93.8	59.9

Table 1. Performance metrics result.

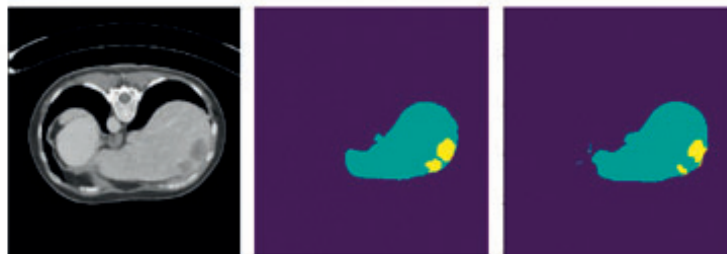


Figure 1. Original CT slice, target annotations and obtained segmentations.

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#### References:

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