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Vascular segmentation in abdominal cavity, with focus on liver vascular system.

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1 Background

Vascular segmentation is a critical task in surgical planning and medical research. Presently, medical data segmentation tasks are predominantly addressed by artificial intelligence, notably UNet (Affane, 2021), ResNet (Sabir, 2022), and Transformers (Wu, 2023) architectures. However, vascular segmentation poses a challenge as 2D segmentation fails to differentiate between vessels and noise in CT data, necessitating the utilization of 3D versions of these architectures. The objective of this study was to develop models capable of segmenting vessels within the liver and its surroundings. Initially, it was necessary to identify a suitable dataset and preprocess the data appropriately. Subsequently, models were trained using various versions of the UNet architecture and evaluated.

2 Data

The dataset 3DIrcad (Soler, 2010), comprising 20 CT scans of patients with liver cancer, containing segmented structures such as arteries, vena cava, portal vein, and venous system, was used for all the created models. Unfortunately, the dataset suffers from low quality, as each file is segmented by a different doctor, resulting in slight variations in the segmentation of each structure, and not all structures are present in every file. Due to this reason and the limited amount of data in the training and the testing dataset (data split in a ratio of 20:80 %, correspond to approximately 10–14 files for training and 1-3 files for testing), there is a significant disparity between validation on training and testing dataset. CT data is normalized to -1000 to 1000 Hounsfield units with a resolution of 512 x 512 x 150 px (0.7 mm x 0.7 mm x 1.6 to 4 mm). For the task requirements, the data was reformatted to a resolution of 1 mm x 1 mm x 1 mm, rescaled to 0-1 intensity, and subsequently randomly cropped into cubes of size 256 x 256 x 128 px, thus creating a data generator that partially addresses the data scarcity issue. Figure 1 shows an example of data from one file in the 3DIrcad dataset.

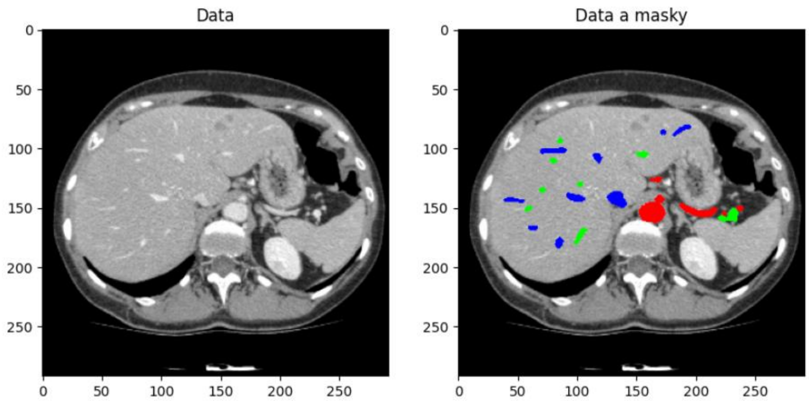

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Figure 1: Example of file in the dataset 3DIrcad. Green – venous system, Blue – portal vein, Red - artery

3 Models and results

In the experiment, three UNet architectures of varying depth were tested (Small – 6 x 2 convolution layers, Medium – 10 x 2 convolution layers, and Large – 16 x 2 convolution layers) with the use of max-pooling and dropout layers to mitigate the impact of the small dataset. For model evaluation, two metrics were employed: accuracy (intersection of areas / predicted area) and dice coefficient (2x (intersection of areas) / (area of prediction + area of mask)). Table 1 displays the results of each model and provides a description of all segmented structures. Highlighted rows indicate that the most successfully segmented structures were the artery and cevy1 (a combination of artery, portal vein, venous system), with the Medium UNet being the overall most successful model. This is likely due to its larger neighbourhood pixel view, yet with a small enough number of parameters to be trained thoroughly.

	Small				Medium				Large			
	Train		Test		Train		Test		Train		Test	
	Dice	Acc	Dice	Acc	Dice	Acc	Dice	Acc	Dice	Acc	Dice	Acc
Artery	0.89	0.99	**0.70**	0.99	0.88	0.99	**0.71**	0.99	0.58	0.99	**0.56**	0.98
Vena cava	0.47	0.98	0.23	0.98	0.57	0.99	0.17	0.99	0.59	0.98	0.15	0.99
Portal vein	0.73	0.99	0.25	0.99	0.39	0.98	0.24	0.99	0.25	0.96	0.21	0.97
Venous syst	0.80	0.98	0.37	0.98	0.79	0.98	0.27	0.98	0.38	0.96	0.11	0.98
Cevy1	0.82	0.98	**0.60**	0.96	0.82	0.97	**0.61**	0.97	0.59	0.96	**0.44**	0.95
Cevy2	0.59	0.99	0.22	0.97	0.40	0.91	0.24	0.95	0.61	0.98	0.21	0.97
Cevy3	0.48	0.98	0.45	0.98	0.67	0.97	0.44	0.98	0.49	0.97	0.39	0.94

Table 1: Results of trained UNet models (Acc – Accuracy, Dice – Dice Coefficient). Small – 6 x 2 convolution layers, Medium – 10 x 2 convolution layers, Large – 16 x 2 convolution layers. Cevy1 - artery, portal vein, venous system, Cevy2 - portal vein, venous system, Cevy3 - portal vein, vena cava.

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