Automatic Segmentation of Abdominal Organs with 3D-UNet

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Abstract. Automatic segmentation of abdominal organs are of great importance for clinical use. Current deep learning based fully-supervised segmentation methods have achieved promising results on abdominal organs. In this paper, we investigate the performance of a fully-supervised segmentation model with limited labeled data on abdominal organs.

Keywords: Automatic Segmentation · Deep Learning.

1 Introduction

Automatic segmentation of abdominal organs are of great importance for clinical use. Current deep learning based fully-supervised segmentation methods have achieved promising results on abdominal organs. However, it requires large annotated datasets thus could be labour-intensive. In recent years, there are plenty of works that focus on achieving powerful model with less labeled data, like few-shot learning [7, 11], weakly supervised learning [5, 10] and semi-supervised learning [9, 13]. Among these approaches, semi-supervised learning utilizes limited annotated images and abundant unlabeled images and has been well-studied.

To investigate the performance of semi-supervised learning in abdominal images, FLARE 2022 challenge [1] provides a small number of labeled cases (50) and a large number of unlabeled cases (2000) in the training set, 50 visible cases for validation, and 200 hidden cases for testing. The segmentation targets include 13 organs: liver, spleen, pancreas, right kidney, left kidney, stomach, gallbladder, esophagus, aorta, inferior vena cava, right adrenal gland, left adrenal gland, and duodenum. However, we are more interested in what kind of performance can be achieved with only annotated datasets and focus on developing a fully-supervised model with appropriate data preprocessing. We train a 3D-UNet [1] on all 50 labeled cases with a hard-region-weighted loss.

2 Method

2.1 Preprocessing

The whole preprocessing contains two parts:

[1] https://flare22.grand-challenge.org/

- All volumes are resampled to [3, 1.5, 1.5] mm along axial, coronal and sagittal dimensions;
- Intensity normalization with segmental linear functions (SLFs) [6] from [-1000, -200, 300, 1000] HU to [0, 0.2, 0.8, 1].

2.2 Proposed Method

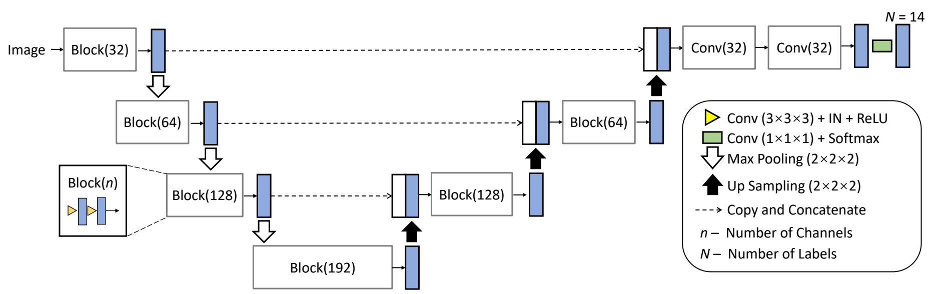

Fig. 1. Network architecture

We adopt the 3D U-Net [1] and the details are illustrated in Figure 1.

Due to the large class imbalance among 13 organs and background area, we use the $ATH - L_{Exp}$ [6], which has the network focus more on hard voxels and small organs.

3 Experiments

3.1 Dataset and evaluation measures

The FLARE2022 dataset is curated from more than 20 medical groups under the license permission, including MSD [12], KiTS [3, 4], AbdomenCT-1K [8], and TCIA [2]. The training set includes 50 labelled CT scans with pancreas disease and 2000 unlabelled CT scans with liver, kidney, spleen, or pancreas diseases. The validation set includes 50 CT scans with liver, kidney, spleen, or pancreas diseases. The testing set includes 200 CT scans where 100 cases has liver, kidney, spleen, or pancreas diseases and the other 100 cases has uterine corpus endometrial, urothelial bladder, stomach, sarcomas, or ovarian diseases. All the CT scans only have image information and the center information is not available.

3.2 Implementation details

Environment settings The development environments and requirements are presented in Table 1.

Table 1. Development environments and requirements.

Windows/Ubuntu version	Ubuntu 18.04.5 LTS
CPU	Intel(R) Gold 6226R CPU @ 2.90GH
RAM	8×16GB;
GPU (number and type)	One NVIDIA GTX 3090 24G
CUDA version	11.0
Programming language	Python 3.9
Deep learning framework	Pytorch (Torch 1.10, torchvision 0.2.2)

Table 2. Training protocols.

Network initialization	"he" normal initialization
Batch size	4
Patch size	48×128×128
Total iterations	8000
Optimizer	SGD with nesterov momentum ($\mu = 0.99$)
Initial learning rate (lr)	0.001
Lr decay schedule	timed 0.9 by 1000 iterations
Training time	8 hours
Augmentations	random affine; random elastic deformation

Training protocols The training protocols and details are presented in Table 2.

4 Results and discussion

The performance of proposed method is reported on the leaderboard of FLARE2022.

5 Conclusion

In this paper, we aim to explore the performance of fully supervised segmentation model on FLARE2022, with the popular 3D U-Net and data augmentation strategies.

Acknowledgements The authors of this paper declare that the segmentation method they implemented for participation in the FLARE 2022 challenge has not used any pre-trained models nor additional datasets other than those provided by the organizers. The proposed solution is fully automatic without any manual intervention.

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