An Implementation of One Kind of nnUNet Variants for MICCAI FLARE21 Challenges

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Abstract. We implemented a kind of nnUNet variants - nnUNetTrainerV2 with Top 10 dice losses– to training MICCAI FLARE21 challenges' dataset which was aimed to segment the liver, kidney, spleen, and pancreas simultaneously. The kind of nnUNet variants was based on nnUNetTrainerV2 with deep supervision. But, loss function involved Top 10 dice losses.

Keywords: nnUNet variant, Top 10, Dice

1. Introduction

In this paper, we present the nnU-Net ("no-new-Net") framework. It resides on a set of three comparatively simple U-Net models that contain only minor modifications to the original U-Net [1]. We omit recently proposed extensions such as for example the use of residual connections, dense connections or attention mechanisms. The nnU-Net automatically adapts its architectures to the given image geometry. More importantly though, the nnU-Net framework thoroughly defines all the other steps around them. These are steps where much of the nets' performance can be gained or respectively lost: preprocessing (e.g. resampling and normalization), training (e.g. loss, optimizer setting and data augmentation), inference (e.g. patch-based strategy and ensembling across test time augmentations and models) and a potential post-processing (e.g. enforcing single connected components if applicable).

2. Method

3D U-Net: A 3D U-Net seems like the appropriate method of choice for 3D image data. In an ideal world, we would train such an architecture on the entire patient's image. In reality however, we are limited by the amount of available GPU memory which allows us to train this architecture only on image patches. While this is not a problem for datasets comprised of smaller images (in terms of number of voxels per patient) such as the Brain Tumour, Hippocampus and Prostate datasets of this challenge, patch-based training, as dictated by datasets with large images such as Liver, may impede training. This is due to the limited field of view of the architecture which thus cannot collect su_cient contextual information to e.g. correctly distinguish parts of a liver from parts of other organs.

Figure 1 illustrates the applied 3D nnU-Net, where a 3D U-Net [2] architecture is adopted.

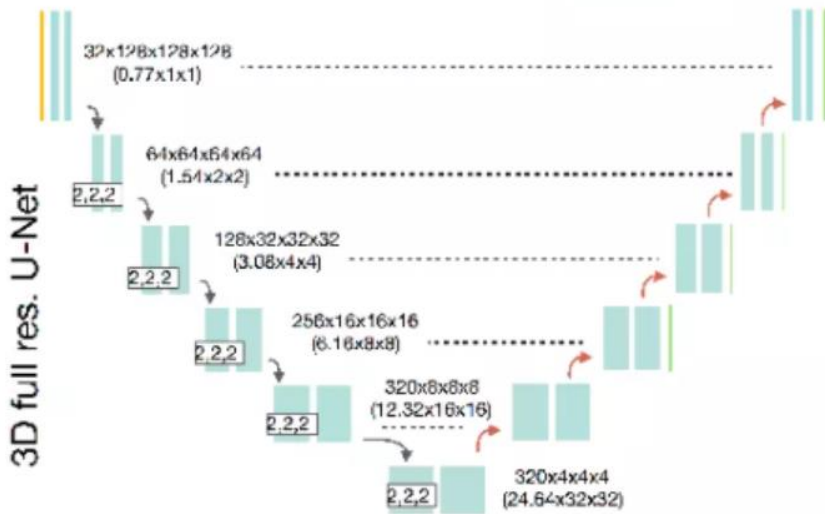

Figure 1. Network architecture

3. Dataset and Evaluation Metrics

3.1. Dataset

- A short description of the dataset used:
  The dataset used of FLARE2021 is adapted from MSD [3] (Liver [4], Spleen, Pancreas), NIH Pancreas [5,6, 7], KiTS [8,9], and Nanjing University under the license permission. For more detail information of the dataset, please refer to the challenge website and [10].

- Details of training / validation / testing splits:
  The total number of cases is 511. An approximate 70%/10%/20% train/validation/testing split is employed resulting in 361 training cases, 50 validation cases, and 100 testing cases. The detail information is presented in Table 1.

Table 1. Data splits of FLARE2021.

Data Split	Center	Phase	#Num.
Training (361 cases)	The National Institutes of Health Clinical Center	portal venous phase	80
	Memorial Sloan Kettering Cancer Center	portal venous phase	281
Validation (50 cases)	Memorial Sloan Kettering Cancer Center	portal venous phase	5
	University of Minnesota	late arterial phase	25
	7 Medical Centers	various phases	20
Testing (100 cases)	Memorial Sloan Kettering Cancer Center	portal venous phase	5
	University of Minnesota	late arterial phase	25
	7 Medical Centers	various phases	20
	Nanjing University	various phases	50

3.2. Evaluation Metrics

- Dice Similarity Coefficient (DSC)

- Normalized Surface Distance (NSD)

- Running time

- Maximum used GPU memory (when the inference is stable)

4. Implementation Details

4.1. Environments and requirements

A description of the environment used for deployment of the method, including but not limited to the items illustrated in Table 2.

The environments and requirements of the baseline method is shown in Table 2.

Table 2. Environments and requirements.

Windows/Ubuntu version	Ubuntu 18.04.5 LTS
CPU	Intel(R) Xeon(R) CPU E5-2678 v3 @2.50GHz
RAM	16×4GB; 2.67MT/s
GPU	Nvidia RTX 2080ti
CUDA version	11.2
Programming language	Python3.8
Deep learning framework	Pytorch (Torch 1.7.1, torchvision 0.8.2)
Specification of dependencies	nnUNetTrainerV2_Loss_DiceTopK10[1]
(Optional) code is publicly available at	nnUNetTrainerV2_Loss_DiceTopK10[2]

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