**Title**

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**Abstract -**

***Index Terms* – computed tomography, abdominal organs, image segmentation, deep learning, nnU-net, FLARE21**

1. **Introduction**

Deep learning – based image segmentation methods have been implemented to achieve high classification accuracy, and have been proved to be a great modality in many clinical scenarios. However, just as the problem - raised by FLARE21 - describes, there is currently a lack of segmentation method that can perform a multi-object detection trained on a diverse dataset, whereas have a high accuracy and efficiency. As a result, most of the neural network methods can only be used in a specific clinical practice, which without doubt create a lot of barriers on its usage.

In late 2020, a U-Net based deep learning framework called nnU-Net [1] was proposed to achieve automated configuration for any datasets. Meanwhile, it is fast and data efficient, which makes it a suitable solution for the problem above. Thus, for FLARE21 challenge, we seek to apply nnU-Net to the given abdomen CT image datasets, trying to achieve a superior segmentation performance.

1. **Method**

Figure 1 illustrates a basic U-Net architecture [2], on which nnU-Net is built. Figure 2 shows how nnU-Net automatically configures for the given input dataset [1]. It builds dependencies between “dataset fingerprint” (i.e., key properties of the dataset) and “pipeline fingerprint” (i.e., key parameters of the method), which gives it ability to generate a suitable solution for the given input data.

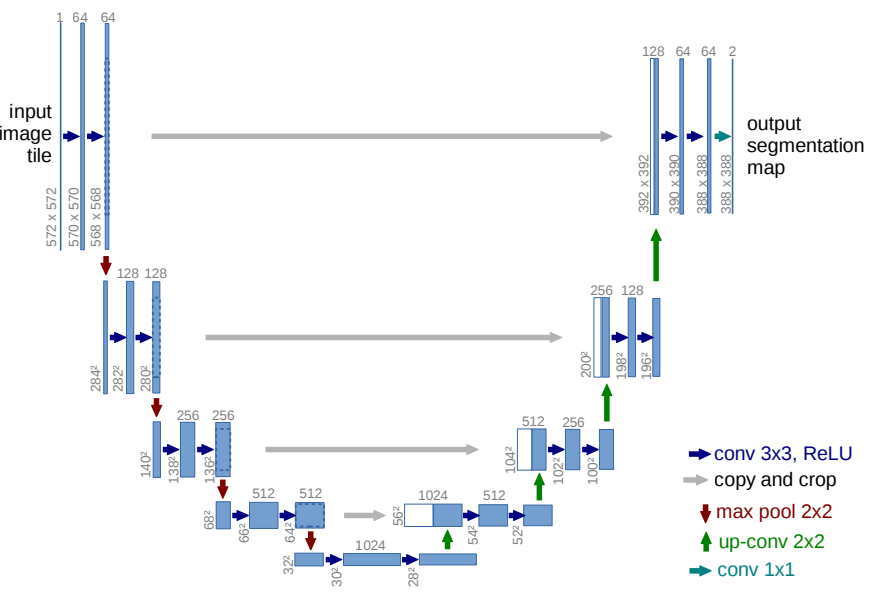


Figure 1. Basic U-Net architecture [2]

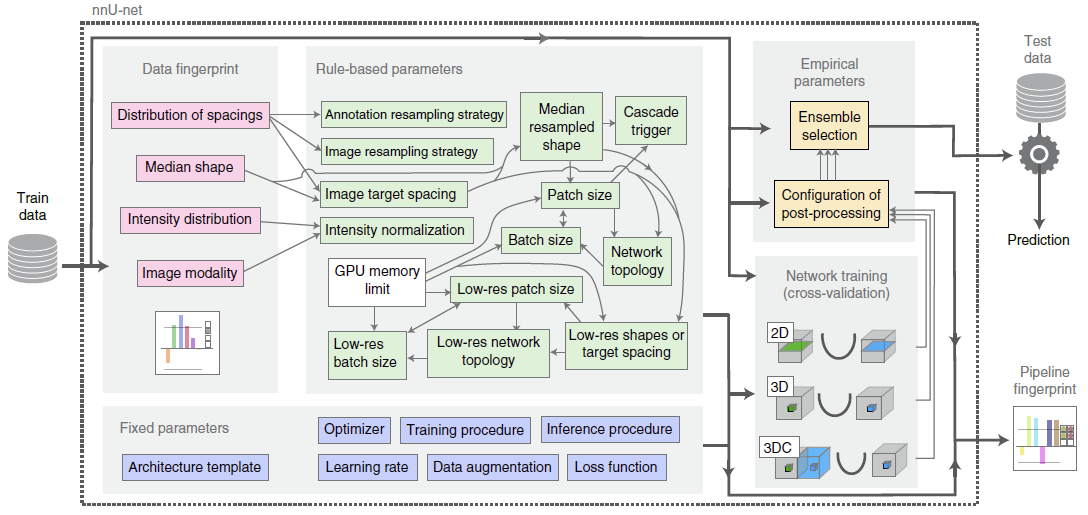


Figure 2. Schematic diagram for the nnU-Net automated method configuration [1]

In this work, we apply the FLARE21 baseline method and use 3d\_fullres configuration. All the hyper-parameters are set as the defaulted ones. In all, there are 30,787,584 trainable parameters among 115 layers. The total FLOPs is 590861472000.

1. **Dataset and Evaluation Metrics**
   1. **Dataset**

The dataset used of FLARE2021 is adapted from MSD [3] (Liver [4], Spleen, Pancreas), NIH Pancreas [5-7], 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].

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. [3-10]

|  |  |  |  |
| --- | --- | --- | --- |
| 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 |

* 1. **Evaluation Metrics**
* Dice Similarity Coefficient (DSC)
* Normalized Surface Distance (NSD)
* Running time
* Maximum used GPU memory (when the inference isstable)

1. **Environments and requirements**

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

Table 2. Environments and requirements

|  |  |
| --- | --- |
| Ubuntu version |  |
| CPU |  |
| RAM |  |
| GPU |  |
| CUDA version |  |
| Programming language |  |
| Deep learning framework |  |
| Specification of dependencies | nnU-Net |

1. **Results**
2. **Discussion and Conclusion**

**Acknowledgement**

The authors of this paper declare that the segmentation method they implemented for participation in the FLARE challenge has not used any pre-trained models nor additional datasets other than those provided by the organizers.

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