Lesions Segmentation from Whole-Body Multi-Modality PET/CT Images Based on nnUNet

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Abstract. The abstract should briefly summarize the contents of the paper in 15–250 words.

Keywords: Deep Learning · Lesions Segmentation · PET/CT · nnUNet

1 Introduction

Positron Emission Tomography (PET) is an imaging technique that can provide unique information about the molecular and metabolic changes associated with disease [1]. And it is playing an increasingly important role in the diagnosis and staging of malignant disease, image-guided therapy planning, and treatment monitoring [2]. The key to PET technology is that it can use labeled molecules of different radionuclides to visualize different disease states. On this occasion, F-18 fluoro-2-deoxyglucose (F-18 FDG), as a PET tracer which can reflect the glucose consumption of tumor tissue, which is applied in PET for imaging of cancer.

However, FDG-PET is not a tumor-specific method in the sense that it can also be seen in healthy tissue or in benign disease as inflammation or posttraumatic repair and could be mistaken for cancer [3]. Hence, CT is used as complementation, which can complete the work of accurate positioning of lesions and organs, can solve the problem of the wrong diagnosis of cancer, thereby efficiently diagnosing malignant tumors.

For the purpose of quantitative PET-CT analysis, a very critical step at the beginning is segmentation of tumor lesions. Before artificial intelligence, this work is usually done by experienced doctors, which is time and labor consuming. Automated PET/CT lesion segmentation thus becomes a necessary task of PET/CT image analysis. With the development of deep learning, the feasibility of this task has been significantly improved.

2 Method

2.1 Dataset

The dataset of training for this challenge is composed of patients with histologically proven malignant melanoma, lymphoma or lung cancer as well as negative control patients who were examined by FDG-PET/CT in two large medical centers (University Hospital Tübingen, Germany University Hospital of the LMU in Munich, Germany) [4].

About the size of dataset, the training dataset consists of 1014 FDG-PET/CT examination cases collected from 900 patients. And there are 200 cases left for test. And lesions of these cases are labeled by two experienced experts.

2.2 Model Architecture

nnUNet The model we use is mainly based on U-Net. The architecture of the network consists of a contracting path and an expansive path [5]. For the contracting path, it is composed of repeated application of two 3x3 convolutions which is each attached with a rectified linear unit (ReLU) and a max pooling layer . In the expansive path, it consists of repeated application of a up-convolution layer, copy and crop part and two 3x3 convolutions which is each followed by a ReLU. The main idea of this design is typical which is composed of a encoder and decoder[9].

Joint segmentation The PET images have relatively low resolution, which can result in some lesions being visible only in a single imaging plane. The 2D UNet model exhibits higher sensitivity to these lesions compared to the 3D model. To improve detection accuracy, we combined the predictions from both the 2D UNet model and the 3D F-Res model. The final prediction was calculated by weighting the softmax outputs of the 2D and 3D models, with a value of set to 0.55 to assign greater significance to the 3D output [10].

References

1. Fletcher, J. W., et al. (2008). "Recommendations on the use of F-18-FDG PET in oncology." Journal of Nuclear Medicine 49(3): 480-508.
2. Blodgett, Todd M., Carolyn C. Meltzer, and David W. Townsend. "PET/CT: form and function." Radiology 242.2 (2007): 360-385.
3. Rosenbaum, Sandra J., et al. "False-positive FDG PET uptake the role of PET/CT." European radiology 16 (2006): 1054-1065.
4. AutoPET II - Automated Lesion Segmentation in PET/CT - Domain Generalization, https://autopet-ii.grand-challenge.org/dataset/. Last accessed 16 Sep 2023
5. Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18. Springer International Publishing, 2015.

6. Author, F., Author, S.: Title of a proceedings paper. In: Editor, F., Editor, S. (eds.) CONFERENCE 2016, LNCS, vol. 9999, pp. 1–13. Springer, Heidelberg (2016). https://doi.org/10.10007/1234567890
7. Author, F., Author, S., Author, T.: Book title. 2nd edn. Publisher, Location (1999)
8. Author, A.-B.: Contribution title. In: 9th International Proceedings on Proceedings, pp. 1–2. Publisher, Location (2010)
9. Isensee, F., Jaeger, P. F., Kohl, S. A., Petersen, J., Maier-Hein, K. H. (2021). nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. Nature methods, 18(2), 203-211.
10. Zhang J, Huang Y, Zhang Z, et al. Whole-Body Lesion Segmentation in 18F-FDG PET/CT[J]. arXiv preprint arXiv:2209.07851, 2022.