Automatic Whole Body FDG PET/CT Lesion and Normal Utake Organs Segmentation using UNet

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Abstract. Multimodal Positron Emission Tomography / Computed Tomography (PET/CT) is essential for diagnosing malignant tumors, evaluating disease status using high-resolution anatomical CT and molecular PET imaging[16]. 18-fluorodeoxyglucose (FDG) PET/CT is widely used for identifying metabolically active tumors, improving accuracy in detecting metastatic disease. Precise tumor quantification and staging are critical prognostic factors[8][3]. Automated deep learning algorithms offer potential for tumor lesion segmentation, but face challenges such as low PET image resolution, tracer uptake variations, and limited focus on tumor segmentation. We propose extending segmentation to include normal tissues for improved performance. Our study focuses on segmenting multiple organs alongside lesions in the AutoPET Challenge 2023 dataset. Using fivefold cross-validation and UNET models, we automate lesion and normal organ segmentation with multimodal PET/CT data from xxx subjects in the AutoPET MICCAI 2023 Challenge. The ensemble of model outputs yielded a dice score of xxx, a Hausdorff distance of xxx, sensitivity of xxx, and specificity of xxx for lesion segmentation in the test dataset (N=150).

Keywords: CT · Abdominal organ segmentation · Multiple organs · nnUNet.

1 Introduction

Whole-body Positron Emission Tomography/Computed Tomography (PET/CT) serves as a prominent modality for tumor imaging, enabling the assessment of localized tumor burden and the early detection of symptomatic metastatic lesions. PET/CT offers a non-invasive approach to quantify metabolically active tumors and plays a pivotal role in initial diagnosis, staging, restaging, treatment planning, and recurrent surveillance across various cancer types. Notably, recent research has unveiled PET/CT's potential to furnish early insights into tumor response to therapy, thereby facilitating the prospect of personalized patient management [2].

Numerous PET-based radiotracers find extensive application in diverse malignant tumors, with 18-fluorodeoxyglucose (18F-FDG) standing as the foremost choice for oncologic imaging. 18F-FDG leverages increased glucose metabolism in malignant tumors for detection [13][6]. This conventional tracer excels at identifying lesions characterized by elevated glucose metabolism in both primary tumors and metastases, particularly showcasing high sensitivity in detecting metastases within solid tumors [4].

Traditionally, lesion annotation relies on expert radiologists to conduct quantitative analyses. However, the automation of lesion annotation is increasingly imperative to circumvent the labor-intensive, error-prone, and time-consuming nature of manual annotation, particularly in the context of whole-body FDG-PET scans. Challenges in developing automated tumor segmentation algorithms encompass issues such as suboptimal PET image resolution, pronounced statistical noise, the uptake of FDG in various highly metabolic normal tissues (e.g., brain and heart) alongside tumor regions, temporal fluctuations in blood pool signals, inter-subject uptake variability, the sparsity of tumor regions in whole-body PET/CT, and data acquisition disparities [7] [1].

Recent advancements in deep learning models have demonstrated their capacity to achieve highly accurate PET/CT lesion segmentation in specific regions, offering a promising avenue to address these challenges. Several recent studies have explored the potential of DL-based automated tumor segmentation in PET or hybrid PET/CT examinations, often focusing on specific disease types or organs such as head and neck cancer, liver, lung, and bone lesions [15],[9],[12],[10].

In our recent study utilizing Ga-68 PSMA PET/CT data[11], we observed a notable enhancement in lesion segmentation performance when normal uptake organs (brain, liver, kidneys...,) were included in the segmentation process through deep learning models. Consequently, we intend to assess the validity of this concept by segmenting various normal uptake organs alongside lesions within the AutoPET 2023 challenge dataset. We trained a 3D residual UNET using five-fold cross validation on AutoPET 2023 data and performed adaptive ensemble to get final results. Our method achieved top performing results in the challenge.

2 Materials and Methods

2.1 Data and Preprocessing

Our study leveraged whole-body FDG-PET/CT data from 900 patients, encompassing 1014 studies generously provided by the AutoPET Challenge 2023, to train our models. To rigorously evaluate algorithm robustness and generalizability, we employed held-out datasets comprising 150 studies. Among these, 100 studies were sourced from the same hospital as the training database, while 50 were selected from a different hospital but adhering to a similar acquisition protocol.

In the initial preprocessing stage, we resampled the CT data to PET resolution and applied necessary normalization procedures. The task of annotating

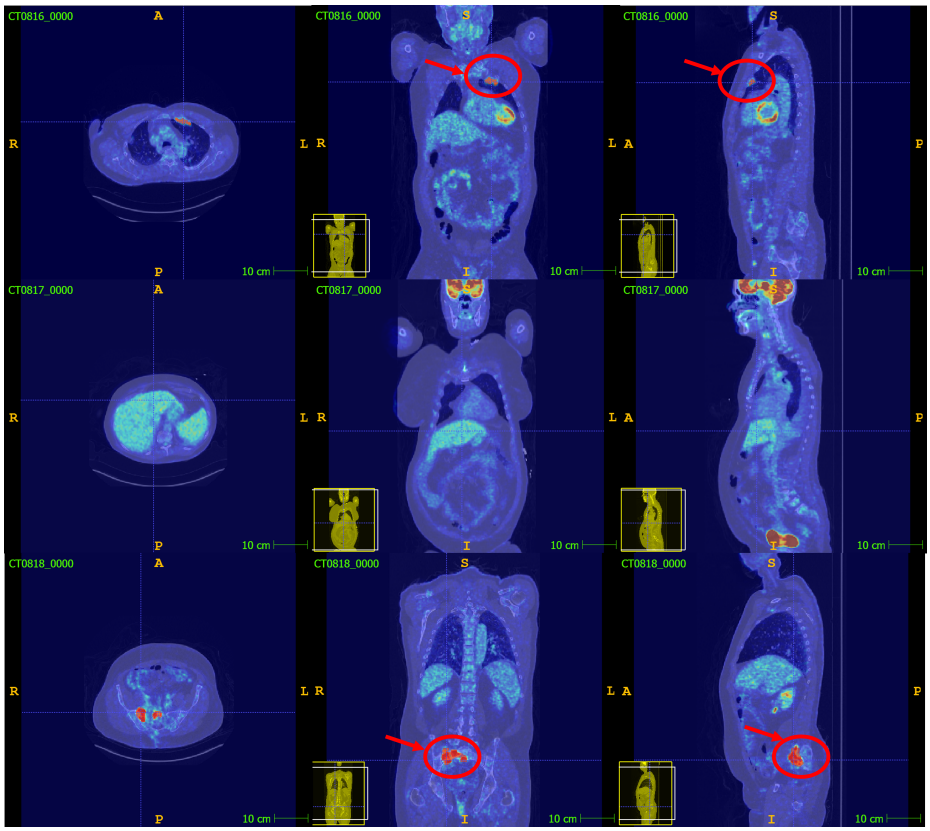

Fig. 1. Representative Whole Body FDG PET/CT scans provided by AutoPET challenge with annotations

both the training and test datasets was undertaken by experts in the field. At the University Hospital Tübingen, a Radiologist with a decade of experience in Hybrid Imaging, coupled with a background in machine learning research, meticulously annotated all the data. Similarly, at the University Hospital of the LMU in Munich, a Radiologist with five years of experience in Hybrid Imaging, complemented by expertise in machine learning research, conducted annotations. The annotation process encompassed the delineation of regions corresponding to the brain, bladder, kidneys, liver, stomach, spleen, lungs, and heart, facilitated through the Totalsegmentator model [14].

Subsequently, we trained the UNET model for the segmentation of both lesions and eight normal uptake organs, employing a rigorous five-fold cross-validation approach with the training set. The resulting model was then uploaded to the challenge portal in docker format for testing. Notably, the model's output adhered strictly to the challenge requirements, focusing solely on the segmentation of lesions.

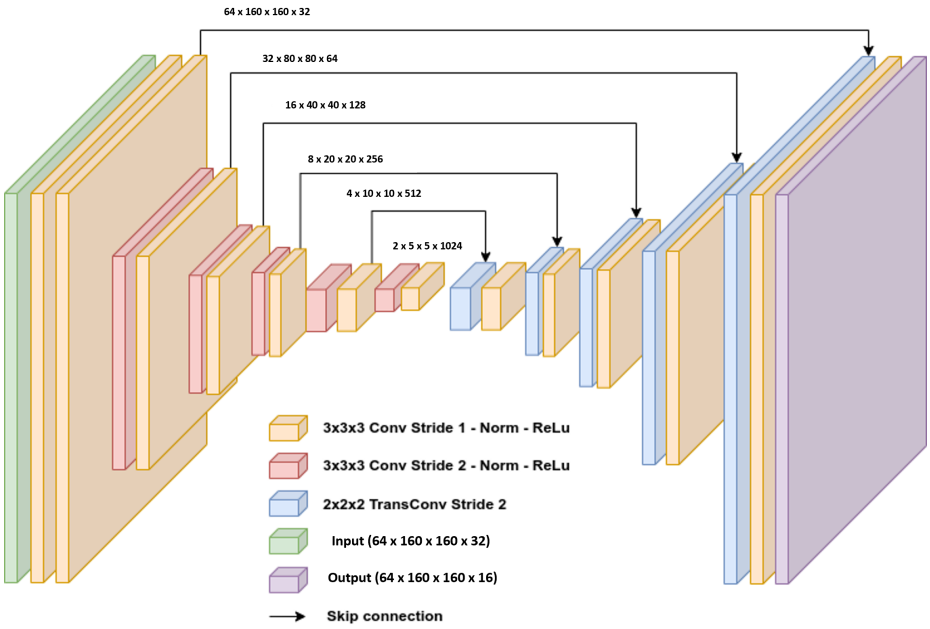

Fig. 2. The layers of the UNET architecture used. The input is a volume of 64x160x160 with one channels, CT. Input is resampled down five times by convolution blocks with strides of 2. On the decoder side, skip connections are used to concatenate the corresponding encoder layers to preserve spatial information.

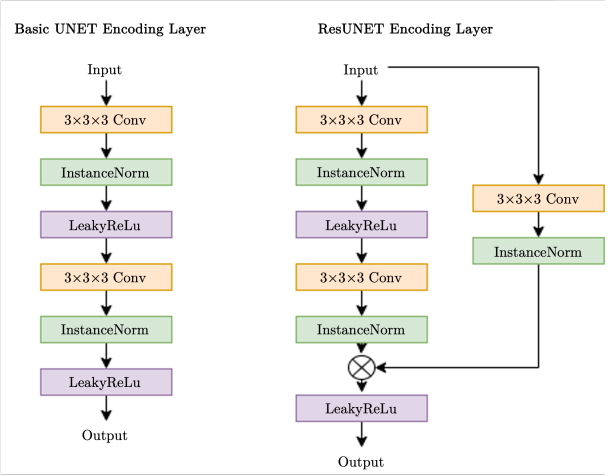

Fig. 3. In one instance of our UNET models, each encoding layer is a series of Convolution, normalization, and activation function repeated twice. In another instance, ResUNET, each encoding layer adds a residual path with convolution and normalization.

2.2 Model Training Methodology

Model Architecture The nnUNET pipeline has achieved top tier performance in multiple medical imaging segmentation competitions. Analysis of the nnUNET pipeline and model architecture has shown that different variations sometimes perform better than the baseline nnUNET architecture [10] [5]. From this, a standard a variant model using residual connections was proposed for training (see Fig. 2 and 3). The input image size of 64x160x160 with one channel, CT is used as input. Input is resampled down five times by convolution blocks with strides of 2. On the decoder side, skip connections are used to concatenate the corresponding encoder layers to preserve spatial information. Instance normalization and leaky ReLU activation in the network layers was used. This architecture initially used 32 feature maps, which then doubled for each down sampling operation in the encoder (up to 1024 feature maps) and then halved for each transposed convolution in the de-coder. The end of the decoder has the same spatial size as the input, followed by a 1x1x1 convolution into 1 channel and a SoftMax function. Models are trained for five folds with loss function of Dice Sorensen Coefficient (DSC) in combination with weighted cross entropy loss were trained. To prevent overfitting augmentation techniques such as random rotations, random scaling, random elastic deformations, gamma correction augmentation, mirroring and elastic de-formation, were adopted. Each of the five models were trained for 1000 epochs with batch size of eight using SGD optimizer and learning rate of 0.01. Dice Similarity Coefficient (DSC), and normalized surface dice (NSD), will be used to assess different aspects of the performance of the segmentation methods.

2.3 Results

We trained a five fold UNet model for automatic whole body lesion segmentation with robust mean dice of 0.xxxx and 0.xxxx dice in validation and held out testing respectively.

2.4 Discussion

Our method achieved similar performance in both cross fold validation ann unseen held out data showing that it generalized well multicenter data. Adaptive ensemble increased the performance by selectively picking model outputs with high contribution to final ensemble. [10] and uncertainty aware segmentation correction may improve the segmentation performance.

2.5 Conclusion

We have trained a 3D UNet and achieved robust and generalized segmentation performance on automatic whole body FDG PET/CT lesion segmentation. We achieved xth rank in MICCAI AutoPET 2023 challenge out of xx teams participated.

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