AutoPET Challenge 2023: Sliding Window-based Optimization of U-Net

Matthias Hadlich^{1,*}, Zdravko Marinov^{1,2,*}, and Rainer Stiefelhagen¹

¹ Institute for Anthropomatics and Robotics, Karlsruhe Institute of Technology, Karlsruhe, Germany

² HIDSS4Health - Helmholtz Information and Data Science School for Health, Karlsruhe/Heidelberg, Germany

Abstract. Tumor segmentation in medical imaging is crucial and relies on precise delineation. Fluorodeoxyglucose Positron-Emission Tomography (FDG-PET) is widely used in clinical practice to detect metabolically active tumors. However, FDG-PET scans may misinterpret irregular glucose consumption in healthy or benign tissues as cancer. Combining PET with Computed Tomography (CT) can enhance tumor segmentation by integrating metabolic and anatomic information. FDG-PET/CT scans are pivotal for cancer staging and reassessment, utilizing radiolabeled fluorodeoxyglucose to highlight metabolically active regions. Accurately distinguishing tumor-specific uptake from physiological uptake in normal tissues is a challenging aspect of precise tumor segmentation. The AutoPET challenge addresses this by providing a dataset of 1014 FDG-PET/CT studies, encouraging advancements in accurate tumor segmentation and analysis within the FDG-PET/CT domain. Code: https://github.com/matt3o/AutoPET2-Submission/

Keywords: Semantic Segmentation · Sliding Window · U-Net

1 Introduction

In the domain of oncological diagnostics, the integration of Fluorodeoxyglucose Positron-Emission Tomography (FDG-PET) and Computed Tomography (CT) has assumed a pivotal role, facilitating comprehensive insights into the metabolic dynamics of various malignant solid tumor entities [1]. FDG-PET, acknowledged for its capacity to delineate glucose consumption within tissues, holds significant promise in therapy control and monitoring, owing to the characteristic escalated glucose uptake by tumor lesions [3]. However, the non-specificity of FDG-PET often introduces interpretational ambiguities, as it may also manifest in benign or healthy tissue [6], potentially leading to erroneous diagnoses.

To mitigate this diagnostic challenge, the fusion of PET with CT has emerged as an integrated approach, combining metabolic data with precise anatomical

^{*} Shared first author

information. This combination enhances tumor detection accuracy [1], [13], offering a cohesive synergy particularly valuable in clinical practice [6].

Within this evolving landscape of medical diagnostics, the Automatic Lesion Segmentation in Whole-Body FDG-PET/CT Challenge (AutoPET)³ embodies a critical juncture. It motivates researchers and practitioners to develop automated, bi-modal methodologies for the three-dimensional segmentation of tumor lesions embedded within FDG-PET and CT scans [6]. The challenge accelerates advancements in deep learning-based automated tumor lesion segmentation through the provision of a large densely annotated dataset of 1014 volumes.

In this work, we propose using the well-known U-Net architecture [15] to tackle the AutoPET challenge. Despite the ubiquity of U-Net models in medical segmentation tasks [9], [4], achieving high performance in the domain of whole-body PET/CT lesion segmentation has remained elusive [12], [17], [8], [16], [7] largely due to the scarcity of training data in preceding studies [3]. Drawing upon the insights provided by the AutoPET Challenge U-Net-based winner from 2022 [16], we undertake a practical investigation to understand the important training parameters of the U-Net model for segmenting lesions. We believe that it is possible to achieve a better and more robust model by focusing on the intricacies of data pre-processing, data augmentation, learning rate scheduling, and crop-size selection during model training. Our work and model are based on prior experiments in interactive segmentation [14]. Thus, for our hyperparameter tuning experiments, we present results using our interactive model. Nonetheless, for our final submission, we exclude the integration of interactive clicks into the model and employ its optimal hyperparameter configuration.

2 Methodology

2.1 Model Architecture

The model used for the challenge is called DynUNet, which is an adaption of the UNet for the MONAI library [2]. Contrary to the default UNet, DynUNet does not use max-pooling for downsampling but instead uses strided convolutions. Additionally, the residual is passed through a convolutional layer such that the input size from the downsampling layer matches the output size of this layer. All of the changes can be traced back to three prior works: [10], [11], and [5].

Our default configuration of the network consists of six layers of filter size [32, 64, 128, 256, 320, 320]. As discussed above, the convolutions are strided with a size of [1, 2, 2, 2, 2, [2, 2, 1]], and the upsampling is thus done in the inverse order. An architectural diagram can be found in Figure 1.

2.2 Data Pre-processing and Augmentation

Pre-processing. We restrict ourselves by using only the PET volumes from the paired PET/CT scans. We apply multiple pre-processing transformations to

³ https://autopet-ii.grand-challenge.org/

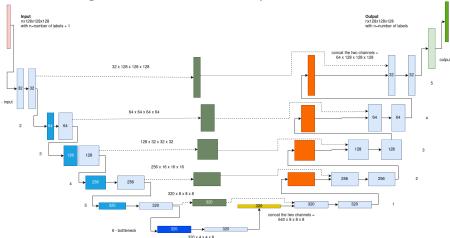


Fig. 1. An overview of the used DynUNet architecture.

each batch of data. Apart from changing the channel order, the orientation is set to a RAS (Right-Anterior-Superiror) coordinate system. As the AutoPET spacing is \approx [2, 2, 3]mm³, the data is resampled accordingly with this fixed voxel size. The intensity of each PET image is scaled based on its voxel intensity statistics with MONAI::ScaleIntensityRangePercentiled to the 0.05 and 99.95 percentiles. During training, a random crop of size 224x224x224 is sampled, with a probability of 0.6 of being centered around a tumor lesion and 0.4 of being centered around the background. To achieve this, we utilize the RandCropByPosNegLabeld MONAI transform. This crop is balanced by the class label of the voxel in the crop's center - in 60% of the cases the voxel is positive, and in the other 40% it is negative. This ensures that the network learns about positive and negative samples in a more balanced training regime.

Data Augmentation. We apply two types of data augmentation - random flipping and random rotation. We apply a random flip on each spatial axis with a probability of 0.1. We also apply a random 90-degree rotation with a probability of 0.1 for each axis.

2.3 Data Post-processing

Since we are using a sliding window approach, the final prediction volume gets stitched from the various output patches. This process is done with a user defined overlap, in our case this was set to 75%.

After the result prediction a softmax is applied.

For the ensemble based solution the two steps mentioned above are done for each of the five networks prediction separately. After the softmax on each

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prediction a voting mechanism combines the different predictions into a single one.

2.4 Hyperparameter Tuning

As explained above most of the different experiments have been run on interactive code. Nevertheless they should be representative in terms of general performance of the network. Variations of +/- 0.5% Dice are to be expected since the guidance signal was non-deterministic.

Sliding window versus normal inferer First of all we compare the sliding window infererence to the normal one, figure 2.4. As it can be seen in the table, on the interactive code the sliding window inferer wins with a lead of 2.81% Dice.

Next different region of interest sizes have been tried out. The best performing one here was the $128 \times 128 \times 128$ crop. Note that the sliding window was active during training. In the thesis it is shown that training with overlap active gains about 1% of Dice.

This overlap means for the 128x128x128 instead a window of size 320x320x320 has been calculated, with calculations being equal to a normal inferer of size 384x384x384. As we can see a lot of overhead calculations are being done by the sliding window inferer. However in the next subsection we will show that the overhead calculations for the overlap actually lead to a better Dice score.

Table 1. Interactive run of Sliding Window versus Simple Inferer

| | Sliding Window | Simple Inferer |
|------|----------------|----------------|
| Dice | 83.83% | 81.02% |

Table 2. Different region of interest sizes compared. Trained on a crop of size $256 \times 256 \times 256$.

| | 64x64x64 | 128x128x128 | 192x192x192 | 256x256x256 |
|-------------------|----------|-------------|-------------|-------------|
| Dice (validation) | 84.74% | 85.22% | 83.66% | 84.75% |
| Dice (training) | 87.99% | 88.46% | 88.98% | 88.79% |

Sliding window overlap Now we will look at the overlap of the sliding window inferer. Table 2.4 shows that increasing the overlap also increases the Dice score of the network. In our experiments the higher the overlap the better the results have been. This can be seen as a way of creating a mini Ensemble with same

weights. The overlap uses a Gaussian fade away to make the regions closer the center weight more heavily when stitching together the final output.

Additionally experiments have been run to verify the impact of training with overlap on. Table 4, which shows a network trained on 0% overlap, overall shows slightly worse results, especially for the higher overlaps it becomes significant. As expected running it with 0 overlap returns slightly better results than the network trained with overlap being forced to use none. We can thus conclude that activating overlap during training enhances the final score.

Table 3. Non-interactive validation runs with different settings for the overlap. The network has been trained on 25% overlap.

| Experiment | Overlap | Dice |
|------------|---------|--------|
| 201 | 0 | 66.33% |
| 202 | 0.25 | 73.04% |
| 203 | 0.5 | 73.54% |
| 207 | 0.75 | 74.07% |

Table 4. Non-interactive validation runs with different settings for the overlap. The network has been trained on 0% overlap.

| Experiment | Overlap | Dice |
|------------|---------|----------------|
| v_208_0.0 | 0 | 66.57% |
| v_208_0.25 | 0.25 | 71.35% |
| v_208_0.5 | 0.5 | 71.99% |
| v_208_0.75 | 0.75 | 72.86 % |

Convergence behaviour with different losses Figure 2 shows the convergence behaviour of the Dice loss vs the DiceCELoss. As it can be seen the DiceCELoss start with a higher initial validation Dice in epoch 10, 73.62% against 70.09%. Also the final Dice metric was a little bit higher, 85.47% for DiceCELoss and 84.62% for Dice loss. However a plateau appears to be reached for both losses. In other experiments with more iterations it was shown that this method can reach a validation Dice of up to 87.60%.

We can thus fully recommend the DiceCELoss as a standard choice for training. It converges faster and also yields higher final scores especially in terms of Dice.

Intensity scaling options Finally a quick comparison of different intensity scaling options. The base run was a pre-calculated batch statistics normalization to the 0.005 and 99.95 percentiles of the intensity. The first ScaleIntensityRangePercentiled applied the same percentiles but this time based on the

statistics of a each item. The last ScaleIntensityRangePercentiled is a base run with no clipping of the intensities, it only normalizes the intensity from 0 to 1.

As we can see the item-wise statistics outperformed the batch-wise statistics and the clipless method.

| Table 5. Different | ScaleIntensity | settings | compared | |
|--------------------|----------------|----------|----------|--|
|--------------------|----------------|----------|----------|--|

| | Base run | ScaleIntensity- | ScaleIntensity- |
|------|-------------------|------------------|--------------------|
| | CosineAnnealingLr | RangePercentiled | RangePercentiled 2 |
| | (104) | (148) | (149) |
| Dice | 85.63% | 86.69% | 85.44% |

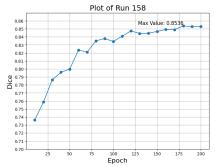
Best parameters A summary of the best found results can be found in table 2.4.

3 Proposed solutions to the AutoPET2 Challenge

We propose two different approaches for the challenge:

- A single network with seven layers as stated above, trained for 800 epochs.
- An cross-validation ensemble of five networks trained on splits of the data. They were trained only without using the validation split. Training was done for N/A epochs. The results of the different networks got combined with an equally weighted voting mechanism. The network themselves are one layer flatter, so contain only six layers. This was mostly done to speed up the training but also to fit the five networks into the GPU memory.

Fig. 2. Comparing the Dice Loss, in MONAI called MeanDice to the DiceCELoss.



(a) Validation Dice of run 158. In this run the DiceCELoss has been used as the loss.



(b) Validation Dice of run 183. In this run the MeanDice has been used as the loss.

Parameter name Setting Network MONAI DynUNet with [32, 64, 128, 256, 320, 320, 320] filters and a depth of seven layers Loss DiceCELoss with squared_pred=False and include_background=True Optimizer Adam Learning rate scheduler CosineAnnealingLR (initial lr=2e-4, eta_min=1e-8) Inferer Sliding window inferer with ROI size 128x128x128, sliding window overlap 0.75 Intensity scaling with Custom Scaling to 0.05% and 99.95% intensity percentiles using ScaleIntensityRanged Automatic Mixed Precision Active

Table 6. Best settings

4 Results

| Method | Train dice | Results on the preliminary test set | | |
|----------------|------------|-------------------------------------|-----------------------|-----------------------|
| | | Dice score | False negative volume | False positive volume |
| Single network | 87.43% | 56.52% | 0.0249 | 1.8015 |
| Ensemble | N/A | 53.82% | 0.4678 | 1.6372 |

Table 7. The results of our method in the AutoPET2 challenge.

5 Post mortem: NaN errors during training if AMP is active

In the preparation for the challenge we ran into NaN errors when training on A100 GPUs, but only when automated mixed precision was on. During the debugging we found out our input already contained NaNs.

The reason in our case was a training crop to positive / negative areas of size 224x224x224. At the borders of the volume this resulted in crops which contained almost only 0s or even only 0s. Our current hypothesis is that the normalization on the crop produces division by 0 errors. This would make especially sense for the intensity scaling which might degrade if the input tensor only contains 0s. However more debugging is necessary to find out the exact transform which produces the NaN errors.

The solution is to add a filter after the pre-transform to remap all NaN values to 0. In our case this fixed the problem and we could resume training with AMP on the A100 GPUs.

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