Unsupervised Domain Adaptation for Pediatric Brain Tumor Segmentation

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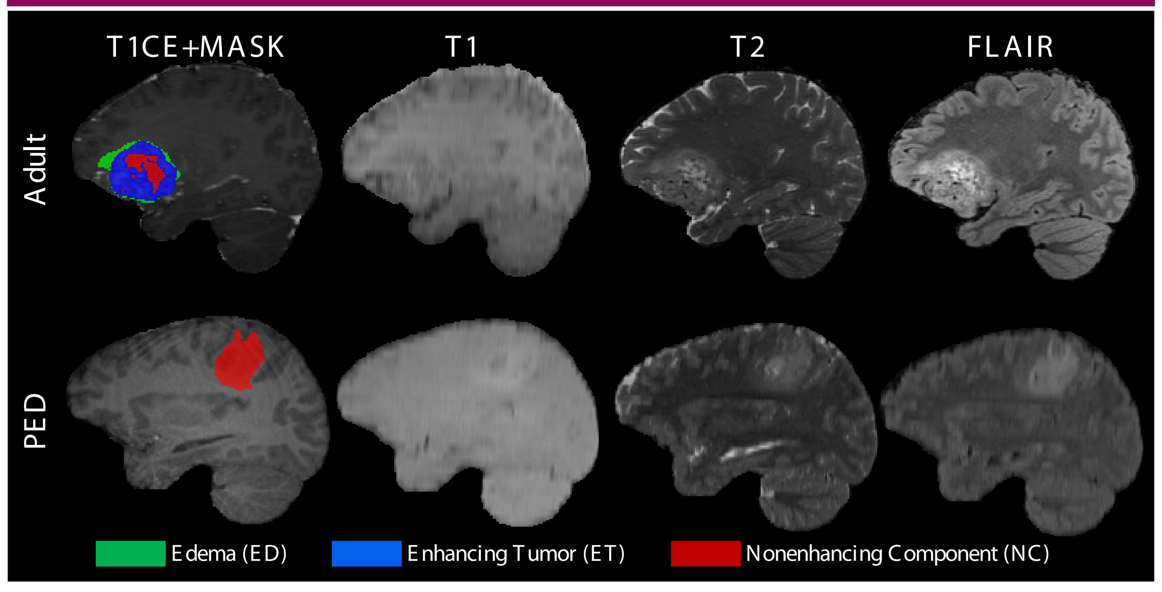
1. Introduction

Pediatric brain tumors are the leading cause of cancer-related mortality in children. In clinical practice, tumor progression is mainly assessed by measuring changes in tumor size from longitudinal scans. Recently, learning-based automatic segmentation tools have simplified the segmentation of subregions in adult brain tumors due to the availability of more annotated data[1]. However, compared to the incidence of adult glioblastomas (GBMs) at approximately 3 in 100,000 people, pediatric diffuse midline gliomas (DMGs) are around three times rarer !

We present here how to entend nnU-Net[2] to learn from both a relatively large, well-annotated source domain (adult) and a smaller, unlabeled target domain (pediatric) segmenting three tumor subregions from four MRI contrast scans.

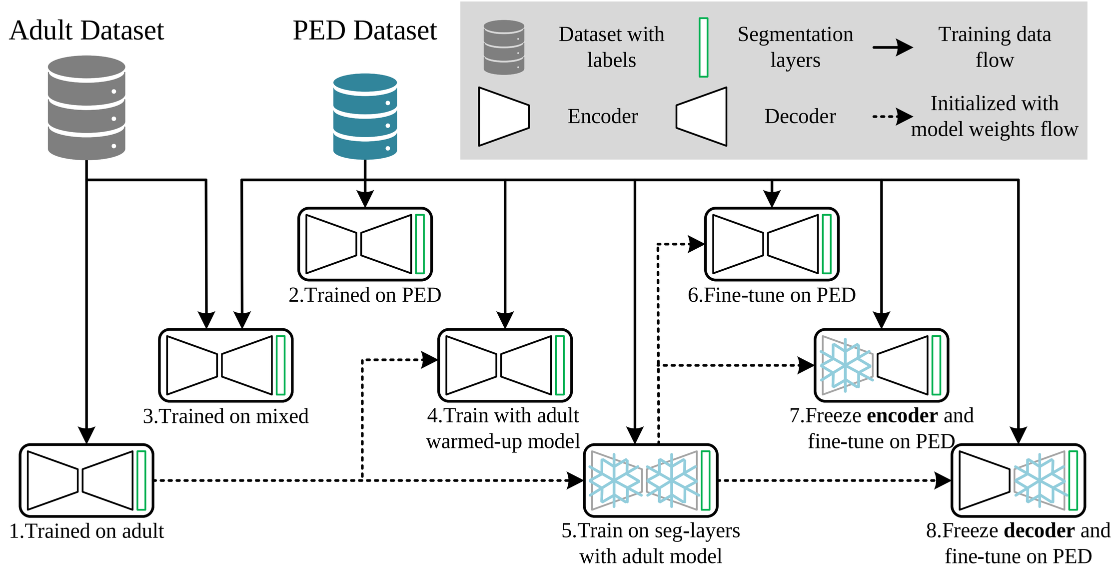
2. Methods

The Data: BraTS Adult Glioma[3] and BraTS-PEDs[1]



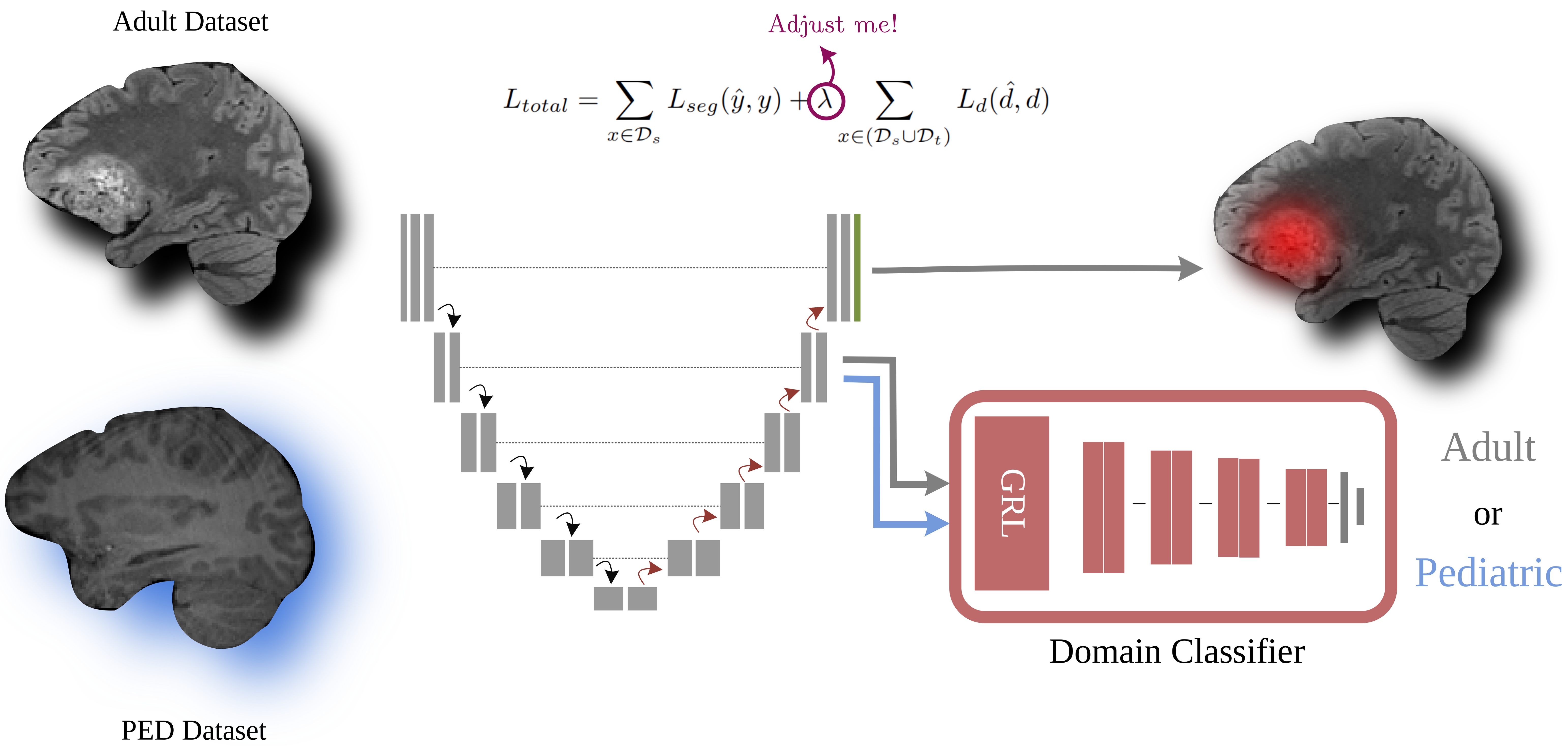
The method: DA-nnUNet (proposed)

We propose Domain-Adapted nnU-Net (DA-nnUNet) with a nnU-Net backbone (for segmentation) and a domain classifier (to learn domain-invariant features), connected via a gradient reversal layer (GRL)[4].



Supervised baselines: 5 transfer learning strategies

We present 3 models trained on either or both of two domains, as well as 5 models initially trained on adult data and then fine-tuned using pediatric data. These models leverage a range of common transfer learning (TL) strategies, such as partially updating network layers or using a reduced learning rate.



3. Results

Results for supervised baselines

Let's compare unsupervised models with the one trained on both pediatric and adult data (model 3, practical upper bound) in median Dice in three subregions: whole tumor (WT: ET+NC+ED), tumor core (TC: ET+NC), and enhancing tumor (ET) --> (ET: 0.716, TC: 0.918, WT: 0.927)

We found:

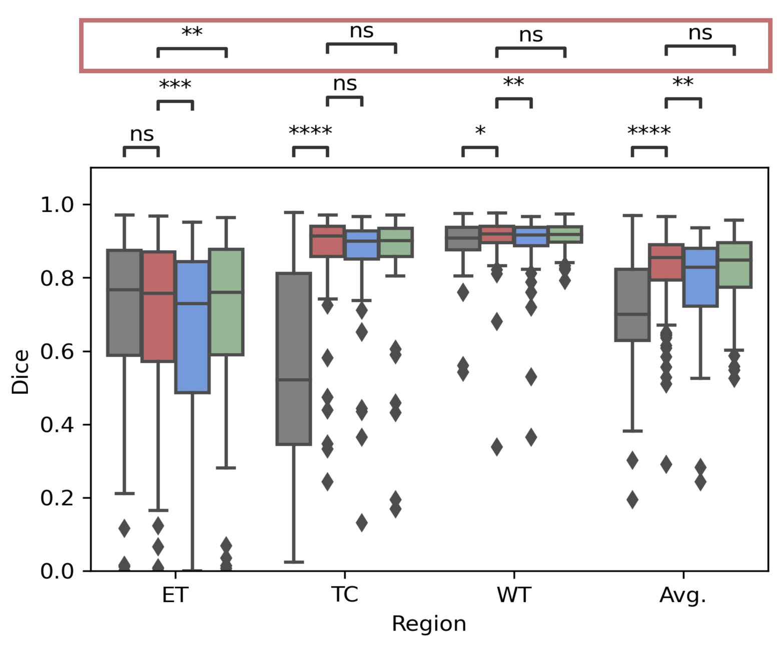
- Model trained with adult data only (model 1) mainly faces challenges in accurately segmenting the TC region. (ET: 0.742, TC: 0.549, WT: 0.913)
- Models 4-8 with different TL strategies achieve comparable results to the upper bound model (best model 4: ET: 0.713, TC: 0.914, WT: 0.922).

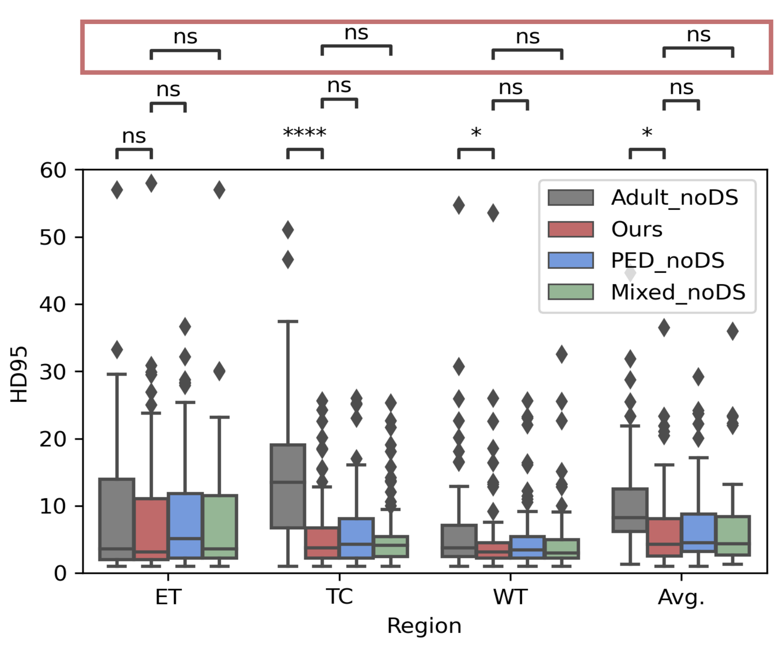
Results for DA-nnUNet

DA-nnUNet achieves segmentation accuracies close to the practical upper bound without requiring any annotations from the pediatric domain!

The practical upper bound v.s. The proposed DA-nnUNet
(ET: 0.716 v.s. 0.713, TC: 0.918 v.s. 0.916, WT: 0.927 v.s. 0.923)

DA-nnUNet is not statistically different from the practical upper bound model in most cases (except for ET), as shown in the figures on the right.





4. Conclusions

Our experimental results show that the proposed unsupervised domain adaptation approach performs similarly to supervised approaches for pediatric tumor segmentation. It has the potential to be used in cases where expensive manual annotations are not available without a significant drop in performance.

Scan me to use the code on your data!

[1] Kazerooni, A. F., et al., "The Brain Tumor Segmentation (BraTS) Challenge 2023: Focus on Pediatrics," ArXiv, 2024.
[2] Isensee, F., et al., "nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation," Nature Methods, 2021.
[3] Menze, B. H., et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," IEEE TMI, 2015
[4] Ganin, Y., Lempitsky, V., "Unsupervised Domain Adaptation by Backpropagation," ICML, 2015.