Cerebral Artery Segmentation with nnU-Net

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Abstract. The precise segmentation of cerebral arteries in MRA scans holds great importance for the quantitative analysis of cerebrovascular diseases, such as assessing the extent of luminal stenosis. Nonetheless, manually performing this segmentation is a daunting task, even for experts, due to the intricate network of cerebral arteries, significant variations between individuals, and the challenge of identifying weak signals in small vessels caused by slow or in-plane blood flow. To address these challenges, deep learning algorithms have been employed. In Cerebral Artery Segmentation Challenge: CAS2023 (https://codalab.lisn.upsaclay.fr/competitions/9804), we utilized the nnU-Net deep learning framework to perform cerebral artery segmentation. Our approach involved employing the 3D full resolution U-Net from nnU-Net and using a combination of Dice and Cross-Entropy (CE) as the loss function. Our model achieved impressive results with a Dice similarity coefficient (DSC) of 0.8765 and a DSCstenosis of 0.8999, securing the 9th position among the 21 participating teams in the challenge.

Keywords: nnU-Net, Artery Segmentation, Deep Learning.

1 Cerebral Artery Segmentation

Stroke is a leading global cause of death, mainly linked to cerebrovascular diseases like stenosis and occlusion of cerebral arteries. Accurate assessment of these conditions is crucial for diagnosis and treatment. Magnetic resonance angiography (MRA) is commonly used, but manually segmenting cerebral arteries from MRA images is challenging due to complexity and weak signals.

2 nnU-Net Deep Neural Network

In this challenge, we chose the nnU-Net algorithm for cerebral artery segmentation based on its strong track record in medical imaging, adaptability to diverse anatomical structures, and customization capabilities. nnU-Net's ability to handle multi-modal and noisy data, coupled with its state-of-the-art performance and active community support, made it a compelling choice. Our approach makes use of nnU-Net, a fully automatic deep learning framework tailored for medical segmentation. To establish a baseline for subsequent modifications, we initially apply nnU-Net without any adjustments. The design choices incorporated in nnU-Net are as follows: Each of images are normalized through mean subtraction and standard deviation division, while non-vessel voxels are assigned a value of 0. The network architecture follows a 3D U-Net structure, featuring an encoder and a decoder interconnected by skip connections. Feature extraction solely relies on plain convolutions, avoiding the utilization of recent architectural variations. Downsampling is achieved using strided convolutions, while upsampling is accomplished through convolution trans-posed.

3 Training Procedure

We employ the nnU-Net in its default configuration for cerebral artery segmentation. The architecture of the neural network follows that of a 3D U-Net at full resolution. This design encompasses both encoding and decoding pathways, with each pathway incorporating five convolutional blocks. Each of these blocks consists of a convolutional layer with dimensions 3x3x3. As the loss function, we used Dice + CE. In addition, we incorporate the instance normalization layer and employ the leaky rectified linear unit activation function. Prior to model input, nnU-Net employs cropping and Z-Score normalization techniques for image preprocessing. We opt for the Stochastic Gradient Descent (SGD) optimization algorithm with an initial learning rate of 0.01. The model is trained over 300 epochs, utilizing a five-fold cross-validation strategy. All model training is conducted on three RTX 3090 GPUs, utilizing a batch size of 2 and a patch size of 256x224x56.

4 Performance on Validation Set

We run our model on the given dataset including 100 TOF-MRA images. From the training data, we used 20 images for validation data. The model achieved the following results for validation: "Dice": 0.8646, "Jaccard": 0.7653, "Precision": 0.8499, "Recall": 0.8947. Figure 1 illustrates the training error and evaluation metric as well.

5 Results on Testing Data

The Challenge Team evaluated the trained model's performance by testing it on 50 previously unseen TOF-MRA images. The assessment involved several evaluation metrics, which included: 1) the Dice similarity coefficient, 2) the Average Hausdorff Distance (AHD), 3) the Dice similarity coefficient in the stenosis region, and 4) the Average Hausdorff Distance (AHD) in the stenosis region. Additionally, they computed a final score using the following formula:

Final Score = 35% × DSC + 35% × AHD + 15% × DSC in stenosis region + 15% × AHD in stenosis region. Table 1 presents the performance of our model across four evaluation metrics. According to the results from the competition organizers, our model (Team: UW) achieved the 9th position out of the 21 participating teams.

Table 1. Performance metrics for cerebral artery segmentation using our method.

Score	Dice	DSCstenosis	AHD	AHDstenosis
0.8801	0.8765	0.8999	0.8874	0.8482

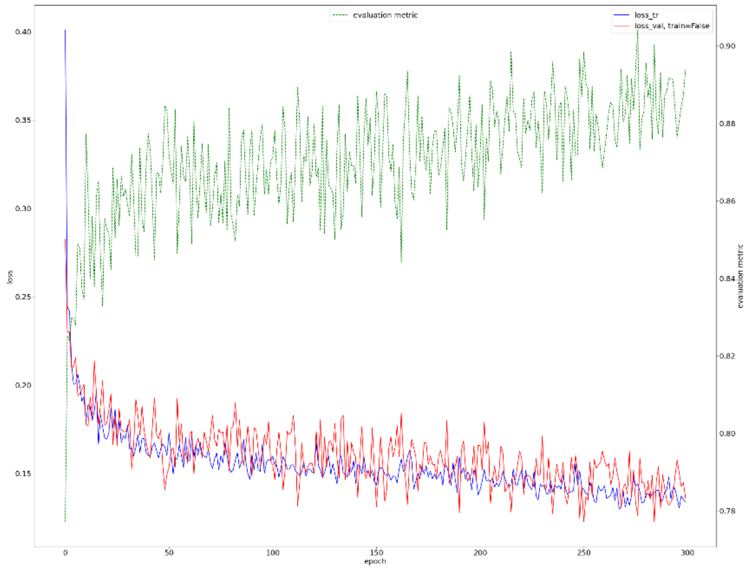

Fig. 1. Training/validation error and Dice coefficient as performance metric

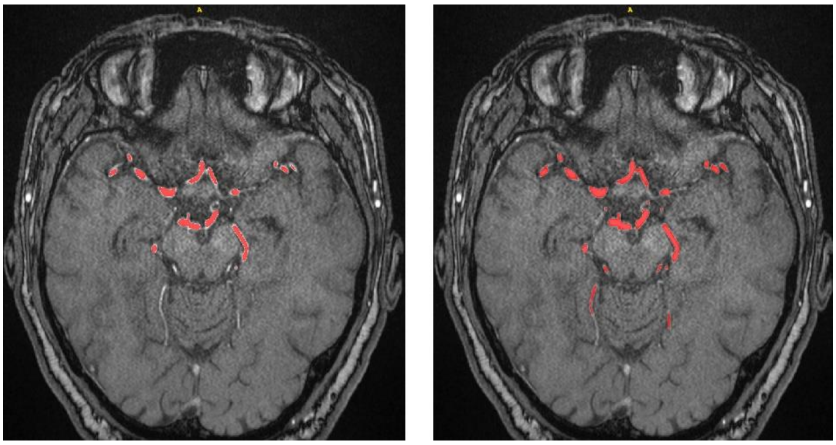

Fig. 2. Left: True mask. Right: Predicted mask by our model

Reference

1. Isensee, F., Jaeger, P. F., Kohl, S. A., Petersen, J., Maier-Hein, K. H.: nnU-Net: a self-configuring method for dep learning-based biomedical image segmentation. Nature methods, 18(2), 203-211 (2018)