

nnU-Net with Modified Loss for Binary Segmentation of Circle of Willis

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1 Introduction

The Circle of Willis (CoW) is a crucial network of brain arteries connecting various regions and is associated with conditions such as aneurysms and stroke. Comprehending its vascular structure is essential in clinical practice, yet there is a lack of efficient analysis tools. CoW anatomy varies among individuals, underscoring the importance of personalized characterization for clinical and research purposes. The Topology-Aware Anatomical Segmentation of the Circle of Willis for CTA and MRA (TopCow) challenge is dedicated to extracting and annotating the CoW’s angio-architecture using magnetic resonance angiography (MRA) and computed tomography angiography (CTA). The TopCow team has made available a dataset with meticulous annotations to stimulate research and benchmarking. To participate in the challenge, section of Binary segmentation of Cow with MRA, we harnessed the nnU-Net deep learning framework, renowned for its recent successes in various medical segmentation challenges and competitions.

2 Methods

2.1 nnU-Net

The nnU-Net introduces a pioneering approach to cutting-edge biomedical segmentation network architecture [1]. This tool is able to automatically tailor its network structure to the characteristics of each specific image dataset. Furthermore, it excels in meticulously defining all surrounding procedures related to architecture. This inherent capacity empowers the network to effortlessly apply systematic rules right from the start, eliminating the necessity for task-specific fine-tuning. Remarkably, nnU-Net achieves superior performance across 19 public international segmentation competitions without the need for manual adjustments, surpassing the capabilities of most specialized deep learning pipelines. This exceptional performance, coupled with its versatile advantages, has led to its widespread adoption and implementation across diverse applications. The framework leverages foundational deep neural networks, including 2D U-Net, 3D U-Net, and cascade U-Net. Additionally, it employs various preprocessing techniques such as data augmentation and normalization to further enhance its capabilities.

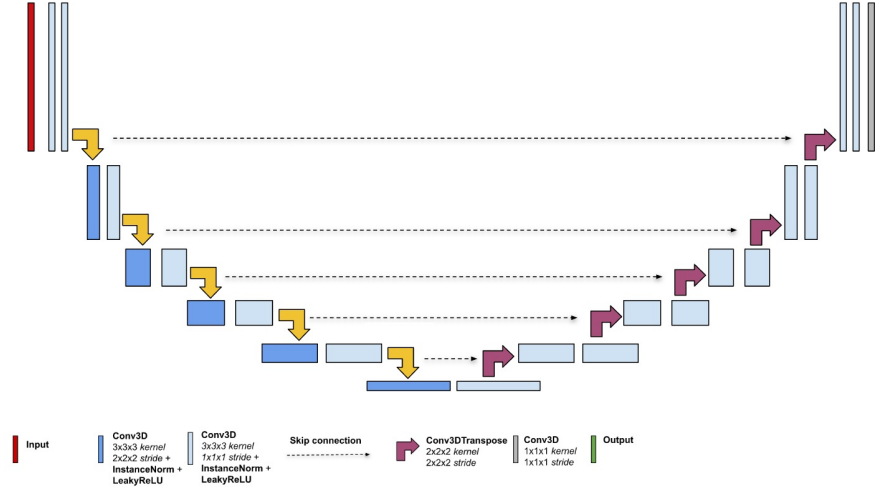


Fig. 1. The 3D U-Net architecture.

2.2 Loss function

For the purpose of binary segmentation of the Circle of Willis using Magnetic Resonance Angiography (MRA) in this particular challenge, a specialized hybrid loss function was employed. This hybrid loss function incorporates three distinct components, namely the Dice loss, Cross-Entropy (CE) loss, and Top-K loss. The Dice loss as a similarity-based loss function frequently used in image segmentation tasks, measures the overlap between the predicted segmentation and the ground truth. In essence, it quantifies the spatial agreement between the two, with higher values indicating better alignment. On the other side, Cross-Entropy (CE) Loss quantifies the dissimilarity between the predicted probability distribution and the actual binary labels. CE loss is particularly effective in penalizing misclassifications and encouraging the model to generate pixel-wise probabilities closer to the true labels. However, to enhance the model's segmentation performance, we applied the Top-K Loss as well. The Top-K loss is a specialized loss function that focuses on the most prominent or dominant structures within the segmented region. It encourages the model to prioritize the most important features or components of the Circle of Willis while segmenting. This loss helps improve the precision and clinical relevance of the model's output by emphasizing the top-K elements in the segmentation. By combining these three distinct loss functions, the hybrid loss function utilized in this challenge offers a comprehensive approach to optimize the segmentation of the Circle of Willis, taking into account both spatial alignment, pixel-wise probabilities, and the importance of specific structures within the region of interest. This combination helps enhance the model's performance in this specific medical imaging task.

3 Experiments

3.1 Data

TopCow challenge organizers supplied a dataset consisting of 90 paired images, encompassing both Computed Tomography Angiography (CTA) and Magnetic Resonance Angiography (MRA) scans. For each case, they included the entire image as well as the Region of Interest (ROI). It's noteworthy that we conducted the training exclusively using the complete MRA images for the specific Binary-MRA segmentation task. In this process, neither the CTA scans nor the ROIs were utilized. It's important to highlight that we refrained from augmenting the training dataset with external data sources to enhance segmentation performance.

3.2 Training & Architecture

In our methodology, we leverage the nnU-Net framework, a specialized deep-learning tool tailored to medical segmentation tasks. To lay the groundwork for subsequent enhancements, our initial approach employs nnU-Net in its default configuration. The neural network architecture is modeled after a 3D U-Net at full resolution, encompassing both encoding and decoding pathways. Each of these pathways integrates five convolutional blocks, with each block comprising a 3x3x3 convolutional layer. We also incorporate instance normalization and employ the leaky rectified linear unit (ReLU) activation function to enhance model performance. Prior to feeding data into the model, we employed cropping and Z-Score normalization techniques as part of the image preprocessing stage. For optimization, we opt for the Stochastic Gradient Descent (SGD) algorithm with an initial learning rate of 0.01. In addition, we adopt a weighted combination loss function that includes Dice, Cross-Entropy (CE), and TopK. By combining these loss components with their respective weights, the hybrid loss function was formulated as: $0.6 * \text{Dice} + 0.2 * \text{CE} + 0.2 * \text{TopK}$. To ensure robust training, our model undergoes training for 500 epochs, employing a five-fold cross-validation strategy. To handle the computational demands, we execute all model training on three RTX 3090 GPUs, utilizing a batch size of 2 and a patch size of 256x224x56. This comprehensive approach equips us with a robust foundation to address the Circle of Willis segmentation using the nnU-Net framework.

3.3 Results

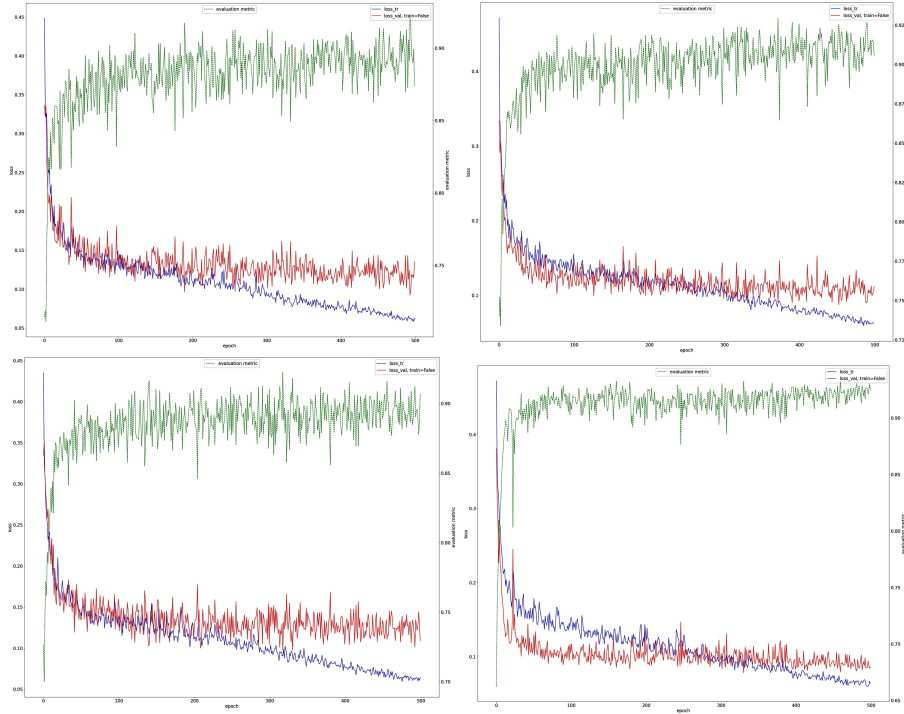
Our model underwent testing on a provided dataset, which comprised a total of 90 MRA images. During the training phase, 20 of these images were set aside for validation purposes. The validation results of our model are detailed in Table 1. Subsequently, our model was put to the test using previously unseen data supplied by the challenge organizers, and the outcomes are presented in Table 2. It is worth noting that, according to the challenge's leaderboard, our team (UW) achieved the 3rd position in the Binary-MRA segmentation task.

Table 1. Performance metrics of our model on validation data.

Fold	Dice	Sensitivity	Jaccard
0	0.887	0.916	0.804
1	0.896	0.894	0.816
2	0.872	0.906	0.781
3	0.912	0.910	0.840
4	0.900	0.905	0.817

Table 2. Performance metrics of our model on testing data.

Method	mean CoW-class Dice	Mean cDice	Betti-0 (Position)	Error
nnU-Net with modified loss	0.9537 ± 0.022	0.9818 ± 0.0193	0.8857 ± 0.8668	

**Fig. 2.** Training and validation error for 4 folds.

4 Acknowledgement

Chengcheng Zhu was supported by United States National Institute of Health (NIH) grants R01HL162743 and R00HL136883.

You can access the code, models, and weight files by visiting the following link: <https://t.ly/Hnw5g>

5 Reference

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