Unruptured Intracranial Aneurysm Segmentation from TOF-MRA Images Using Cascaded 3D Convolutional Neural Networks

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Introduction

Intracranial aneurysms are found in 3% of the general population, and some groups have a higher risk. If an aneurysm ruptures it causes bleeding in the brain (subarachnoid hemorrhage).

Automatically segmenting unruptured intracranial aneurysms from TOF-MRA images allows analysis of the size and shape of the aneurysms which may provide new biomarkers for use in rupture risk prediction models. Eventually, this may result in more informed decisions being made regarding treatment of unruptured intracranial aneurysms.

The Aneurysm Detection And segmentation (ADAM) challenge includes TOF-MRA and T2/T1 weighted MR imaging using 1T, 1.5T and 3T MRI scanners. The total is 113 cases, with 93 cases containing at least one untreated, unruptured intracranial aneurysm, and 20 scans of subjects without intracranial aneurysms. The aneurysms range in size, with a range of maximum diameter from 0.7mm to 15.9mm. 18% of the scans contain multiple aneurysms and 7.5% of the scans contain treated aneurysms.

Methods

For each case, we use TOF-MRA image, which was preprocessed using n4biasfieldcorrection to correct bias field inhomogeneities. Our image preprocessing also includes normalization and uniformly resampling pixel spacing to 0.35 × 0.35 × 0.54 mm^3.

Our method contains segmentation and classification. Due to the small amount of data, we used fine-tuning in segmentation and classification. We chose a pre-trained 3D UNet[1] to segment aneurysm from image patches. Figure 1 illustrates the segmentation network architecture. After segmentation, there are many false positives (FPs), besides aneurysms. So, we trained and used a classifier to reduce those false positives. Figure 2 illustrates the classification network architecture. The input to the two networks is a single channel 64 × 64 × 32 voxel patch of the image. Data augmentation such as random rotation, width shift, height shift and left-right flip along each xyz directions was used in training. Also, we used cross validation and ensemble method to improve model robustness and segmentation accuracy.

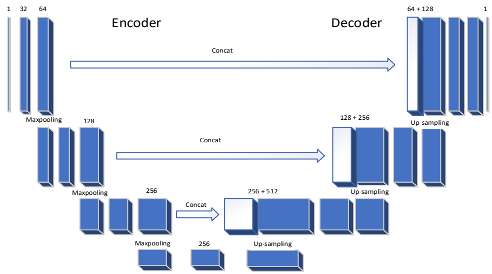


Figure 1. The 3D UNet segmentation model architecture.

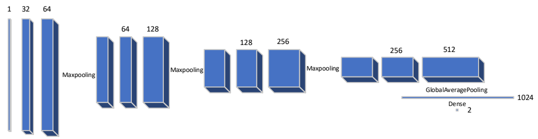


Figure 2. The 3D CNN classification model architecture.

Experimental Methods

Our train data is from 80% of the dataset, and the rest 20% of the dataset is for our test data. In the segmentation part, for each preprocessed TOF-MRA image, we cut the image into 64 × 64 × 32 patches for training. In the classification part, positive patches are cut from preprocessed TOF-MRA image with aneurysms, and negative patches are output FPs of the segmentation network.

When testing, with a MRA image input, we used sliding window to predict the whole image. The window size is 64 × 64 × 32 with an overlap of 32 × 32 × 16 voxels for each of the xyz directions. We concatenated segmented patches to a binary mask with aneurysm as label 1 and background as label 0.

We independently trained three paths using ensemble method. Each path includes a segmentation and a classification models trained by different train and test data split. The final mask result is generated using majority voting from the output masks of those three paths.

Results

We evaluate our methods with Area under the Free-Response ROC Curve (FROC) and dice coefficient. Figure 3 shows the FROC after segmentation from one path, and figure 4 shows the FROC after classification. We picked sensitivity 0.65 with 1 FP per image as the output of this path. Mean dice coefficient in the test split for detected aneurysms is 0.33.

Similarly, the performance for the other two paths have sensitivities 0.76 and 0.67, with 1.7 and 1.4 FPs per image respectively.

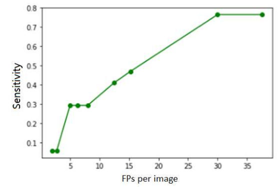


Figure 3: FROC after segmentation.

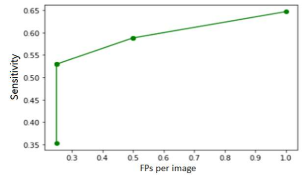


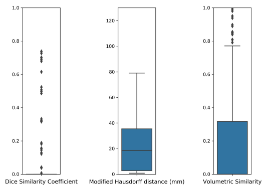
Figure 4: FROC after classification.

Team: Stronger	Task 1 Rank: 0.38	Task 1 Place: 8 th
	Task 2 Rank: 0.57	Task 2 Place: 7 th

(lower rank is better)

Task 1	False Positives	Sensitivity
Average	0.45	0.2
Rank	0.02	0.74

Task 2	Dice Coefficient	Modified Hausdorff Distance (mm)	Volumetric Similarity
Average	0.07	24.42	0.21
Rank	0.84	0.28	0.59



Discussion

We have developed a fully automated detection system that automatically segments aneurysms from TOF-MRA images. However, we believe there are still rooms to optimize the performance of each model in our system if more time and data are involved. Also, we didn't use the additional structural MRA images. They may contain some useful information .

References

1. Z. Zhou, et al. "Models genesis: Generic autodidactic models for 3d medical image analysis." MICCAI 2019.