AneurysmNet: Deep Neural Network-Based Segmentation of Aneurysms in 3D-MR Angiography

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Introduction

An aneurysm is a swelling of an artery as opposed to stenosis, which is a narrowing of the vessel. In an attempt to potentially augment clinician performance in medical imaging interpretation and reduce time of diagnosis, a two inputs single output deep learning model is used to uplift the challenges proposed by the ADAM committee.

Keywords: Aneurysm, Deep Learning, Multi-Input Single Output, Segmentation.

Vessel Segmentation

The following algorithm defines the key steps to extract the vessel tree from an MRA volume:

- MRA images resample using Trilinear interpolation to anisotropic voxels ($0.5 \times 0.5 \times 0.5$ mm)
- Calculate mean η and standard deviation σ of the center quarter region
- Extract connected regions with voxels intensity $\geq \eta - 2\sigma$
- Perform morphological transformations on the initial mask with different filters (closing and erosion)
- Extract the inner volume that satisfies voxel intensity $\geq \eta + 2\sigma$
- Extract connected components that have:
  1. Volume $\geq 2.7\%$ of the inner volume
  2. Gravity center that lies in the center quarter of xy plane
- Perform more morphological transformations (mostly dilation and closing)

AneurysmNet: Pipeline

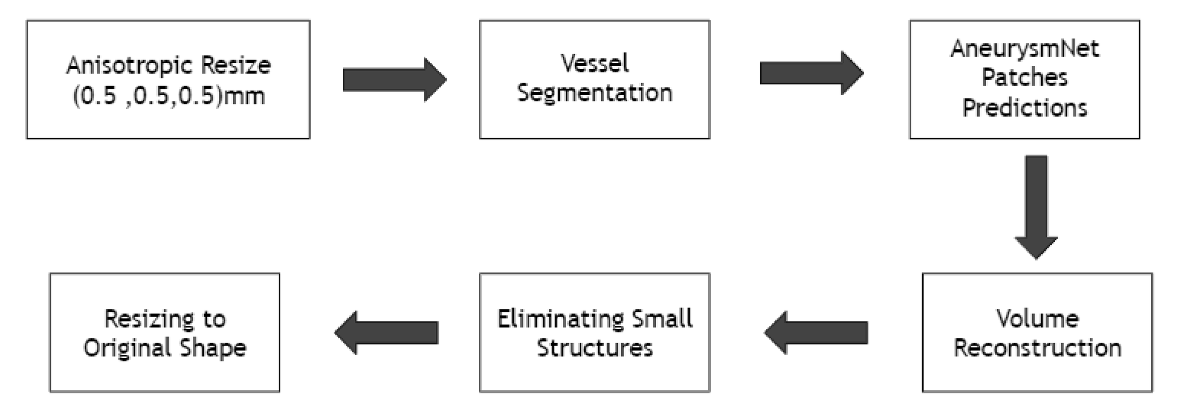


Figure 1: Aneurysm Segmentation Pipeline

- Anisotropic Resize: This includes a nyul and udupa normalization as a part of the preprocessing step to standardize the input data
- Vessel Segmentation: A crucial procedure to extract the essential structures of the MRA (vessels).
- AneurysmNet DL model: At the heart of this pipeline lies the double inputs single output deep learning model that shoulder the prediction task.
- After the prediction step, a reconstruction procedure of regrouping the prediction patches and a reshaping to original dimension is carried after eliminating the small structure ($< 0.3mm$) yielded by the DL model.

Double Input Single Output DL Classification Model

The network consists of two channels that go hand in hand in order to determine if a patch contains an aneurysm or not. The first channel is highly inspired by [1] which contains three convolutional layers, two maxpooling layers and two fully-connected layers. This channel process the MIP 2D image which highlights the important features in the patch but fails to point the 3D relationships among the structures in this 2D display. Another drawback can manifest itself when other insignificant sturctures with high values can obscure the relevant information we seek. To overcome this, we process, simultaneously the 3D patch in its totality by the means of the second channel. The 3D patch overwhelmingly possesses more information than the MIP transformation which can lead to a dilution of features extraction effort. However, coupling the 3D and the MIP inputs together, makes the model localize the search of relevant features on the aneurysm deflation shape in the 2D and 3D space. The process of the two independent channels comes together with a concatenation layer that brings in a common feature map. The output layer has a single unit, and the logistic function is applied to the output to convert it into the probability of being positive (which ranges from 0 to 1). We employ a rectified linear unit(ReLU) function as the activation function for all layers except the output layer.

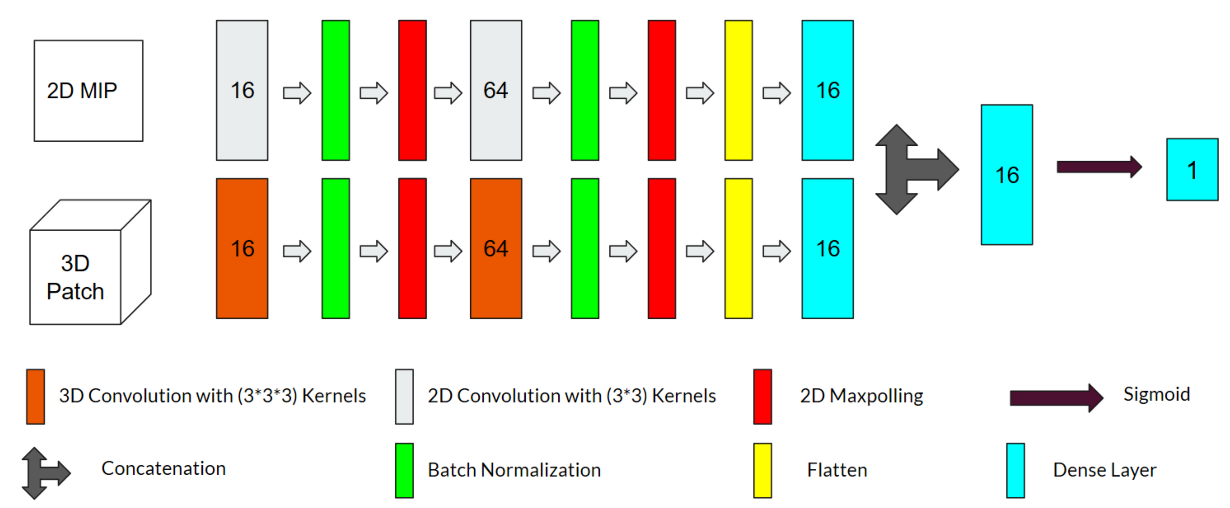


Figure 2: Double Input with 3D and 2.5D images and single output model

Preprocessing

Working with different MRA volumes that were acquired with different magnetic field strength and multiple modalities is a bit challenging especially when it comes to generalizing a model. To overcome this challenge, we use the Nyul and Udupa [2] normalization to provide standardized patient volumes to the neural network model. We resample the original TOF volume to an anisotropic voxel size of ($0.5 \times 0.5 \times 0.5$ mm) to provide a constant structure to the filters we will use inside the deep learning model.

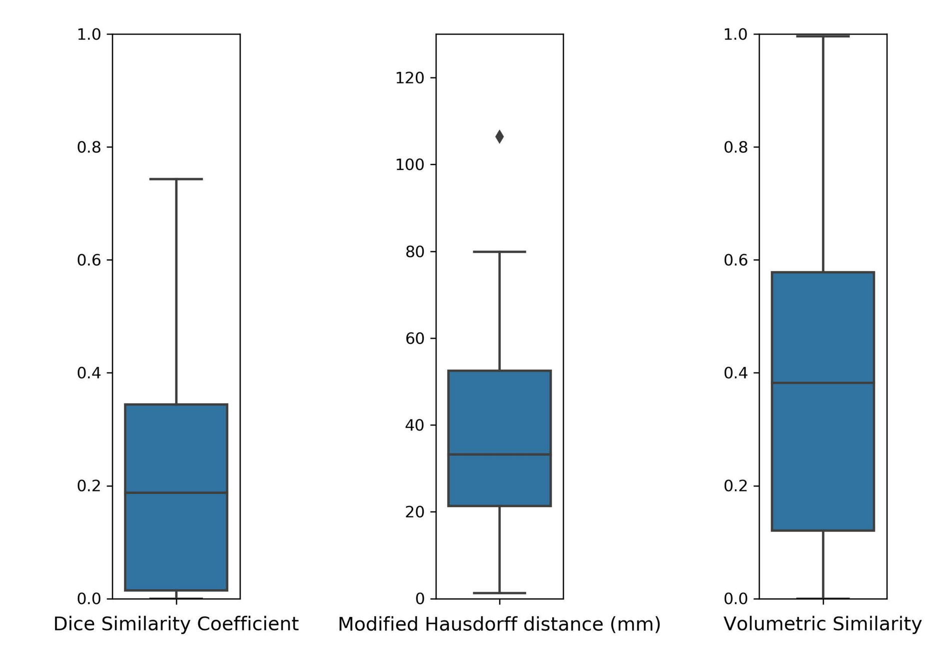
Results

Team: xlim	Task 1 Rank: 0.09	Task 1 Place: 5 th
	Task 2 Rank: 0.41	Task 2 Place: 5 th

(lower rank is better)

Task 1	False Positives	Sensitivity
Average	4.03	0.7
Rank	0.18	0

Task 2	Dice Coefficient	Modified Hausdorff Distance (mm)	Volumetric Similarity
Average	0.21	36.82	0.39
Rank	0.5	0.5	0.22



Conclusion

During this work we faced a big and major challenge which is the high false positive ratio. In order to decrease this ratio, two inputs deep learning model has proven to be able to eliminate a big portion of mispredictions that results from misinterpretation of the MIP transformation or the lack of channel attention of the 3D patches.

References

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