ADAM Challenge Submission

July 2020

1 Proposed Method

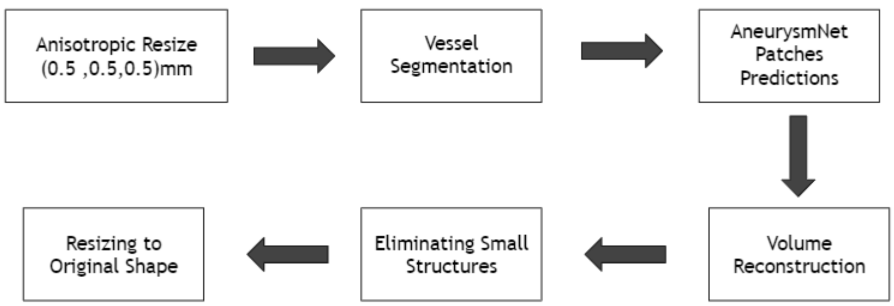

Figure 1: Maximum Intensity Projection Principle

1.1 Preprocessing

1.1.1 Anisotropic Resize

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.

1.1.2 Nyul and Udupa Normalization [2]

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 normalization to provide standardized patient volumes to the neural network model.

1.1.3 Vessel Segmentation

- 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)

1.2 AneurysmNet: Deep Learning

1.2.1 Data Preparation: Maximum Intensity Projection

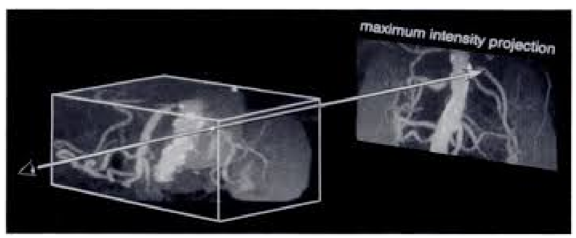

Figure 2: Maximum Intensity Projection Principle

In an attempt to reduce the dimensionality of the data, we use the MIP (Maximum Intensity Projection) technique which basically projects in the visualization plane the voxels with maximum intensity that fall in the way of parallel rays traced from the viewpoint to the plane of projection. This means that, a projection along two opposite planes leads to two symmetric images. In this work, using a patch of $16 \times 16 \times 16$, we realize the MIP transformation along 9 different axis (X, Y, Z, XY, YX, XZ, ZX, ZY and YZ) to finally obtain 9 2D images of 16×16 resolution. The latter images are concatenated a final 144×16 image that represent a projection of the original 3D patch. Based on the above figure 3, we can clearly notice the disparity between the distribution or the form of a healthy, elongated vessel and an aneurysm or in many cases a bifurcation or high curved areas.

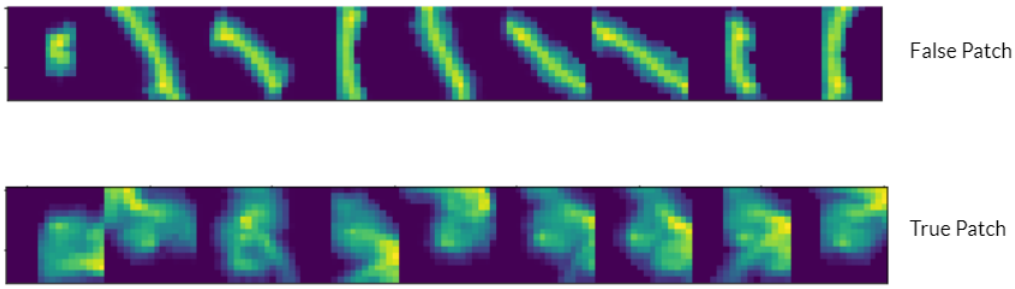

Figure 3: True and False Patches Visualization

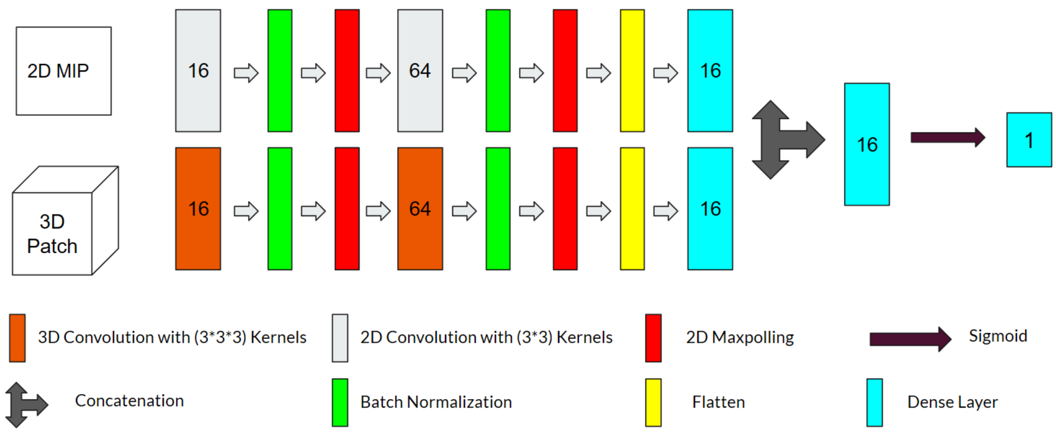

Figure 4: Double Input with 3D and 2.5D images and single output model

1.2.2 Architecture: AneurysmNet

The network consists of two channels that goes 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 possess 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 independant 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. Batch normalization is performed before each ReLU function. We utilize the Adam method to optimize the network weights.

References

[1] Nomura Y et al. Nakao T, Hanaoka S. Deep neural network-based computer-assisted detection of cerebral aneurysms in mr angiography. *J Magn Reson Imaging*, 2018.

[2] László G. Nyúl, Jayaram K. Udupa, and Xuan Zhang. New variants of a method of mri scale standardization. *IEEE Trans. Med. Imaging*, 19(2):143–150, 2000.