Automated Vessel Segmentation in MRI Data

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Motivation

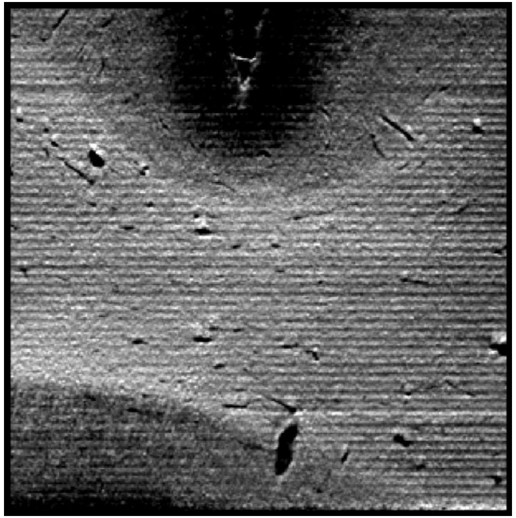
- Accurate vessel segmentation is crucial for early diagnosis of vascular diseases.
- Enables better visualization and analysis of blood flow patterns.
- Assists in treatment planning and monitoring of disease progression.
- Facilitates automated medical image analysis and reduces manual workload.
- Supports the development of advanced computer-aided diagnostic tools.
- Essential for research in angiogenesis and other vascular-related studies.

Previous Approaches

Type	Source	Accuracy	Limitations
K means	Gehad Hassan	0.75	Dataset image quality was high, ungeneralizable to global image datasets. Only Diabetic Retinopathy.
CNN	LMBiS-net	0.7873	Low number of learnable parameters (0.172 million)
Math Modeling	Stanford vessel segment	0.7832	higher sensitivity (misses fewer small vessels) at the cost of a lower precision (more false positives)
Structural Modeling	IterNET	0.726	Low true positive rate of 0.34
Math Modeling	Cross-modality learning approach	0.7726	Algorithms can generate spurious results (dots).
Full-Connect NN	Stanford vessel segment	0.7047	Small percentage (0.61%) of pixels in the training images

DATA

- Lots of .jpeg images that are converted to .nii format
- Each .nii image is a 3d image that has voxels in .2 microns
- The data has a total 600 images which results into 600.nii images that are either 128 or 256 voxel cubes.



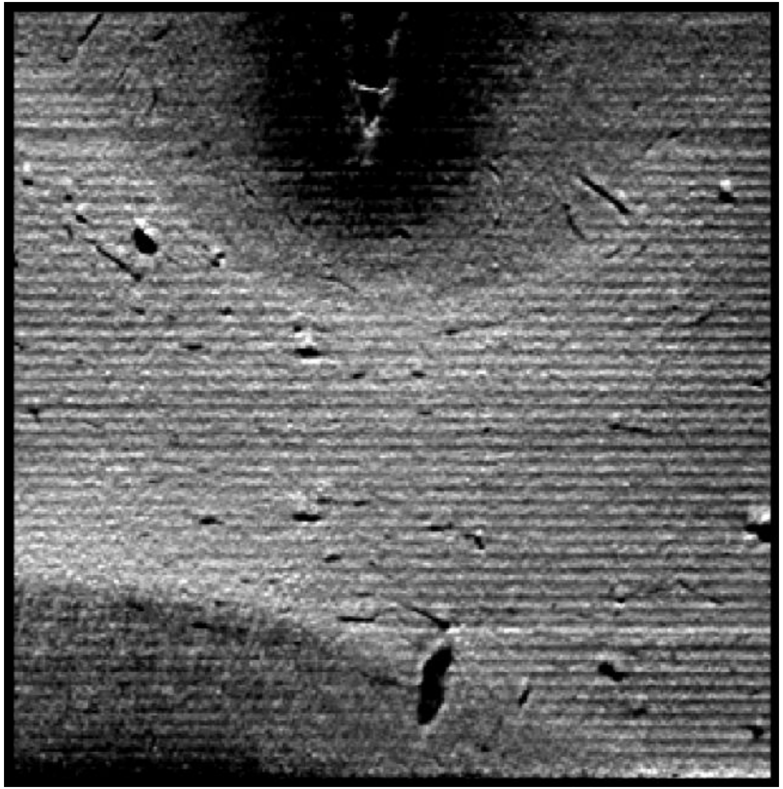
Pre-Processing

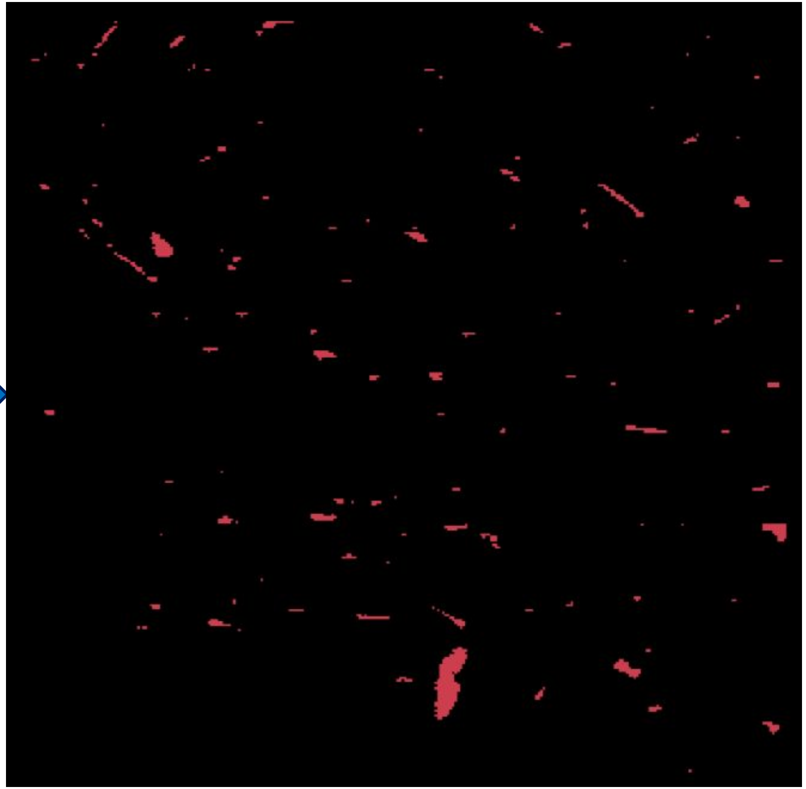
- The .nii images were split into multiple smaller 64 voxel cube images to save computational time.
- A total of 1000 .nii images were used for this project selected based on:
  - Clarity of image
  - Amount of vessels we can see
  - Amount of noise in the image
  - Amount of variability(good representability of all variables)

```
'shape': (128, 128, 128),
'voxel_size': 0.02,
'nb_levels': RandInt(1, 4),
'tree_density': Uniform(0.1, 0.2),
'tortuosity': Uniform(1, 5),
'radius': Uniform(0.01, 0.1),
'radius_change': Uniform(0.8, 1.2),
'nb_children': RandInt(1, 4),
'radius_ratio': Uniform(0.25, 1),
'device': 'cuda'
```

Feature	Definition
nb_levels	The amount of parent vessels / starting vessels the image has.
tree_density	The starting thickness of the parent vessel.
tortuosity	The amount of curl a blood vessel has / how spirally a blood vessel is.
radius	The thickness of the blood vessel.
radius_change	The change in radius from a parent blood vessel to a branching blood vessel.
nb_children	The amount of branching blood vessels that a parent blood vessel has.
radius_ratio	The change in radius in the blood vessel throughout its length.

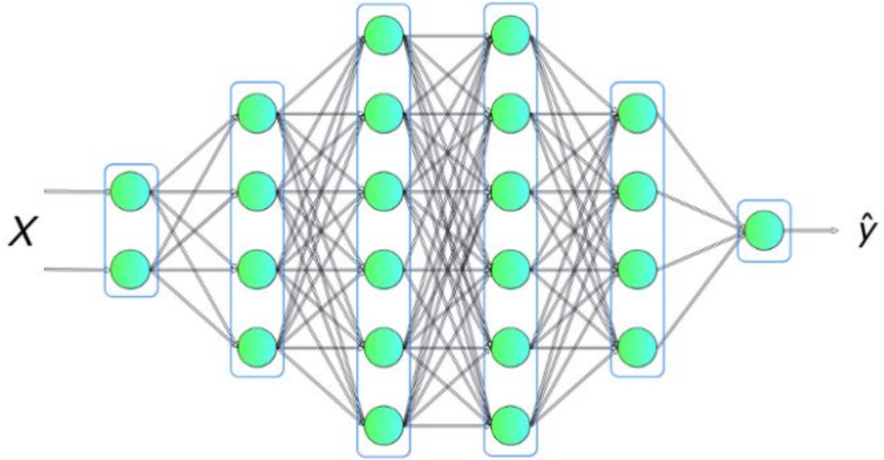
DATA





METHODS

- A previous research paper used a fully connected neural network (FCNN) to find blood vessels in MRI images.
- A FCNN consists of layers where each neuron is connected to every neuron in the previous layer.
- Given an input vector, weights, and biases, the output of a layer is computed using a non-linear activation function such as ReLU or sigmoid.
- FCNNs are effective for learning global patterns but struggle with data that exhibits strong spatial locality, such as images.



METHODS

- CNNs improve on FCNNs by using convolutional layers that exploit local spatial structure in data.
- A convolutional layer applies a set of learnable filters over the input, producing feature maps.
- For an input image and filter, the convolution operation can be expressed as a convolution operation.
- CNNs reduce the number of trainable parameters by sharing weights across different spatial locations, making them more efficient for image data.

For a 2D image H and 2D Filter(kernel) F,

(**1**) **Convolution Operation** : $\mathbf{G} = H * F$

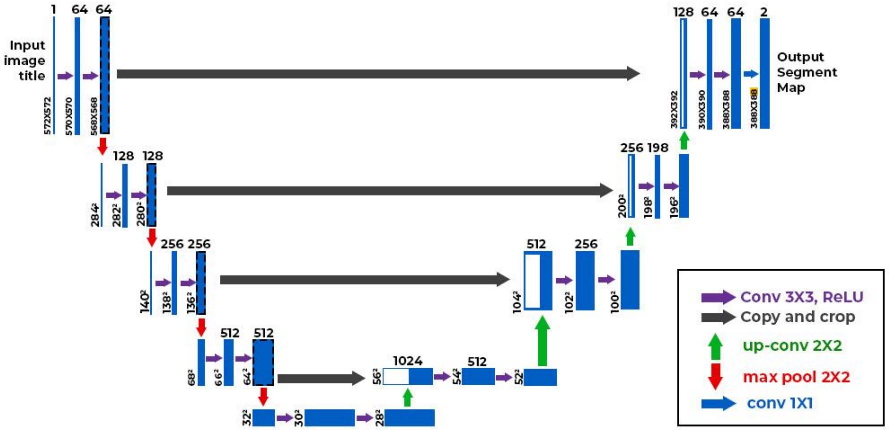
$$G[i,j] = \sum_{u=-k}^{k} \sum_{u=-k}^{k} H[u,v]F[i-u, j-v]$$

(**2**) **Correlation Operation** : $\mathbf{G} = H \oslash F$

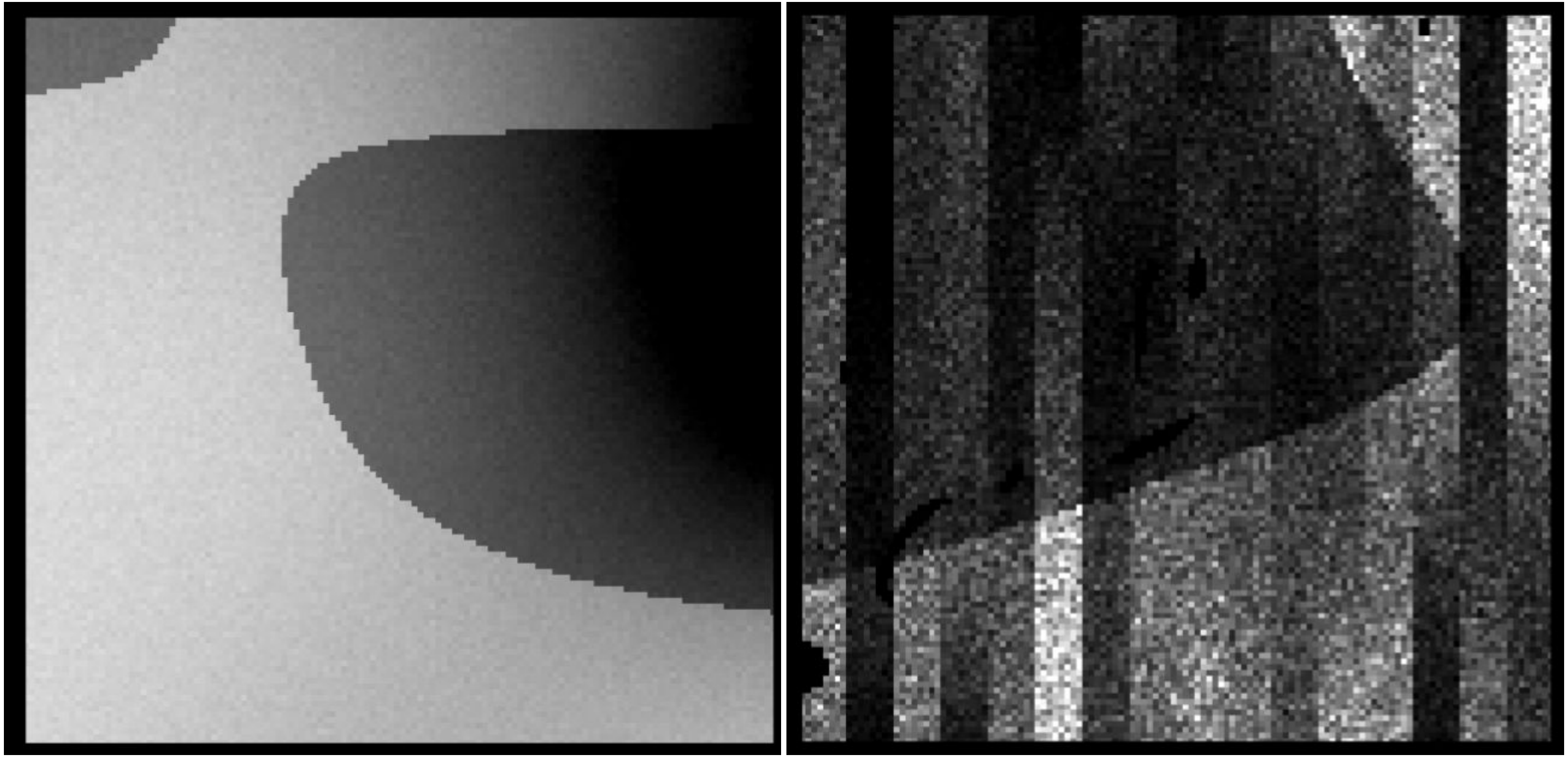
$$G[i,j] = \sum_{u=-k}^{k} \sum_{u=-k}^{k} H[u,v]F[i+u, j+v]$$

METHODS

- U-Nets build on CNNs, specifically for image segmentation tasks, by employing a symmetric encoder-decoder structure with skip connections.
- The encoder extracts hierarchical features while progressively reducing spatial resolution, such as the size of a blood vessel or the amount of blood vessels.
- After each feature extraction, the image is decreased by a certain factor; if the factor is 2, every 4 pixels in a 2 by 2 box would be converted to 1 pixel.
- The pixel would be the value that occurs the most or the average of the values.
- The decoder then upsamples the feature maps to reconstruct a segmented image.

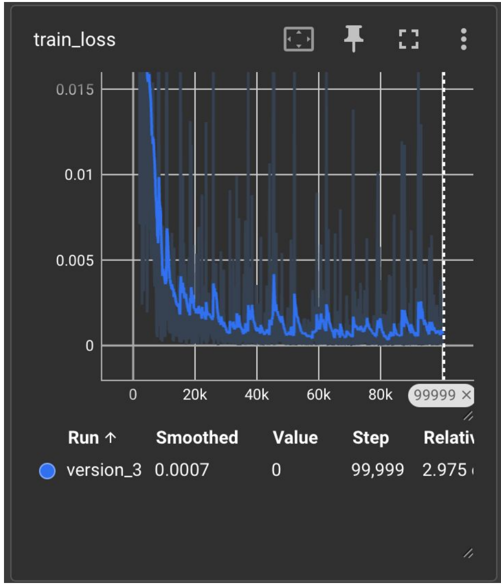


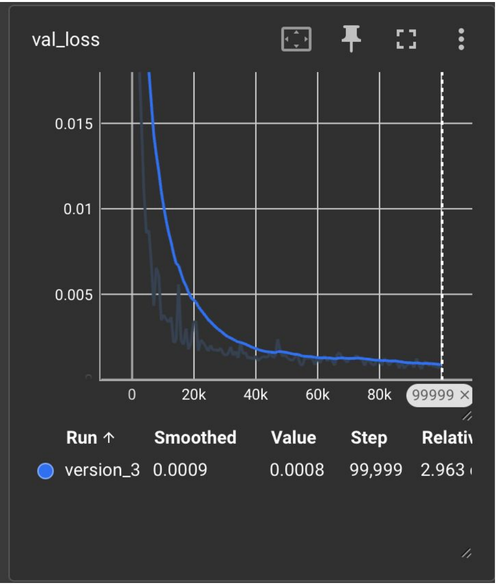
Noise Examples



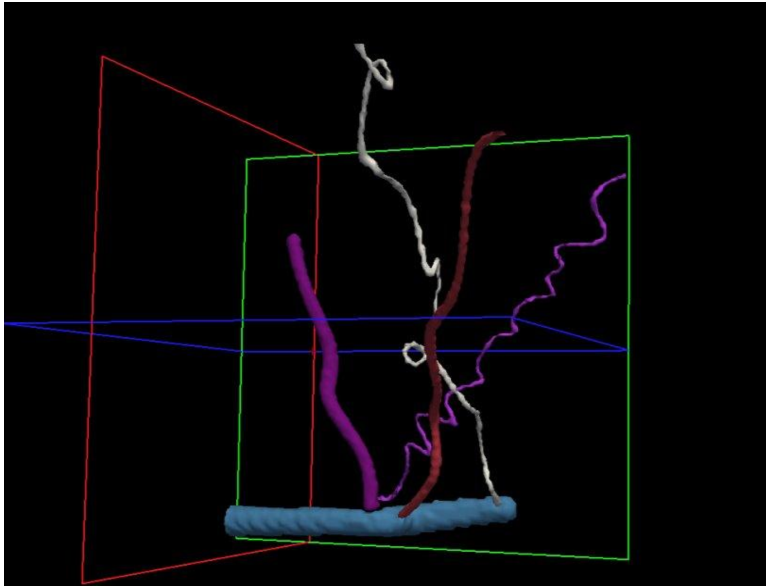
Model Training

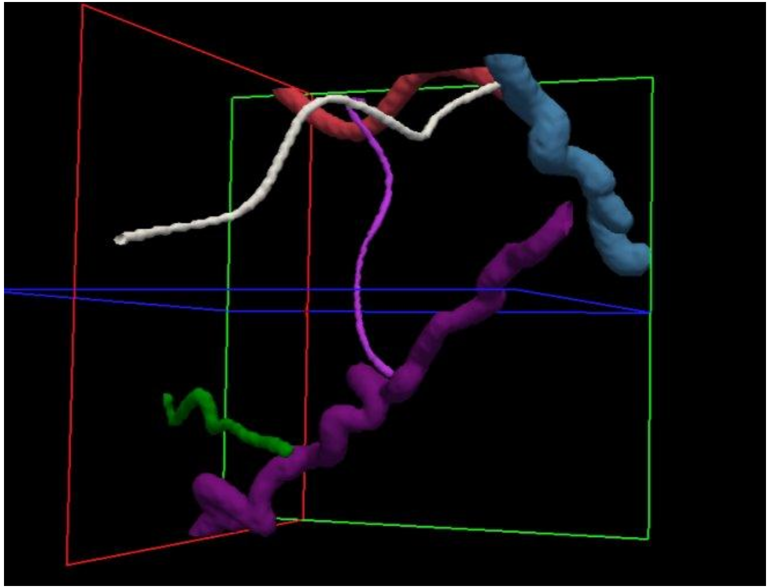
- 1000 volumes
- 0.8 Training to validation
- 100,000 steps
- 1 batch size
- 0.001 learning rate

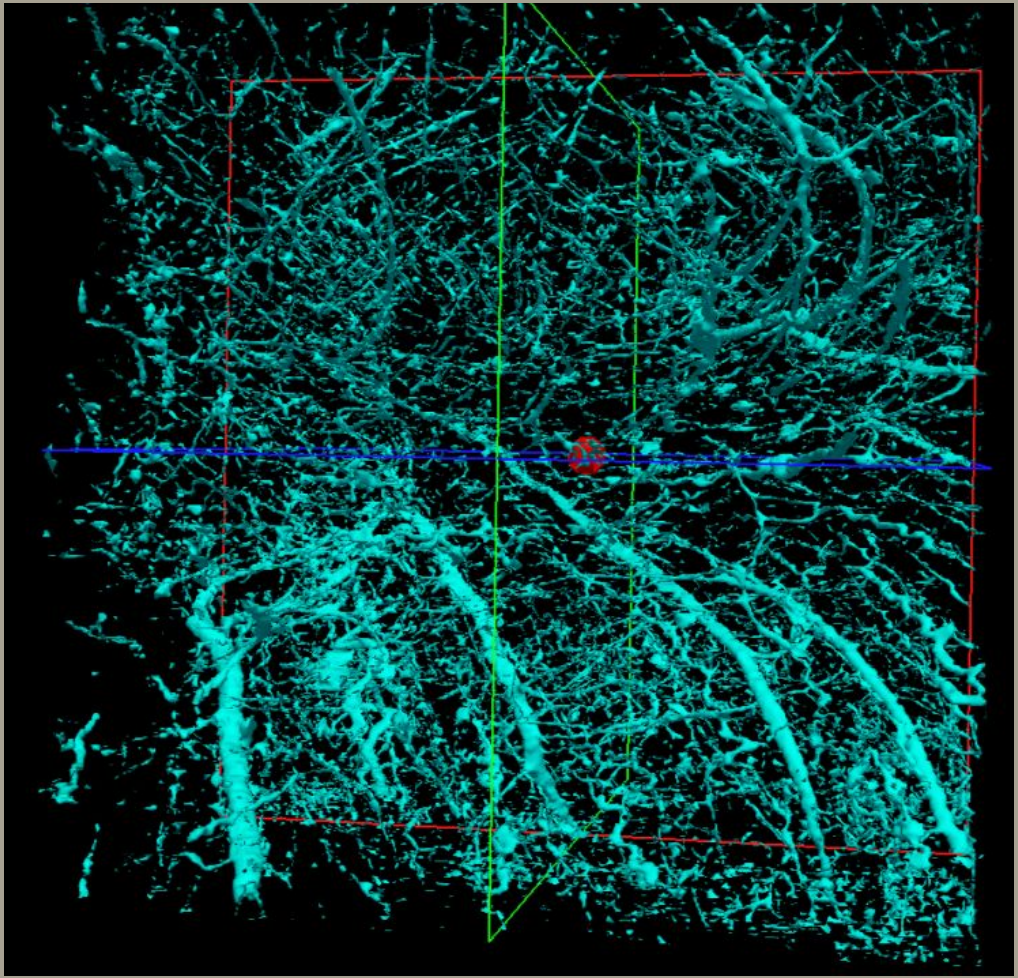




Vessel Example







Final Product

Results

The F1-score, also known as the Dice similarity coefficient (DSC), is a popular metric used to evaluate the performance of a classification model. It takes into account both precision and recall, aiming to strike a balance between them, and can be expressed as:

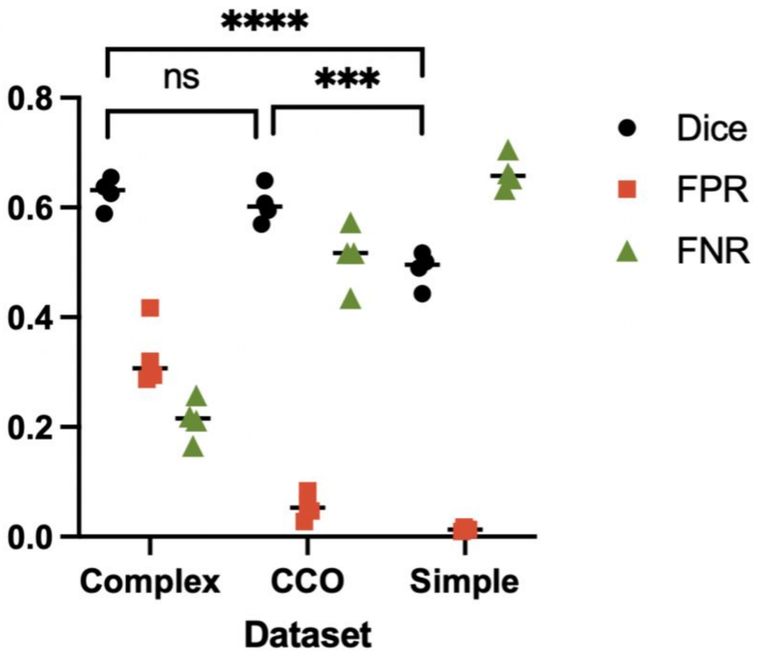
$$F_1 - Score = \frac{2 \times T_P}{(2 \times T_P) + F_P + F_N}$$

We also use False Positive Rate (FPR) and False Negative Rate (FNR)

$$FPR = \frac{FP}{Actual\ Negative} = \frac{FP}{TN + FP} \qquad FNR = \frac{FN}{Actual\ Positive} = \frac{FN}{TP + FN}$$

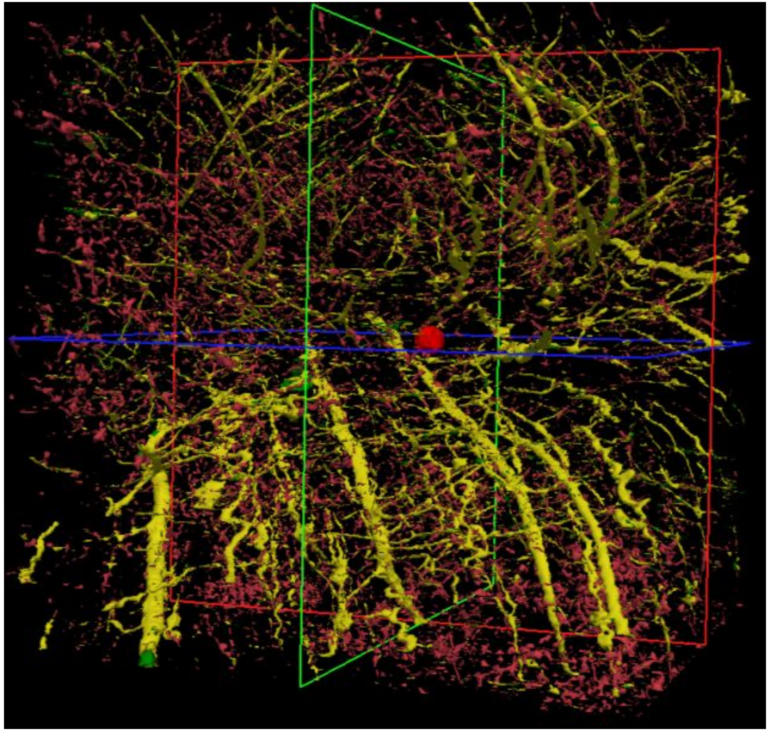
Results

FCNN results

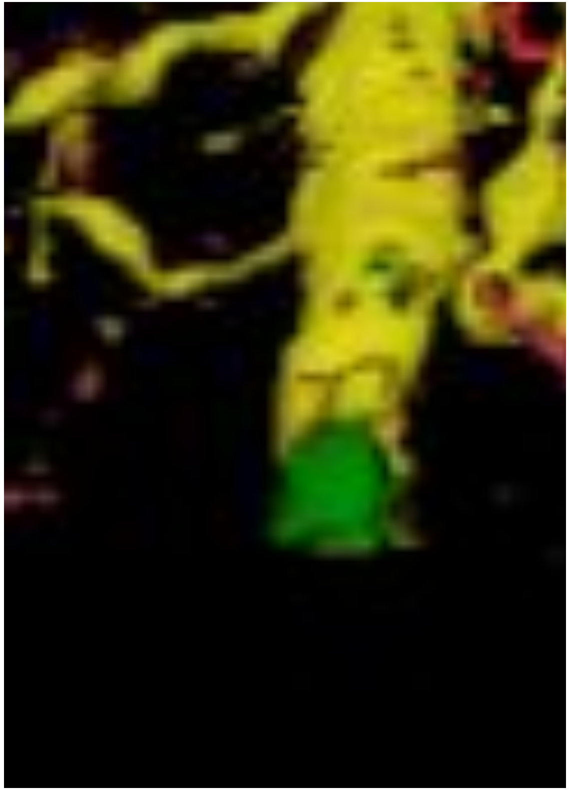


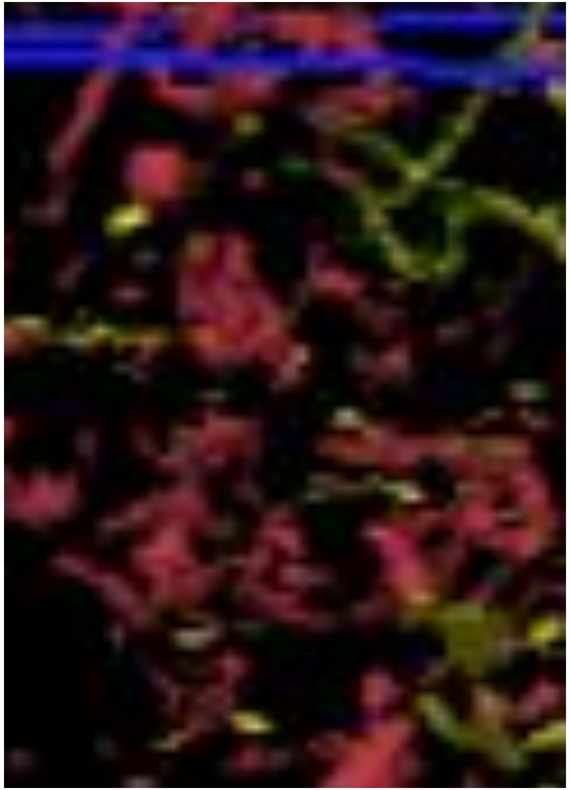
Our results:

- Dice = 0.681
- FPR = 0.194
- FNR = 0.289



Results





Conclusion

- U-net algorithm performed better than the one FCNN one used in the paper.
- Based on the train loss, we could have trained the algorithm a bit more steps.
- Another thing we noticed was how much the algorithm highlighted small little blobs on the images.
  - We can code it is that if there are no children blood vessels or parent blood vessels then we remove the blobs that were labeled as vessels.
  - We can do is denote a size where if a vessel takes up fewer than a certain amount of space than its not considered a blood vessel and can subsequently be removed

Questions?