Introduction

Carotid artery stenosis is a common disease responsible for roughly 25% of all strokes. In carotid stenosis, plaque deposits in the carotid artery narrow the vessel and reduce or block blood flow.

We present two deep learning methods for automating grayscale carotid ultrasound screening:

1. An object localization model that crops out extraneous graphical and textual information in grayscale ultrasounds.
2. A convolutional neural network trained to detect signs of stenosis in grayscale carotid ultrasounds. We present a robust analysis of current architectures and their shortcomings in the context of this dataset.

Dataset

21,000 grayscale Ultrasound Screen-captures

Screen-captures include the actual ultrasound image surrounded by extraneous textual and graphical features.

In order to crop the ultrasound image from the 21,000 screen-captures, we trained an image localization model. We built a GUI to label a training dataset for the model.

Sparsity Loss

The dataset was labeled at the exam-level. In an abnormal exam, only around 10% of the images will show signs of stenosis. Thus, our dataset presents a challenging multiple instance learning problem with sparse sets.

We utilized Sparsity Loss to discourage misclassification.

Model Architecture

Image Localization

Abnormality Detection

We achieved a 92.1% validation Intersection Over Union (IOU), which measures overlap of predicted region with ground-truth.

Abnormality Detection in Carotid Ultrasounds with Convolutional Networks

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Results

Variational Auto-Encoder

Image Localization

Abnormality Detection

Our models showed a tendency to overfit, regardless of the regularization methods we used (L2, Dropout, Data Augmentation, etc.)

Conclusion & Future Work

According to the team at AIMI, the localization model we built is capable of completing a task in seconds that previously took months to complete by hand.

We also presented a robust analysis of several CNN architectures for abnormality detection. The success of future abnormality detection models will likely depend on 1) more labeled data or data labeled at the image level and/or 2) new techniques for handling sparse sets in multiple instance learning problems.