



Deep Learning Methods for Assisting in QCA Stenosis Analysis of RCA

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Background

- ❖ Cardiologists use invasive coronary angiography, which involves fluoroscopy (continuous x-ray) and radio-opaque contrast, to determine the presence and severity of stenosis. This also informs the need and decision to pursue coronary revascularization.
- ❖ Stenosis severity is generally determined by visual estimation of the percent diameter narrowing within a coronary artery, which has substantial inter-reader variability.
- ❖ A more reliable and accurate determination of stenosis severity is quantitative coronary angiography (QCA), which is challenging to perform in real-time. QCA is a computer-assisted procedure, which involves visually annotating diseased coronary segments and the area surrounding each stenosis to determine the percent stenosis.
- ❖ Angiographic core labs select a single still frame of a single angle image for the most reliable determination of percent diameter stenosis. Currently human-aided computer technology are used in this clinical work flow.

Objectives

- ❖ Develop analytical tools to automatically segment still-frame invasive coronary angiography images of the right coronary artery, identifying diseased segments of interest and the surrounding areas. This is an essential first step for creating an automated reading system.
- ❖ The right coronary artery was selected as an initial research focus due to its frequency of analysis in coronary angiography.

Data

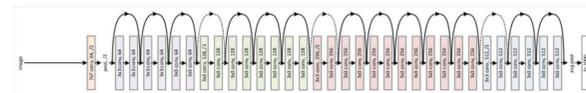
- ❖ De-identified ^{1,2} 1024 still-frames of right coronary artery taken during coronary angiography ("rca-qca images")
- ❖ Data elements include still-frame images (512x512 pixels) and segmented-out stenosis lesion "stenosis mask" annotated as part of the QCA assessment.

❖ 1: Data collected from various clinical studies available via Yale Cardiology Research Group's Core Laboratory. Images are already annotated.
 ❖ 2: IRB Exemption 2000021836 "Machine Learning Models for Assessment of Coronary and Peripheral Angiography Images"

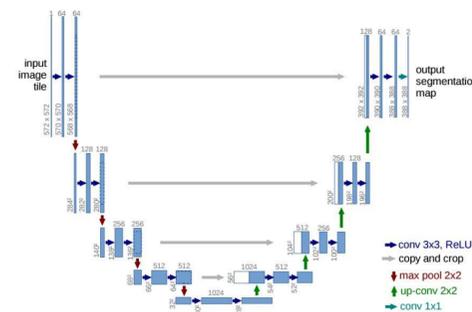
Methods

- ❖ Trained 'U-Net' style "SegNet" convolutional neural network to automatically segment stenosis mask in coronary angiography images. U-Net architecture preferred due to its success in other biomedical segmentation tasks.
- ❖ Trained "SegNet" on varying levels of image localization demonstrating proof of concept: Improving performance with smart localization.
- ❖ Trained localizing "LocalNet" convolutional neural network for training models to localize neighborhood of stenosis.
- ❖ Dice Coefficient used as the main segmentation quality metric. Dice Coefficient is a measure of similarity in shape between the true and predicted segmentation mask.
- ❖ Dataset split 70:15:15 for train, validation, and test sets respectively.

❖ **Figure 1.1: ResNet Architecture adapted for LocalNet**
 ❖ One of the models used to design LocalNet



❖ **Figure 1.2: U-Net Architecture adapted for SegNet**



❖ **Figure 1.3: Dice Coefficient (Segmentation Metric)**

$$\frac{2 * |X \cap Y|}{|X| + |Y|}$$

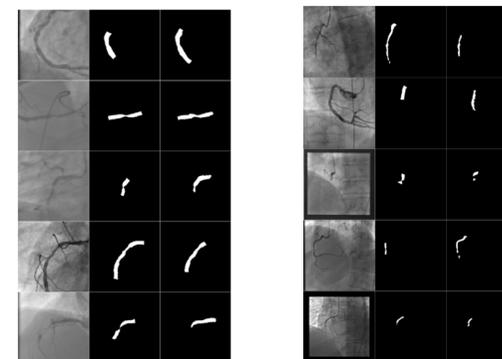
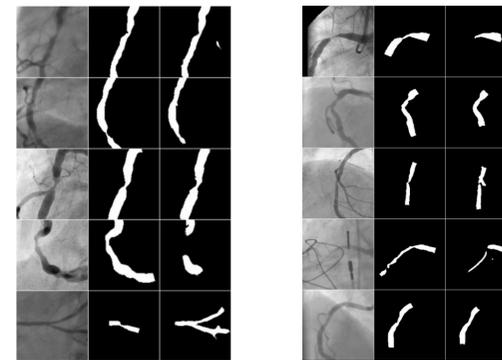
Results

❖ **Table 1: SegNet: Segmentation Accuracy by Image Focus**

| Dice | Image Pixel Size (Centered Around Area of Stenosis) | | | |
|------|---|---------|---------|---------|
| | 512x512 | 256x256 | 192x192 | 128x128 |
| | 0.4061 | 0.6475 | 0.7273 | 0.7476 |

❖ **Figure 2: SegNet: Visualization by Image Focus**

- ❖ Top Left: 128x128, Top Right: 192x192, Bottom Left: 256x256, Bottom Right: 512x512
- ❖ 5 rows represent 5 test set images.
- ❖ Left column: RCA image; Mid Column: Ground Truth Stenosis Mask; Right Column: Predicted Stenosis Mask.



❖ **Table 2: LocalNet Stenosis Localization Error using by CNN Motif**

| Mean Squared Error | LocalNet Architecture Motif | | | |
|--------------------|-----------------------------|-------------|-------------|-------------|
| | ResNet50 | InceptionV2 | DenseNet121 | DenseNet201 |
| | 0.0172 | 0.0221 | 0.0273 | 0.0354 |

Conclusion

- ❖ To our knowledge, we develop the first imaging tool that automatically segments stenosis masks from rca-qca still frame images without clinician assistance.
- ❖ We trained SegNet, a neural network that has capability to automatically analyze rca-qca images by segmenting out the stenosis mask, a crucial step in QCA analysis.
- ❖ We demonstrated that SegNet improves in performance with improved localized focus around area of interest.
- ❖ We trained LocalNet, a neural network that can automatically identify the local point of stenosis. This tool can be combined with SegNet to localize the SegNet and further improve segmentation performance.

Follow-up Work

- ❖ Train end-to-end deep learning pipeline combining the localization and segmentation steps to improve segmentation performance.
- ❖ Train deep learning pipeline applies learned stenosis mask segmentation to further classify stenosis severity (i.e. percentage of stenosis), which is the main clinical objective.
- ❖ Expand analysis to learn segmentation and stenosis intensity from multi-angle, x-ray short-video, which would reach clinical applicability to current QCA work flow.

References

- ❖ Nallamothu BK, et al. Circulation 2013;113:1793.
- ❖ Ronneberger O, et al. MICCAI 2015;9351:234
- ❖ Zhang H, et al. JAMA 2018;10:1001.