Segmentation and Quantification of Breast Arterial Calcifications (BAC) on Mammograms

Xiaoyuan (Sophie) Guo

PhD candidate

Supervisor: Imon Banerjee

Emory University

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Outline

- Introduction of BAC background
- Challenges of BAC segmentation
- Methods to detect BAC
- Quantifications of BAC

Background

- A mammogram is an X-ray picture of the breast.
- Doctors use a mammogram to look for early signs of breast cancer[1].
- According to American Cancer Society's recommendations, women aged 45 to 54 should get mammograms every year.
- Breast Arterial Calcifications (BAC) are frequently observed on screening mammography[2].

A mammogram with breast arterial calcifications

[1] https://www.cdc.gov/cancer/breast/basic_info/mammograms.htm
[2] Breast Arterial Calcification: A Potential Surrogate Marker for Cardiovascular Disease

Background

- BAC have been considered as an incidental finding without risk for breast cancer.
- However, studies indicate that BAC might contribute to cardiovascular disease (CVD).
- BAC can be used as a potential risk predictor for CVD events such as heart attack and stroke.
- Evaluation of BAC may be helpful in identifying high-risk women without additional cost or radiation exposure.
- Manual detection of BAC in mammograms is an extremely laborious process.

Challenges

- BAC characteristics
  - Narrow
  - Along with vessels
  - Fragmented
  - High pixel intensity
  - Varied length and width

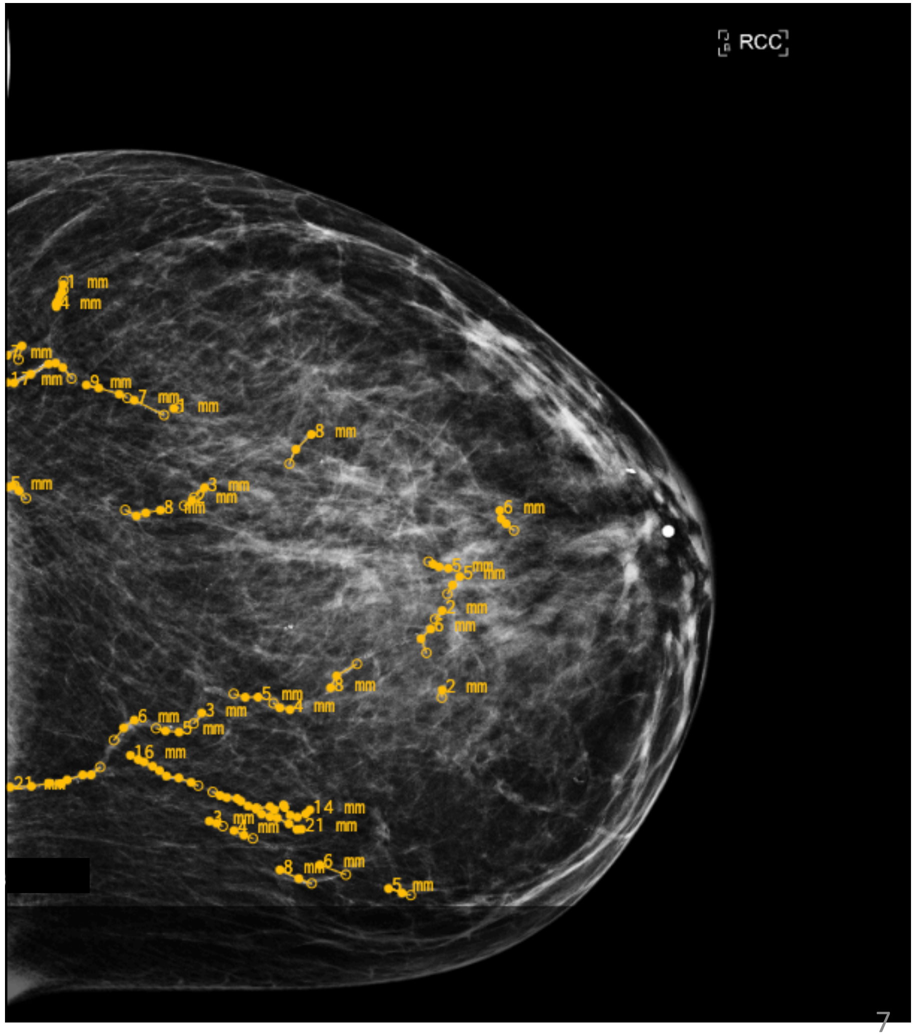
- Mammogram size: 4Kx3K
- Calcification area takes ~1%
- Hard to annotate accurately

Aims

- Develop an automatic pipeline to detect BAC accurately on mammograms
- Speed the computation to process large mammograms data
- Test the effectiveness of BAC detectors in unseen data
- Quantify BAC based on the detection
- Demonstrate the usefulness of quantifications in tracking BAC progression

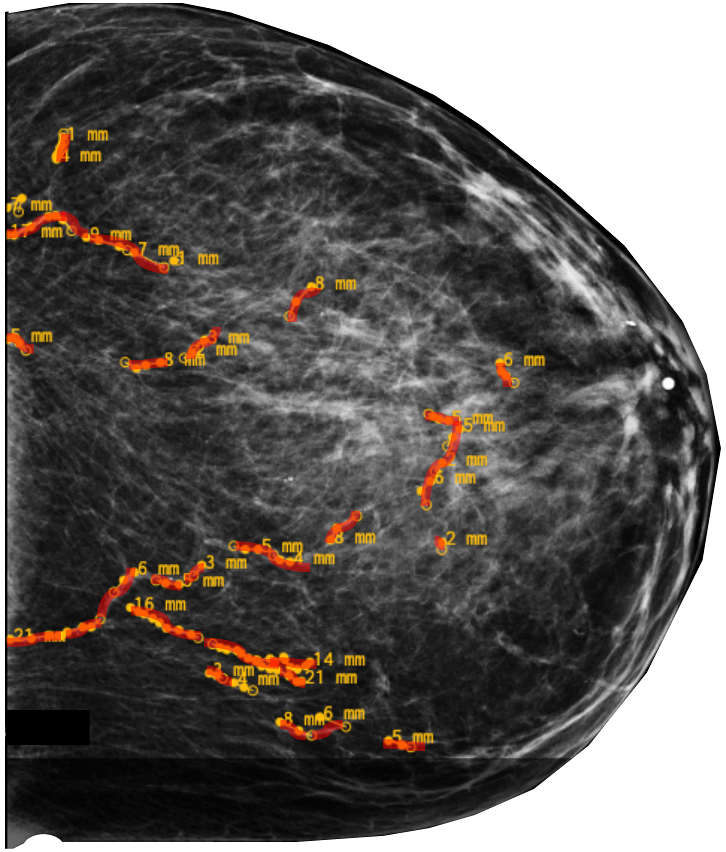
BAC Annotations

- Line-style annotations
- No width information



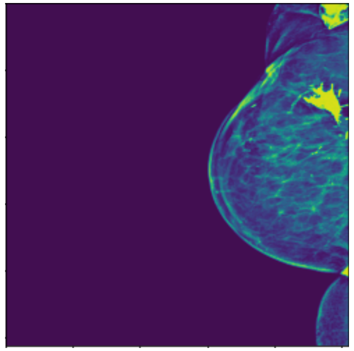
BAC Annotations

- Line-style annotations
- No width information
- Scanner/label information
- Discontinuous

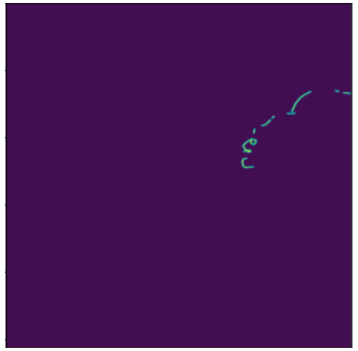


Attempts

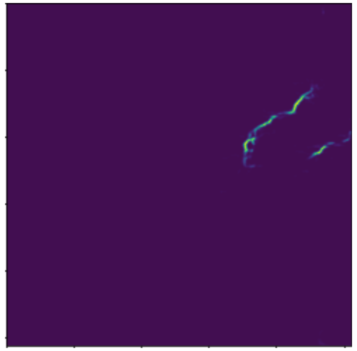
- Resize original mammograms to smaller sizes, e.g. 256x256, 512x512,…
- Segment with U-Net and resize to the original size



Resized Image



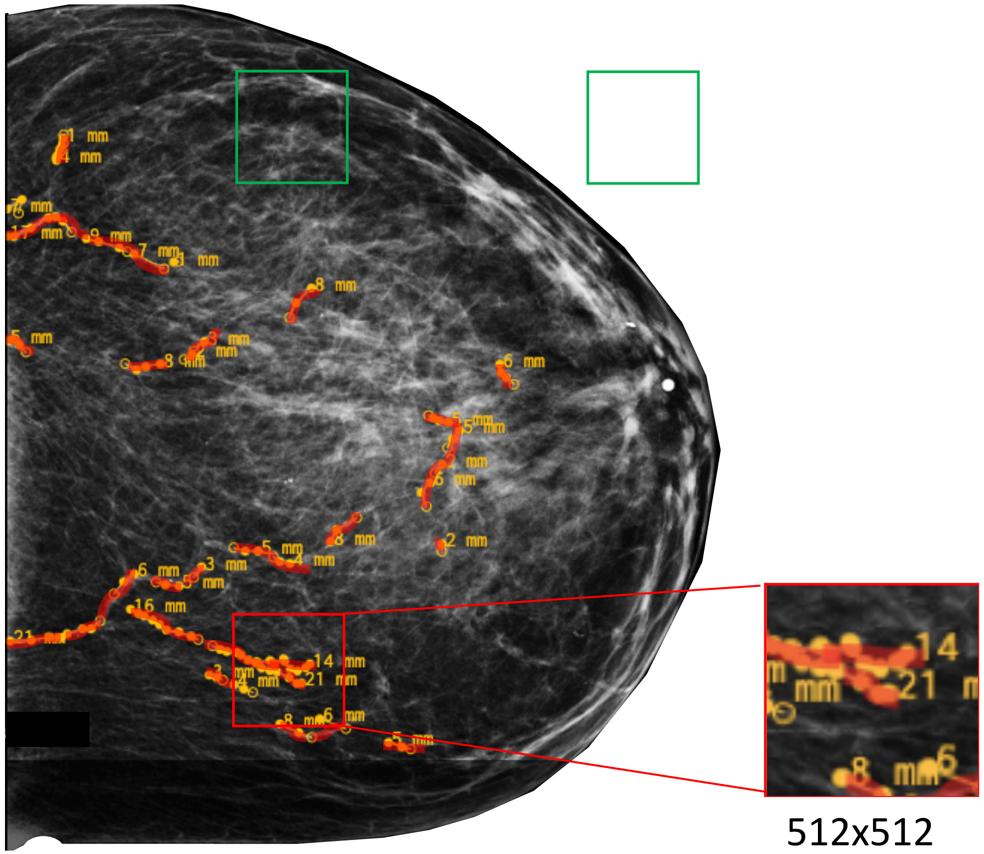
Groundtruth



Results

Recall	Precision	Accuracy	F1_score	Jaccard index
0.6435	0.4293	0.9975	0.5150	0.3468

Patchwise Segmentation



512x512

- Patchwise segmentation is used due to the large image size and the memory limitations.
- Patches with only background/ no BAC are avoided to enhance model training efficiency.
- Small overlapping across neighbor patches can help improve whole-image-size segmentation accuracy after concatenating all patches back.

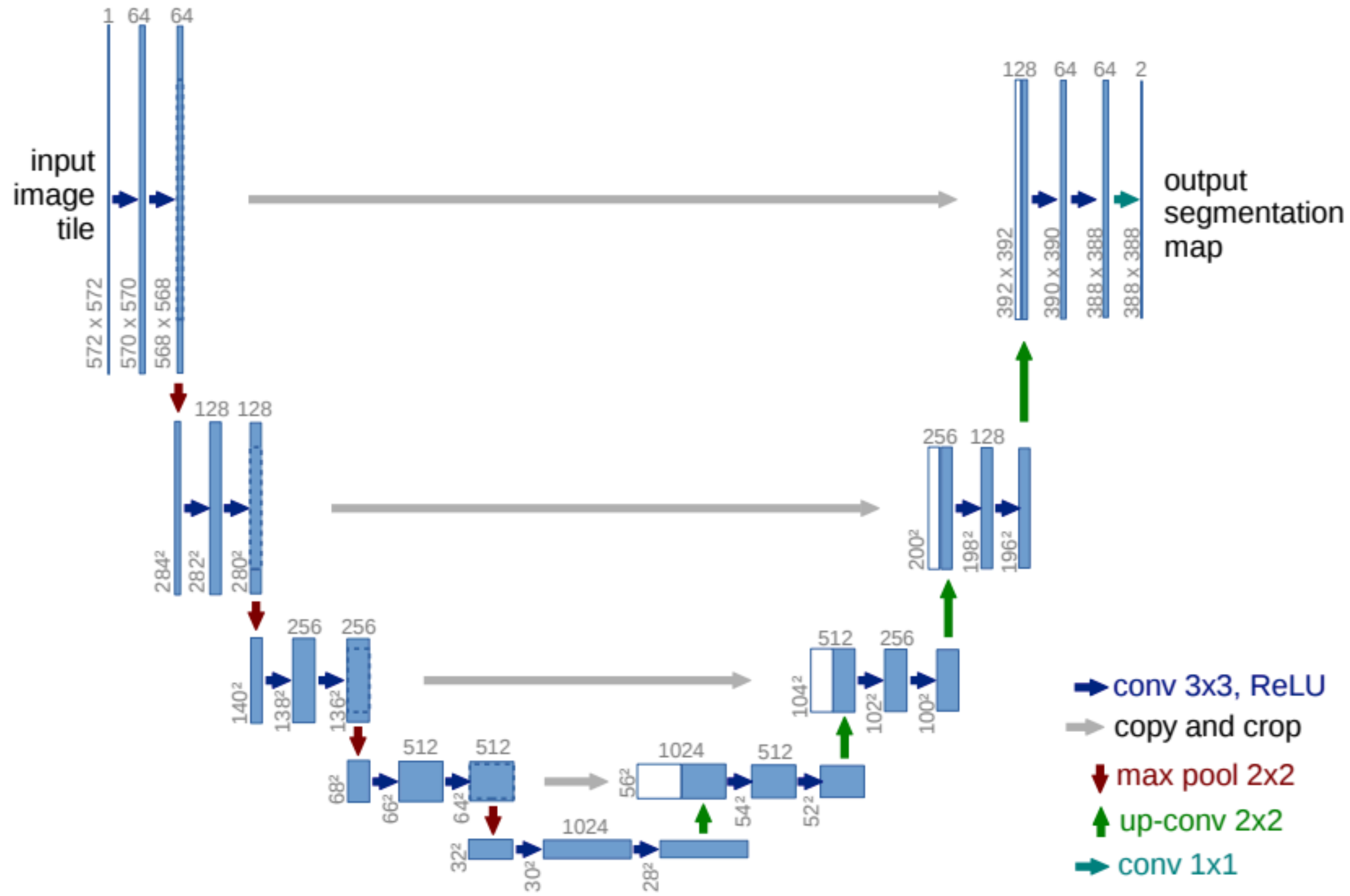
Dataset

- In total, 661 2D full-field digital mammograms (FFDM) from 216 subjects
  - 4096x3328 pixels or 3328x2560 pixels

- Train: 527 mammograms →3,455 patches
- Validation: 134 mammograms→ 901 patches

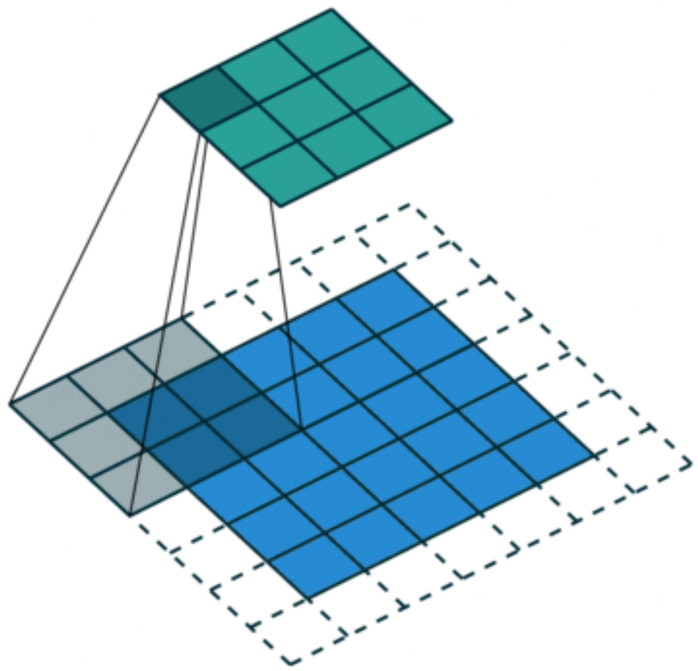
- Patches are in size of 512x512 pixels with 60 pixels overlapping.

U-Net

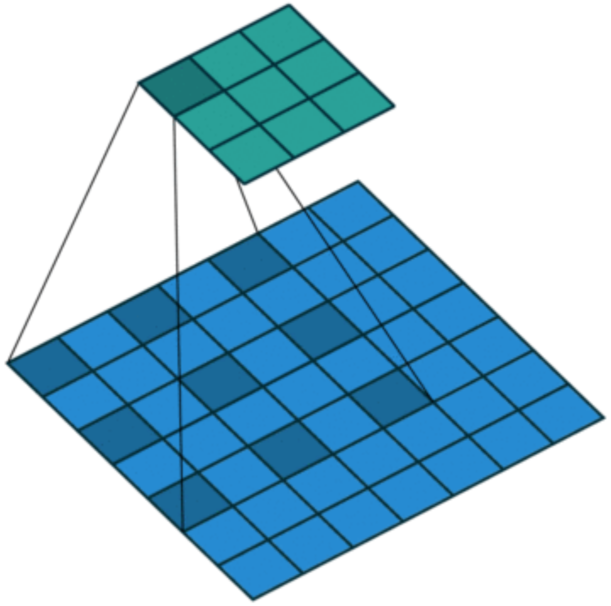


Ronneberger, et. al. "U-net: Convolutional networks for biomedical image segmentation." 2015.

Dilated Convolution



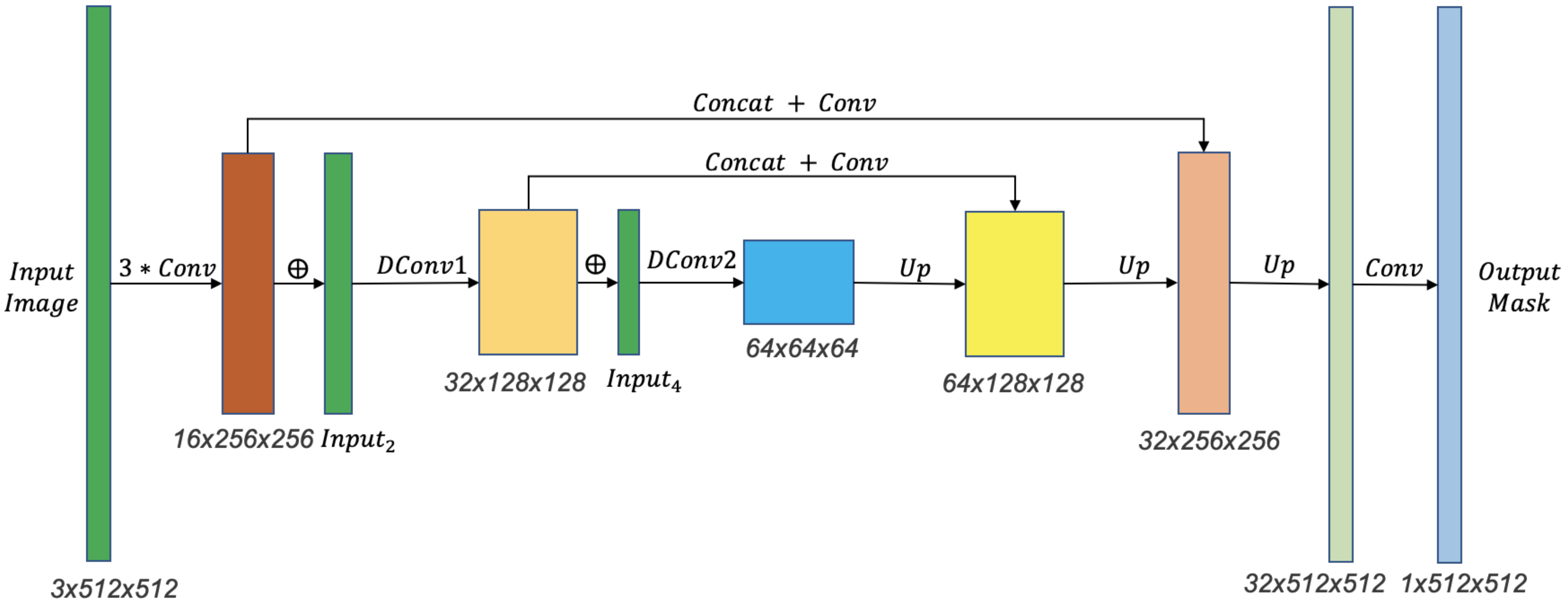
Standard Convolution



Dilated Convolution

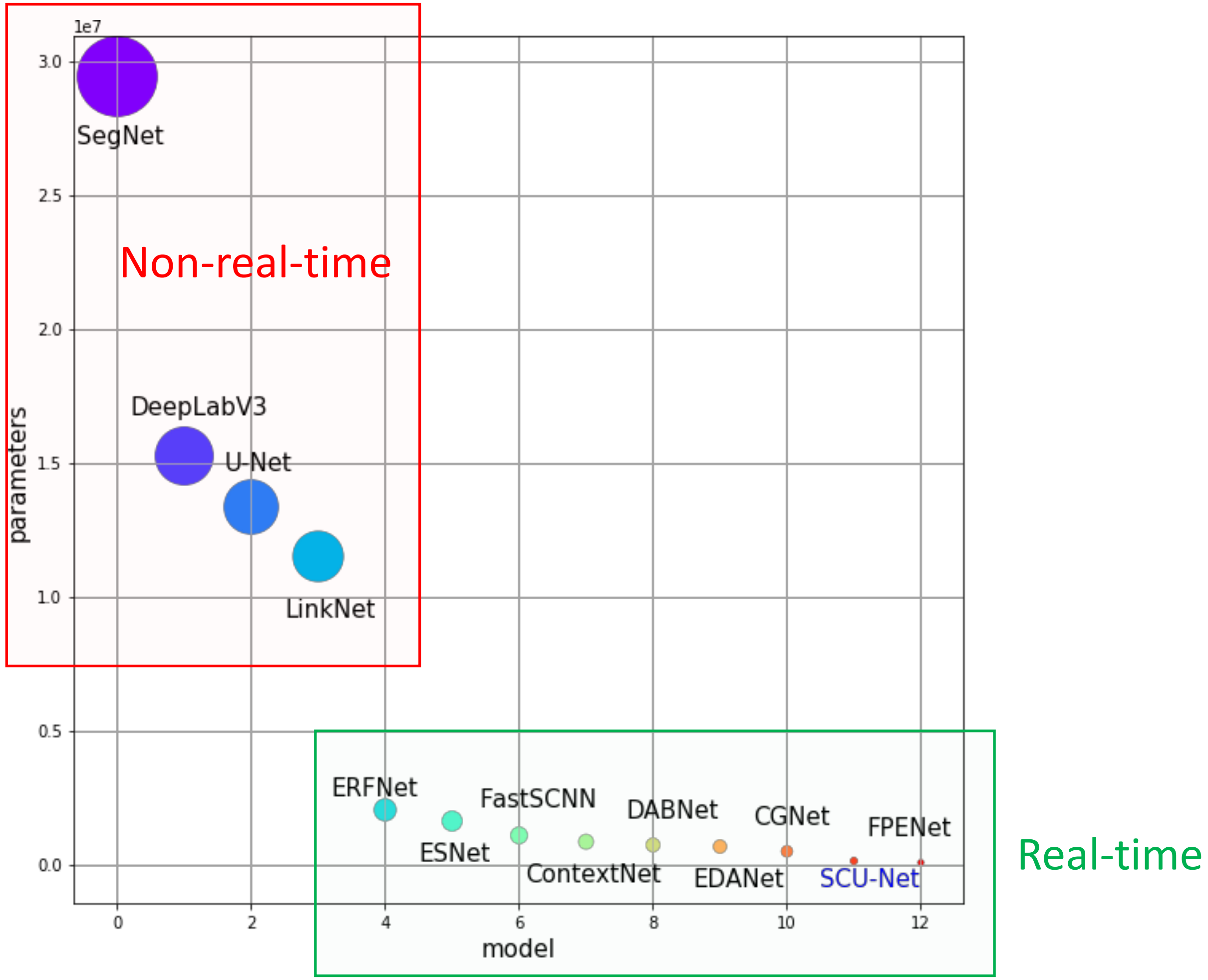
https://towardsdatascience.com/review-dilated-convolution-semantic-segmentation-9d5a5bd768f5

SCU-Net for Fine Vessel Segmentation

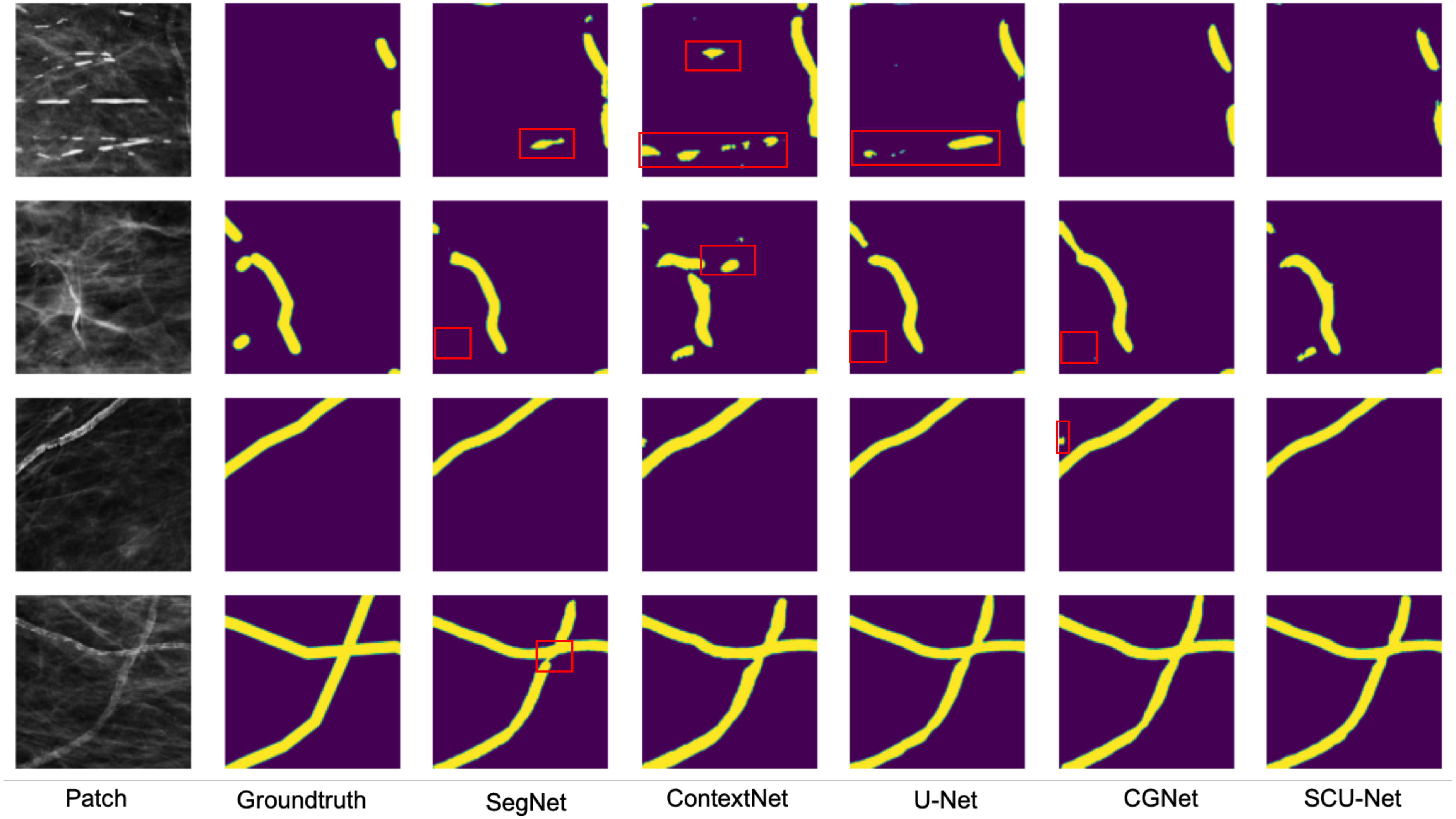


⊕: Concat $Input_i$: Downsampled input image with factor of i $DConv$: Dilated Convolution Up: Upsampling

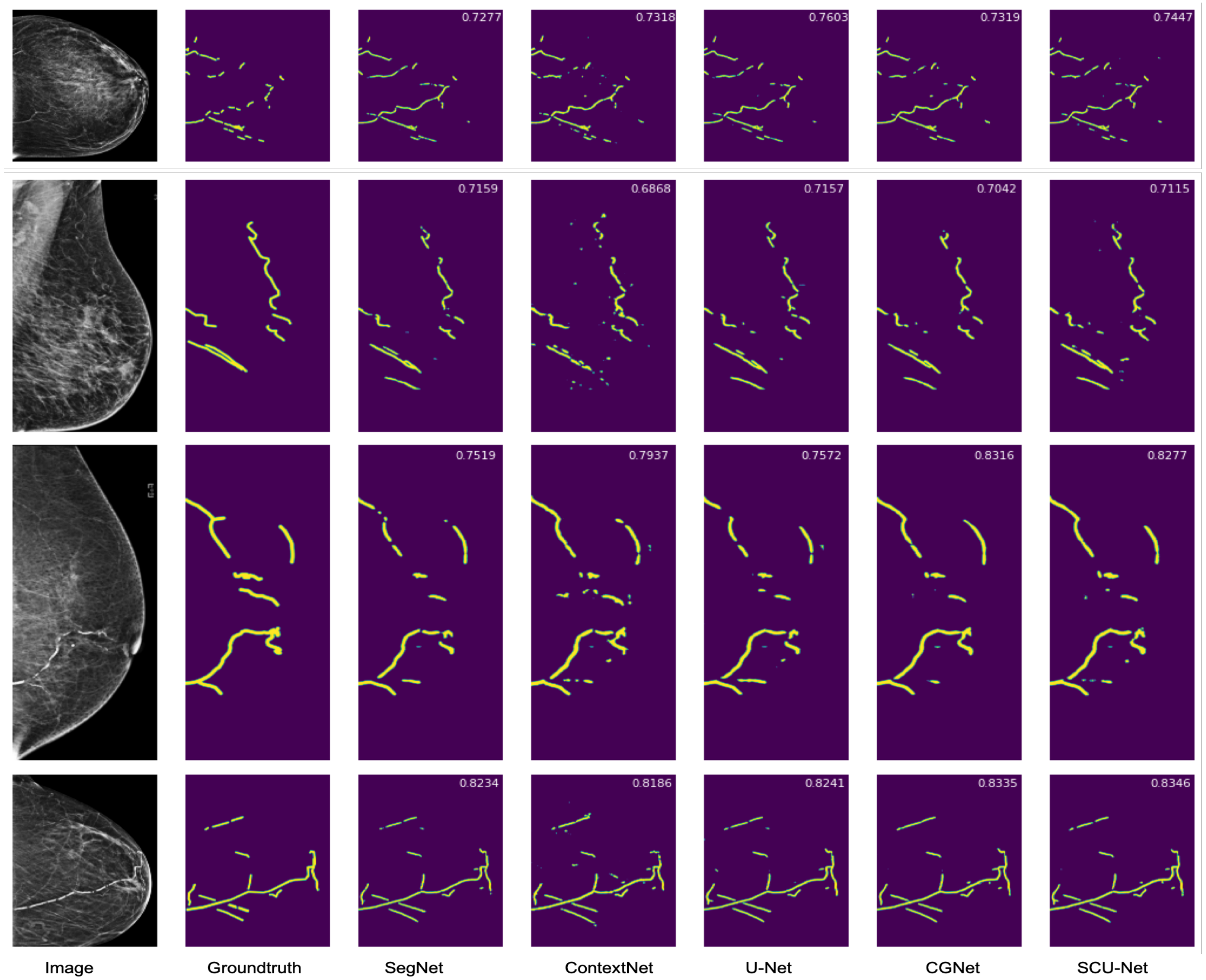
Model Comparison



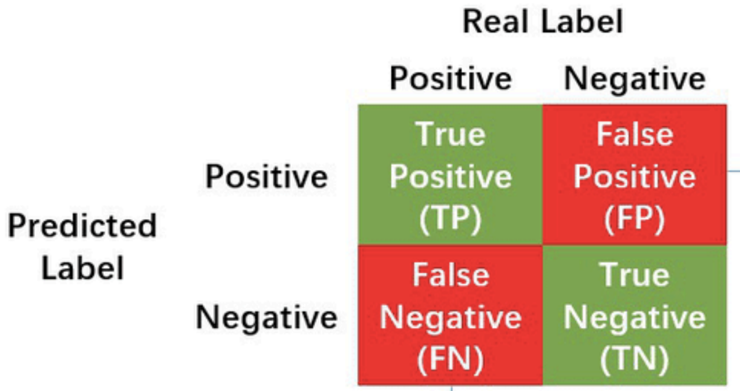
Patchwise results



Whole-image-size results

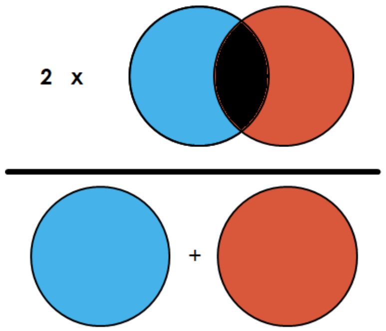


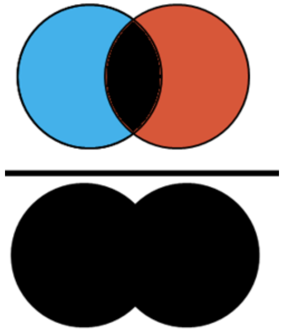
Segmentation Evaluation Metrics



$$\text{Precision} = \frac{\sum \text{TP}}{\sum \text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\sum \text{TP}}{\sum \text{TP} + \text{FN}} \qquad \text{Accuracy} = \frac{\sum \text{TP} + \text{TN}}{\sum \text{TP} + \text{FP} + \text{FN} + \text{TN}}$$





$$F1 - score(Dice\ score)$$

$$= \frac{2 \times Recall \times Precision}{Recall + Precision}$$

$$= \frac{2 \times TP}{TP + FP + TP + FN}$$

$$JaccardIndex(IoU)$$

$$= \frac{TP}{TP + FP + FN}$$

https://www.researchgate.net/figure/Calculation-of-Precision-Recall-and-Accuracy-in-the-confusion-matrix_fig3_336402347
https://towardsdatascience.com/metrics-to-evaluate-your-semantic-segmentation-model-6bcb99639aa2

Quantification of Segmentation Results

Table 2: Quantitative evaluation results for **image patches** (columns without background) and **whole images** (columns with gray background) in the validation dataset, subscripts denote standard deviation.

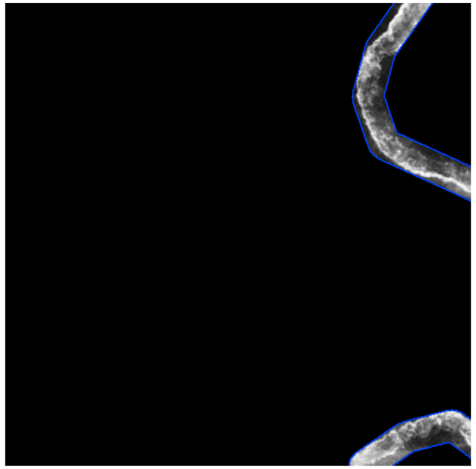
tab:res

Method	*Recall*		*Precision*		*Accuracy*		*F1-score*		*Jaccard*	
SegNet	$0.707_{\pm0.100}$	$0.764_{\pm0.159}$	$0.704_{\pm0.095}$	$0.743_{\pm0.128}$	$\mathbf{0.981_{\pm0.005}}$	$\mathbf{0.998_{\pm0.002}}$	$0.676_{\pm0.084}$	$0.734_{\pm0.098}$	$0.554_{\pm0.079}$	$0.589_{\pm0.113}$
DeepLabV3	$0.742_{\pm0.099}$	$0.781_{\pm0.154}$	$0.709_{\pm0.088}$	$0.726_{\pm0.134}$	$\mathbf{0.981_{\pm0.005}}$	$\mathbf{0.998_{\pm0.002}}$	$0.692_{\pm0.084}$	$\mathbf{0.735_{\pm0.100}}$	$0.568_{\pm0.081}$	$\mathbf{0.590_{\pm0.118}}$
U-Net	$0.738_{\pm0.092}$	$0.789_{\pm0.144}$	$0.704_{\pm0.088}$	$0.723_{\pm0.141}$	$\mathbf{0.981_{\pm0.005}}$	$\mathbf{0.998_{\pm0.002}}$	$0.689_{\pm0.074}$	$\mathbf{0.735_{\pm0.097}}$	$0.562_{\pm0.073}$	$\mathbf{0.590_{\pm0.112}}$
LinkNet	$0.748_{\pm0.095}$	$0.801_{\pm0.151}$	$0.675_{\pm0.096}$	$0.690_{\pm0.137}$	$0.979_{\pm0.006}$	$0.997_{\pm0.002}$	$0.676_{\pm0.082}$	$0.720_{\pm0.101}$	$0.550_{\pm0.080}$	$0.572_{\pm0.114}$
ERFNet	$\mathbf{0.788_{\pm0.088}}$	$\mathbf{0.826_{\pm0.133}}$	$0.669_{\pm0.086}$	$0.673_{\pm0.151}$	$0.979_{\pm0.006}$	$0.997_{\pm0.002}$	$0.694_{\pm0.075}$	$0.724_{\pm0.106}$	$0.568_{\pm0.077}$	$0.578_{\pm0.123}$
ESNet	$0.757_{\pm0.096}$	$0.796_{\pm0.164}$	$0.684_{\pm0.091}$	$0.707_{\pm0.137}$	$0.980_{\pm0.005}$	$0.997_{\pm0.002}$	$0.687_{\pm0.083}$	$0.727_{\pm0.108}$	$0.563_{\pm0.081}$	$0.581_{\pm0.122}$
FastSCNN	$0.687_{\pm0.105}$	$0.738_{\pm0.171}$	$0.662_{\pm0.100}$	$0.695_{\pm0.136}$	$0.979_{\pm0.006}$	$0.997_{\pm0.002}$	$0.647_{\pm0.096}$	$0.697_{\pm0.112}$	$0.522_{\pm0.092}$	$0.545_{\pm0.124}$
ContextNet	$0.723_{\pm0.093}$	$0.765_{\pm0.165}$	$0.631_{\pm0.090}$	$0.628_{\pm0.150}$	$0.977_{\pm0.006}$	$0.997_{\pm0.003}$	$0.643_{\pm0.083}$	$0.671_{\pm0.123}$	$0.509_{\pm0.081}$	$0.517_{\pm0.130}$
DABNet	$0.750_{\pm0.096}$	$0.804_{\pm0.143}$	$0.692_{\pm0.095}$	$0.706_{\pm0.142}$	$\mathbf{0.981_{\pm0.005}}$	$\mathbf{0.998_{\pm0.002}}$	$0.686_{\pm0.082}$	$0.734_{\pm0.102}$	$0.564_{\pm0.079}$	$0.589_{\pm0.118}$
EDANet	$0.771_{\pm0.094}$	$0.810_{\pm0.150}$	$0.666_{\pm0.096}$	$0.682_{\pm0.137}$	$0.980_{\pm0.005}$	$0.997_{\pm0.002}$	$0.685_{\pm0.085}$	$0.723_{\pm0.102}$	$0.559_{\pm0.083}$	$0.575_{\pm0.117}$
CGNet	$0.766_{\pm0.090}$	$0.798_{\pm0.149}$	$0.689_{\pm0.087}$	$0.703_{\pm0.138}$	$0.980_{\pm0.005}$	$0.997_{\pm0.002}$	$0.696_{\pm0.074}$	$0.730_{\pm0.102}$	$\mathbf{0.569_{\pm0.075}}$	$0.584_{\pm0.118}$
SCU-Net	$0.778_{\pm0.085}$	$0.789_{\pm0.137}$	$0.682_{\pm0.082}$	$0.708_{\pm0.140}$	$0.980_{\pm0.005}$	$0.997_{\pm0.002}$	$\mathbf{0.698_{\pm0.074}}$	$0.729_{\pm0.093}$	$\mathbf{0.569_{\pm0.074}}$	$0.581_{\pm0.110}$
FPENet	$0.682_{\pm0.106}$	$0.730_{\pm0.173}$	$\mathbf{0.715_{\pm0.095}}$	$\mathbf{0.750_{\pm0.130}}$	$\mathbf{0.981_{\pm0.005}}$	$\mathbf{0.998_{\pm0.002}}$	$0.666_{\pm0.092}$	$0.721_{\pm0.114}$	$0.544_{\pm0.087}$	$0.575_{\pm0.129}$

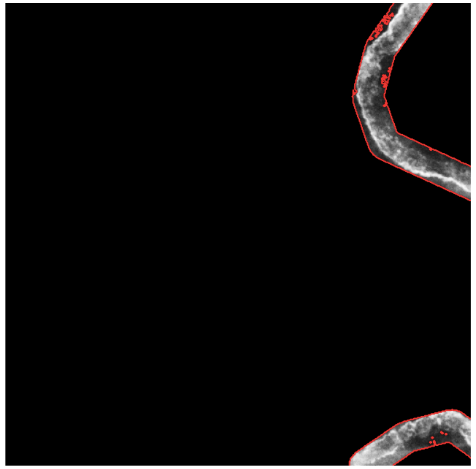
BAC Quantification

- Vessel segmentation is an intermediate task to achieve BAC quantification.
- BAC quantification metrics should consider the total calcification area, intensities of pixels within the area, thresholded pixel intensities and counts within the calcified area.
- PM: sum of mask probability metric $\mathcal{PM} = \sum_{i=0,j=0}^{m,n} p_{i,j}$
- AM: sum of mask area metric $\mathcal{AM} = \sum_{i=0,j=0}^{m,n} 1_{p_{i,j}>0.5}$
- SIM: sum of mask intensity metric $\mathcal{SIM} = \sum_{0\leq i\leq m, 0\leq j\leq n | p_{i,j}>0.5} \mathcal{I}_{i,j}$
- TAMx: sum of mask area with threshold intensity x metric $\mathcal{TAM}_X = \sum_{0\leq i\leq m, 0\leq j\leq n | p_{i,j}>0.5} 1_{\mathcal{I}_{i,j}>\mathbf{X}}$
- TSIMx: sum of mask with intensity threshold x metric $\mathcal{TSIM}_X = \sum_{0\leq i\leq m, 0\leq j\leq n | p_{i,j}>0.5, \mathcal{I}_{i,j}>\mathbf{X}} \mathcal{I}_{i,j}$

Intensity Threshold Selection



GT



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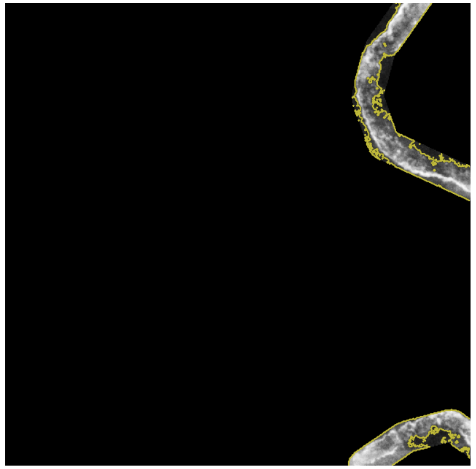

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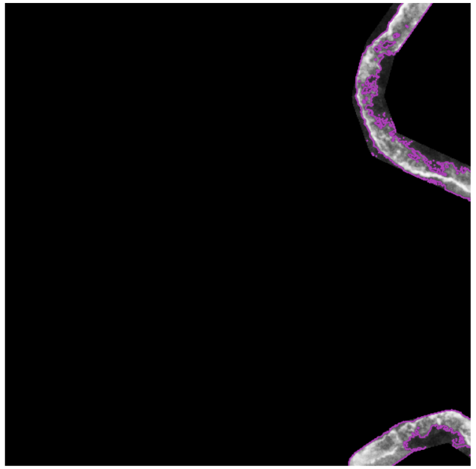

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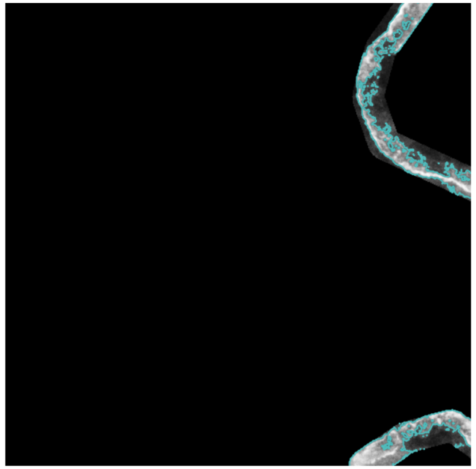

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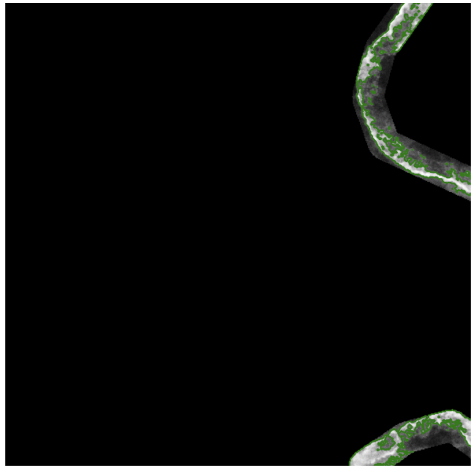

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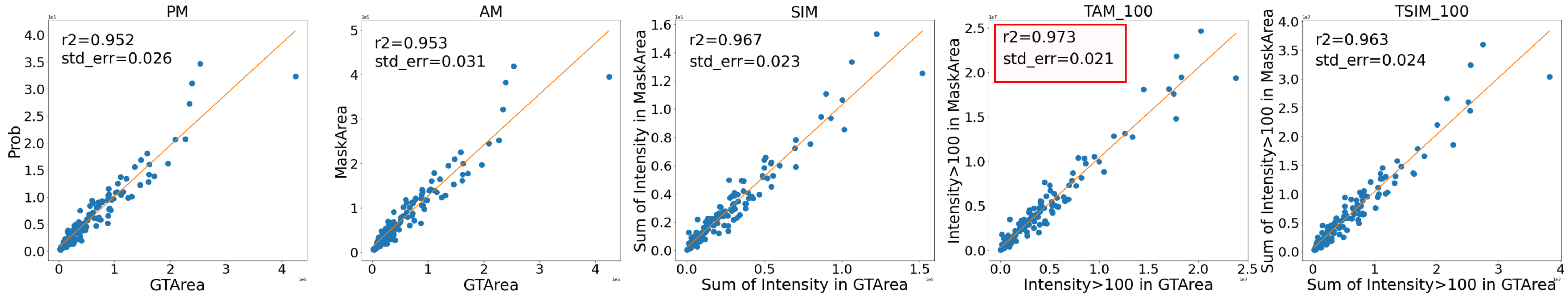
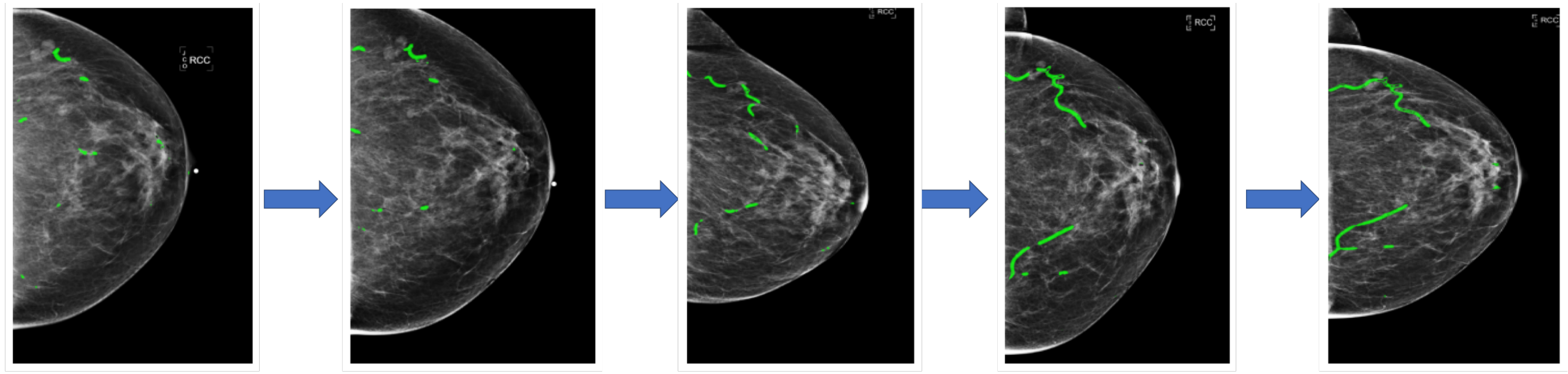
BAC Quantification Correlation Evaluation

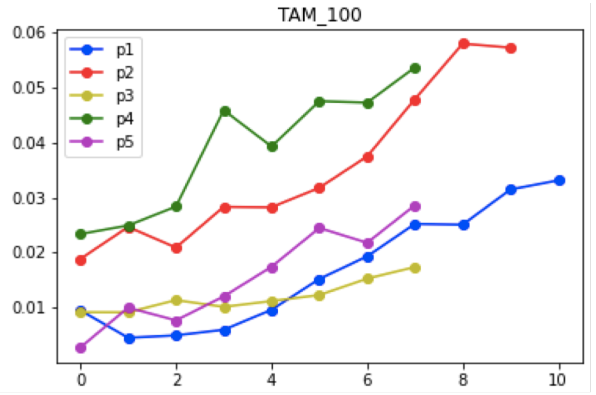


Evaluation of BAC Longitudinally

- Examine 26 new subjects not included in the original dataset
- Each subject had 5~12 years imaging history with all four standard screening mammography views (i.e., LCC, RCC, LMLO, RMLO)
- 961 mammograms in total



09/29/2009 10/08/2012 10/28/2014 01/23/2018 02/26/2020



Conclusion

- Propose a lightweight and accurate semantic segmentation model SCU-Net for vessel calcification segmentation on mammograms
- Adopt a patch-based way to detect calcified pixels on high-resolution images
- Compare both patch and whole results with state-of-the-art models
- Propose five BAC quantification metrics
- Quantify BAC based on predicted calcification masks
- Track the progression of BAC for subjects longitudinally
- Useful for large retrospective studies

Paper Source

- **Title:** SCU-Net: A deep learning method for segmentation and quantification of breast arterial calcifications on mammograms

- **Authors:** Xiaoyuan Guo, W Charles O'Neill, Brianna Vey, Tianen Yang, Thomas J Kim, Maryzeh Ghassemi, Ian Pan, Judy Wawira Gichoya, Hari Trivedi, Imon Banerjee

- **Journal:** Medical Physics 2021