Breast Cancer Detection in Mammograms using Deep Neural Networks

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Aim

To develop deep neural networks for computer aided detection of breast cancer lesions in Indian mammograms. Objectives of the study include:

- To reproduce state of the art results
- To employ other suitable object detection frameworks and compare performance
- To ensure accurate performance on mass, calcification and small, big lesions
- To test on AIIMS dataset using various annotation schemes
- To develop a photometric network for density contrast normalization

Our code can be found at:
`https://github.com/anvitmangal/bcd/`

Introduction

- Breast cancer impacts 1.5 million women all over the world each year. In Indian urban cities, it is the most common type of cancer today
- Women in India fall prey to breast cancer in their 40s, much earlier than in foreign countries
- Non-availability of expert radiologists, diagnostic centres and timely treatment is a major concern
- Existing detection systems are far from perfection
- Minimal research has been done so far on Indian datasets which are different from foreign cases
- We experimented with various datasets including DDSM, INBreast and AIIMS.
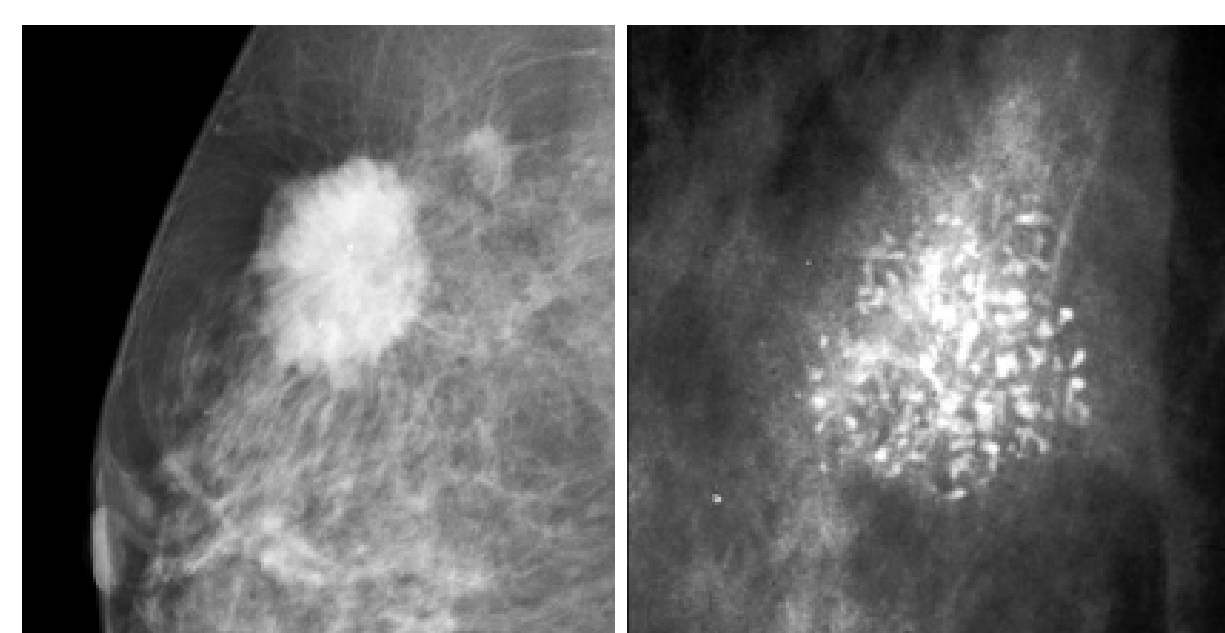

Figure 1: Mass (left) and Calcification (right)

State of the Art

The state of the art method employs Faster RCNN object detection framework to classify and localize breast lesions as benign or malignant.
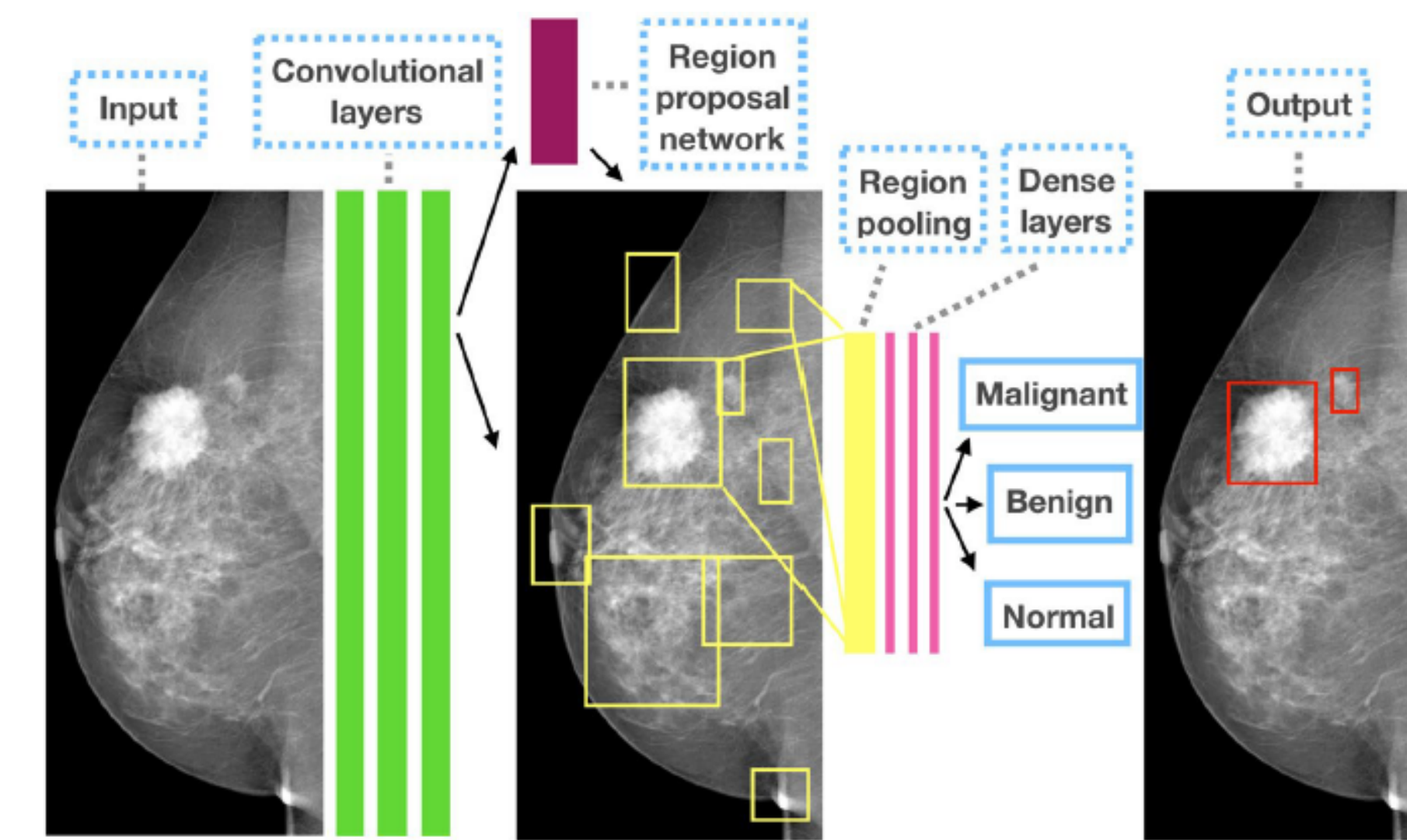

Figure 2: State of the Art Architecture

The reported results are:

- 0.95 AUC for classification
- 0.9 sensitivity at 0.3 average false positives per image in the FROC curve for detection

RetinaNet Framework

We implemented RetinaNet which uses Feature Pyramid Network and Focal Loss since mammograms present features which are to be picked at multiple scales. RetinaNet was trained on the combination of DDSM, INbreast and AIIMS including normal images. Masses could be large and small while calcifications can be large when clustered together and extremely small for present in isolation as spots. Hence, RetinaNet can prove to be useful for such an application.
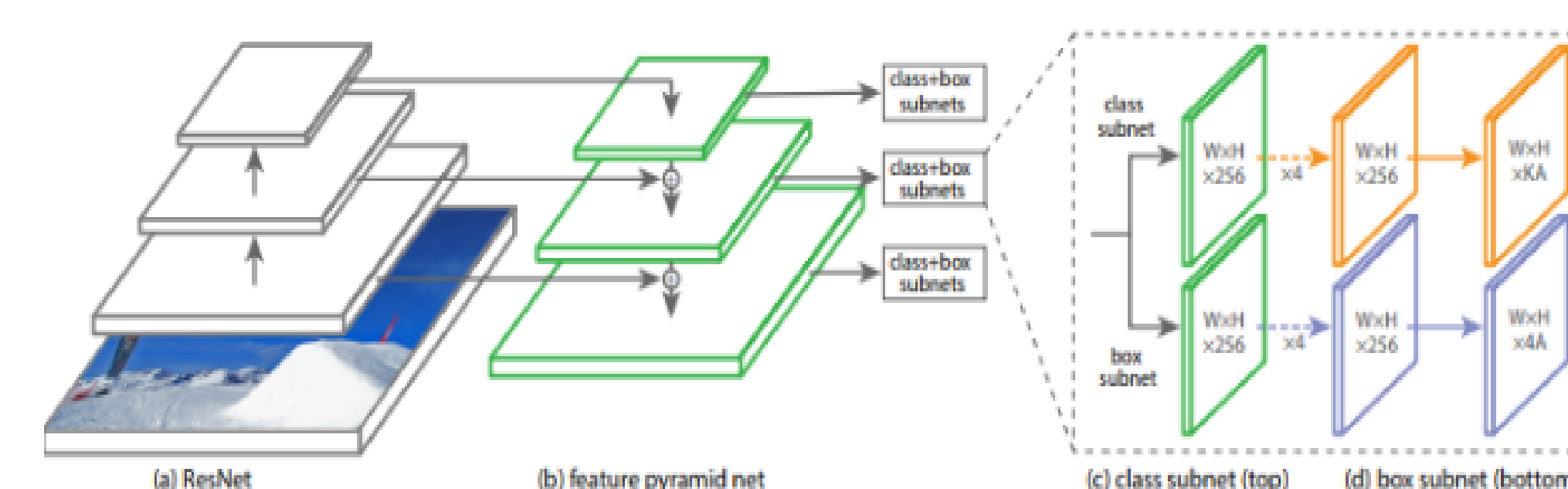

Figure 3: RetinaNet Architecture

Attention Visualization

To validate the results, we proposed a novel technique to visualize the attention maps produced by the network and study the salient regions:

Algorithm 1 Perturbation Analysis
1: initialise s1,s2,s3 using K-Means clustering on the training data for 3 scales for objects
2: **for** each test image **do**
3:     $orig \leftarrow$ original bbox predictions
4:     **for** each scale si **do**
5:         make occlusions on image
6:         **for** each occluded image **do**
7:             $occ \leftarrow$ occluded bbox predictions
8:             $iou \leftarrow$ IOU($orig$, occ)
9:             add 1-iou to pixels in occluded region
10:        **end for**
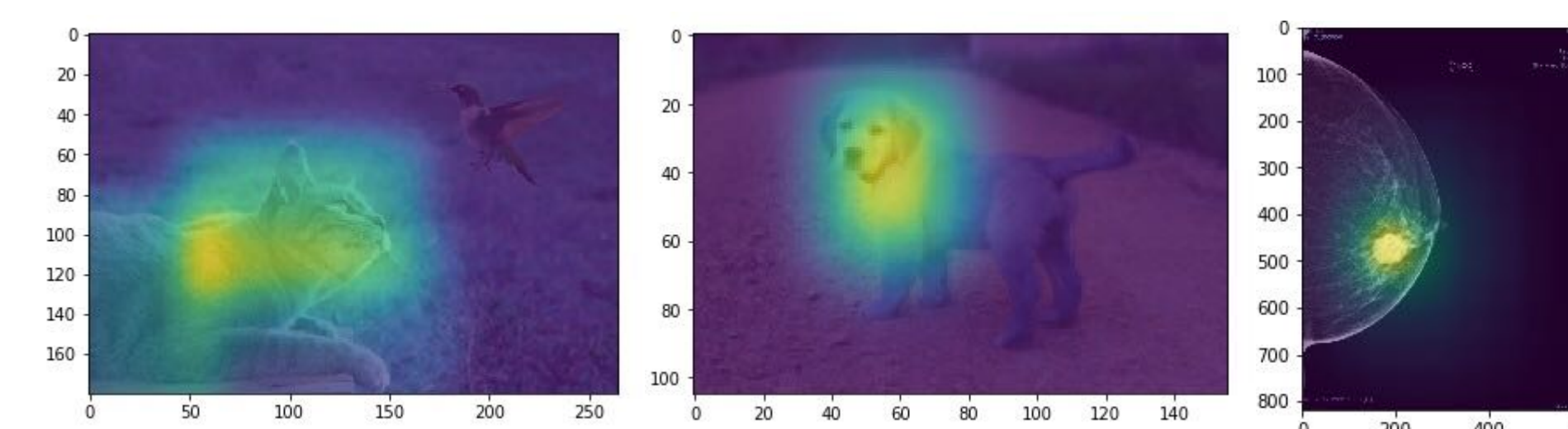11:   **end for**
12: **end for**

Figure 4: Attention maps for a) Cat, b) Dog c) Breast

Proposed Model

To tackle the problem of identifying breasts with variable tissue densities, we designed a network for density contrast modification and intensity normalization using photometric transformation. This network was used for preprocessing and output images were fed into the RetinaNet model
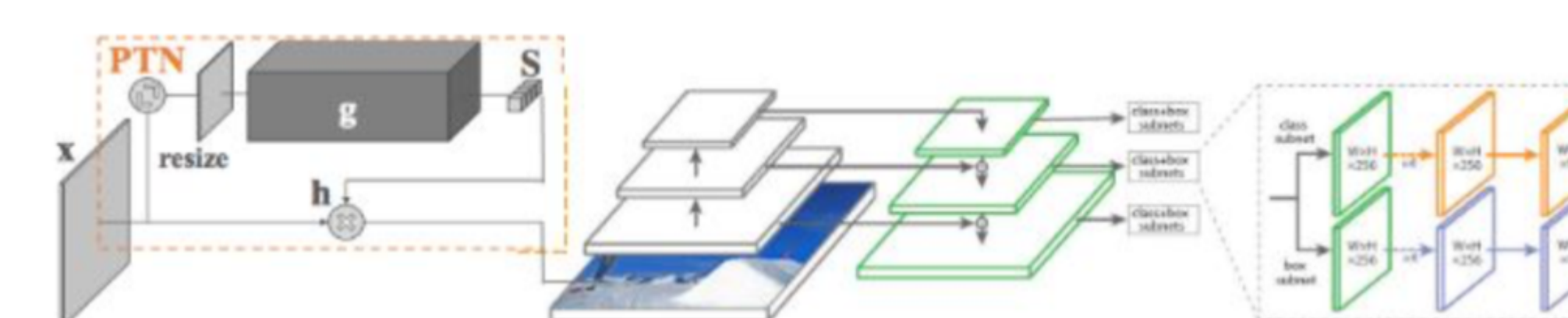

Figure 5: Photometric Transformer Network with RetinaNet

Results

We designed and implemented novel algorithms and deep neural networks for preprocessing, visualization and performance enhancement.

Dataset	FRCNN	RetinaNet
INBreast	AUC: 0.941	AUC: 0.946
	Sens: 0.8 at 0.3 FP	Sens: 0.9 at 0.3 FP
AIIMS	AUC: 0.805	AUC: 0.847
	Sens: 0.68 at 0.3 FP	Sens: 0.857 at 0.3 FP

Other Experiments

- Achieved similar performance on Mass vs Calcification for both models on INbreast, but on AIIMS, Retinanet outperformed FRCNN by missing fewer malignant lesions and correctly identifying more masses and calcifications
- We also tested on small masses wherein both networks gave similar AUC while for localization, RetinaNet performed better than FRCNN
- On 20,000 image-labelled AIIMS data, RetinaNet gave a higher AUC compared to FRCNN

We have built and trained the photometric transform network and are currently testing it and experimenting further by adding hinge loss and modifying hyperparameters
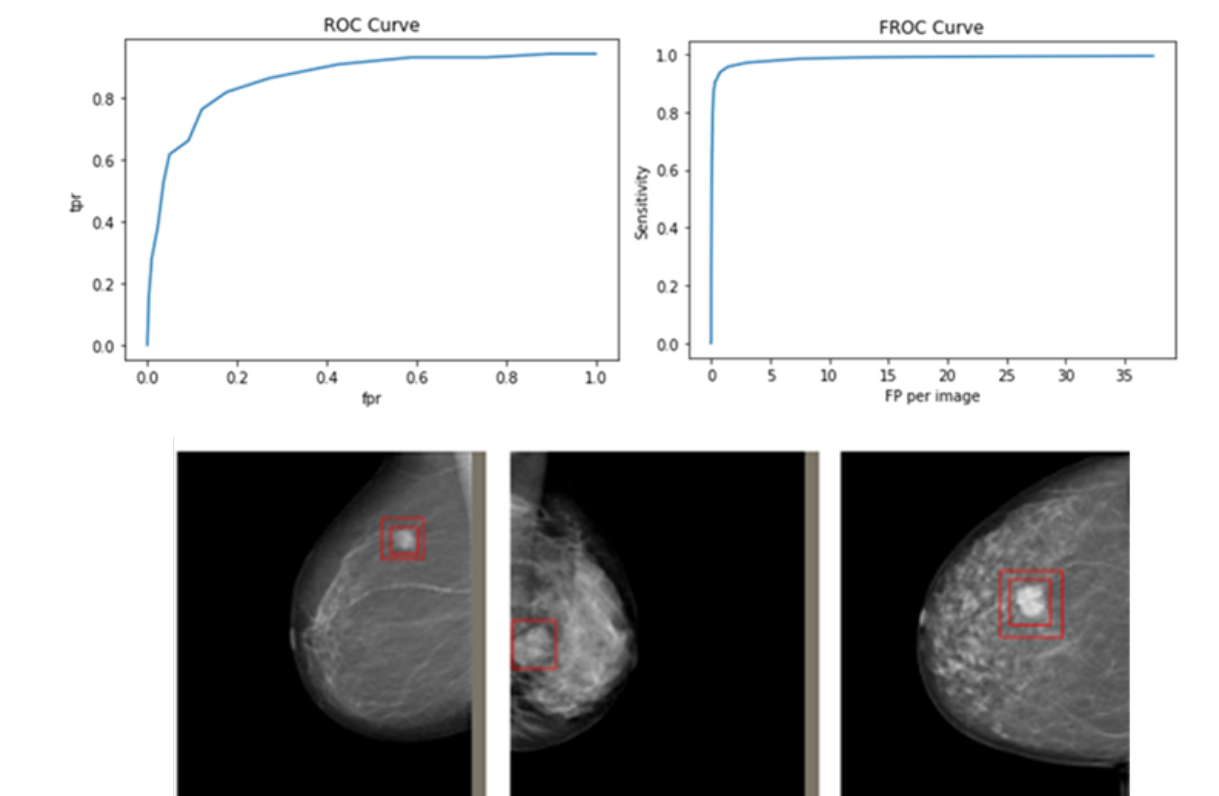

Figure 6: ROC, FROC curves & Visualizations on RetinaNet

References

- State of the Art https://github.com/riblidezso/frcnn_cad
- RetinaNet Implementation https://github.com/yhenon/pytorch-retinanet
- Photometric Transformer Network https://arxiv.org/pdf/1905.02906.pdf