Breast Cancer Detection in Mammograms using Deep Neural Networks

*Anvit Mangal[1] *Surabhi S. Nath[1]

Advisors: Prof. Chetan Arora[2] Prof. Subhashis Banerjee[2]

IIIT Delhi[1] IIT Delhi[2]

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.

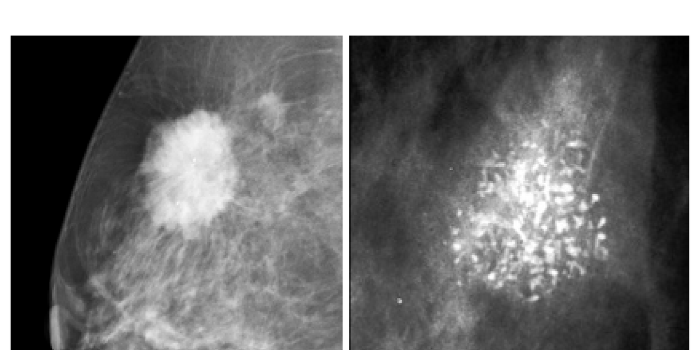

Figure 1: Mass (left) and Calcification (right)

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.

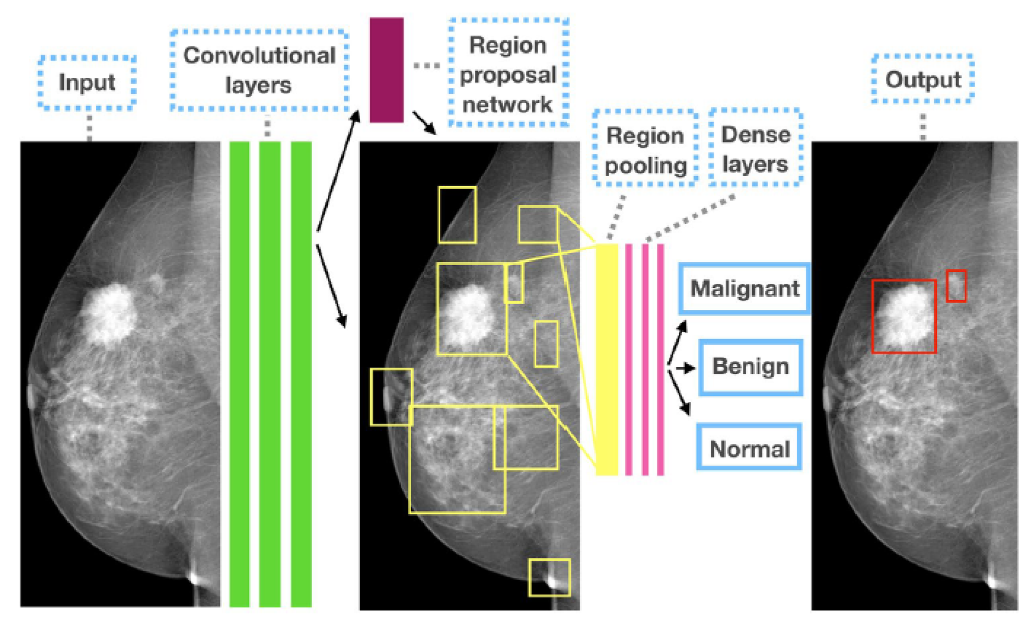

Figure 2: State of the Art Architecture

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.

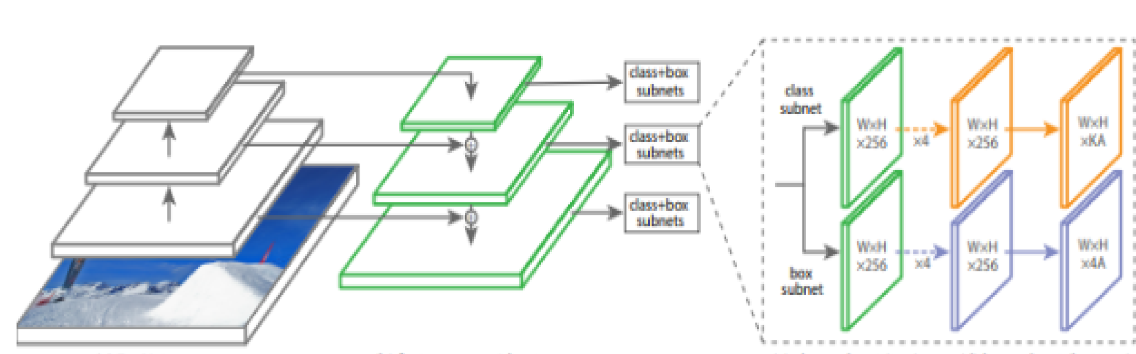

Figure 3: RetinaNet Architecture

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

initialise s1,s2,s3 using K-Means clustering on the training data for 3 scales for objects
for each test image **do**
  $orig \leftarrow$ original bbox predictions
  for each scale si **do**
    make occlusions on image
    for each occluded image **do**
      $occ \leftarrow$ occluded bbox predictions
      $iou \leftarrow$ IOU($orig$, occ)
      add 1-iou to pixels in occluded region
    end for
  end for
end for

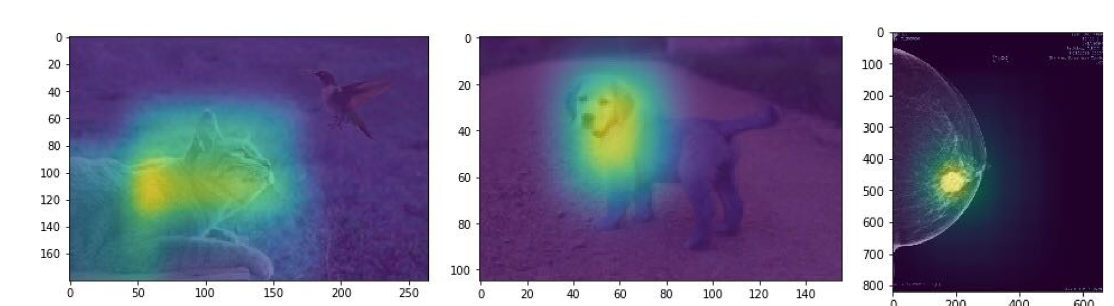

Figure 4: Attention maps for a) Cat, b) Dog c) Breast

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

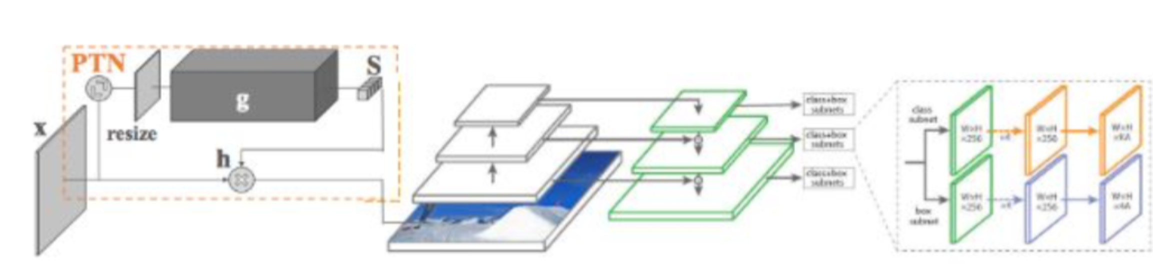

Figure 5: Photometric Transformer Network with RetinaNet

Results

We designed and implemented novel algorithms and deep neural networks for preprocessing, visualization and performance enhancement. Our model outperforms the state of the art framework.

- Attained 0.941 AUC and 0.88 sensitivity at 0.3 FP in reproducing state of the art Faster RCNN framework on INBreast dataset and 0.946 AUC and 0.9 sensitivity at 0.3 FP using RetinaNet on INBreast dataset
- Obtained 0.805 AUC and 0.68 sensitivity at 0.3 FP using FRCNN and 0.847 AUC 0.857 sensitivity at 0.3 FP using Retinanet on AIIMS dataset.
- 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

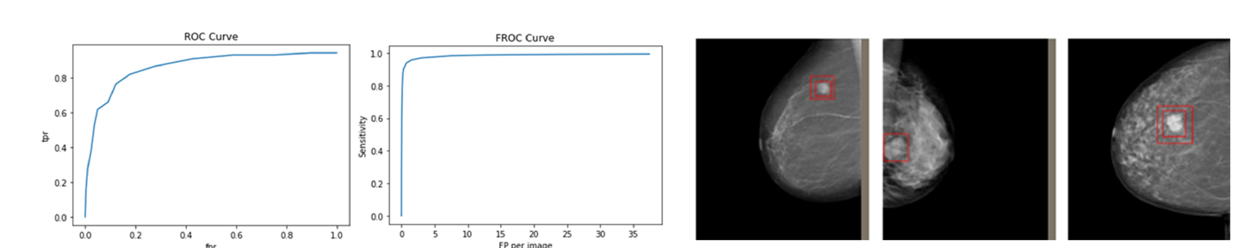

Figure 6: ROC, FROC curves & Visualizations on RetinaNet

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`