

Deep Learning for Breast Cancer Detection

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The B-Team

1. Overview

- **Data:** >200k screening mammograms, >5k biopsy reports
- To effectively apply deep learning methods to breast cancer detection, many **sub-problems** need to be solved
- We catalog our significant progress on multiple sub-problems, each contributing improved performance and newfound insight

2. Contributions

- Patchwise classification model using pretrained convolutional layers attain significant validation AUC—used to **generate features for exam-level cancer classification model**
- Mammogram+Patchwise features lead to **98% test AUC on cancer classification** for both benign and malignant classes
- Mammogram-wise image registration allows for effective **incorporation of prior exam information** and improved performance on BI-RADS and cancer classification
- Adapted Mask-RCNN for high-resolution mammograms for **lesion detection and localization**

3. Multi-View CNN for Cancer Detection

- ResNet-based architecture, pretrained on BI-RADS classification
- Four view: [L-CC, R-CC, L-MLO, R-MLO]
- Multi-class prediction:
 - [Benign/Not Benign], [Malignant/Not Malignant]

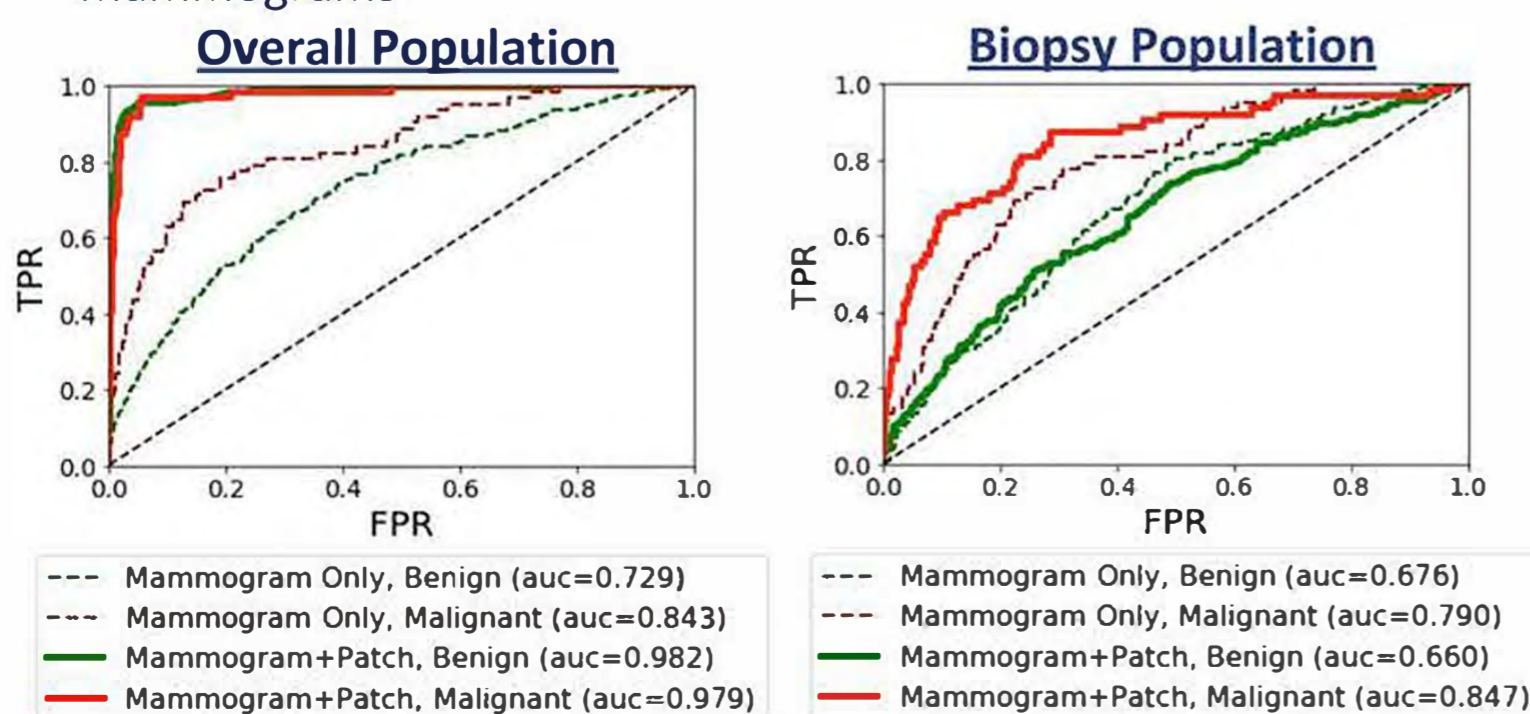
4. Patch Classification

- Sample **256x256** patches from high-resolution mammograms
- Patch classification allows model to solely focus on **local** information for cancer detection, while allowing for higher-capacity models
- **Models used:** DenseNet and ResNet
- **Transfer learning:** Initializing weights from models pretrained on ImageNet led to better performance, over training from scratch
- **Ensembling:** Based on a 21-model library, we composed an ensemble using forward stepwise selection

Model	Val AUC	Test AUC
Model Ensemble	0.875	0.801
Best Single Model (DenseNet)	0.856	0.777

5. Exam-level Cancer Prediction

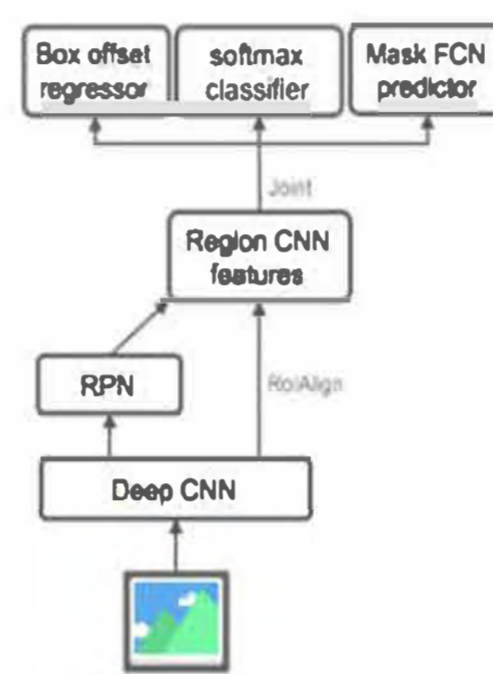
- Using a patch-classification model, we generate a map of predicted probabilities, and use them as an additional input channel to our ResNet
- Combination of **local** and **global** information from mammograms



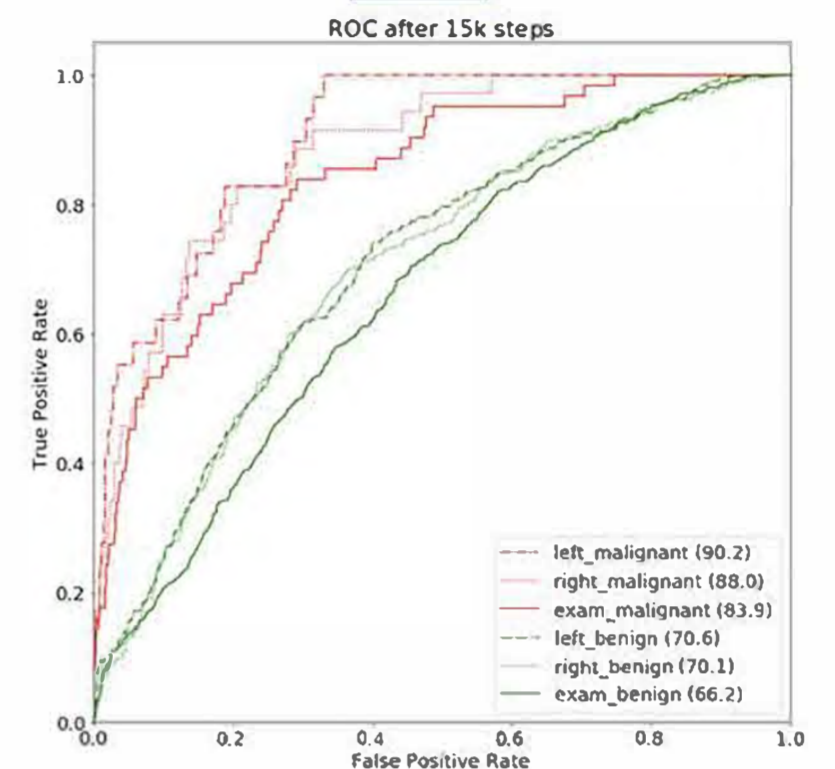
6. Lesion detection using Mask-RCNN

- **Goal:** Adapt Mask-RCNN for high-resolution, multi-view, noisy-labeled images
- **Modifications:** Image-level prediction branch, Lowering IoU threshold, raising NMS threshold, prediction over multiple views

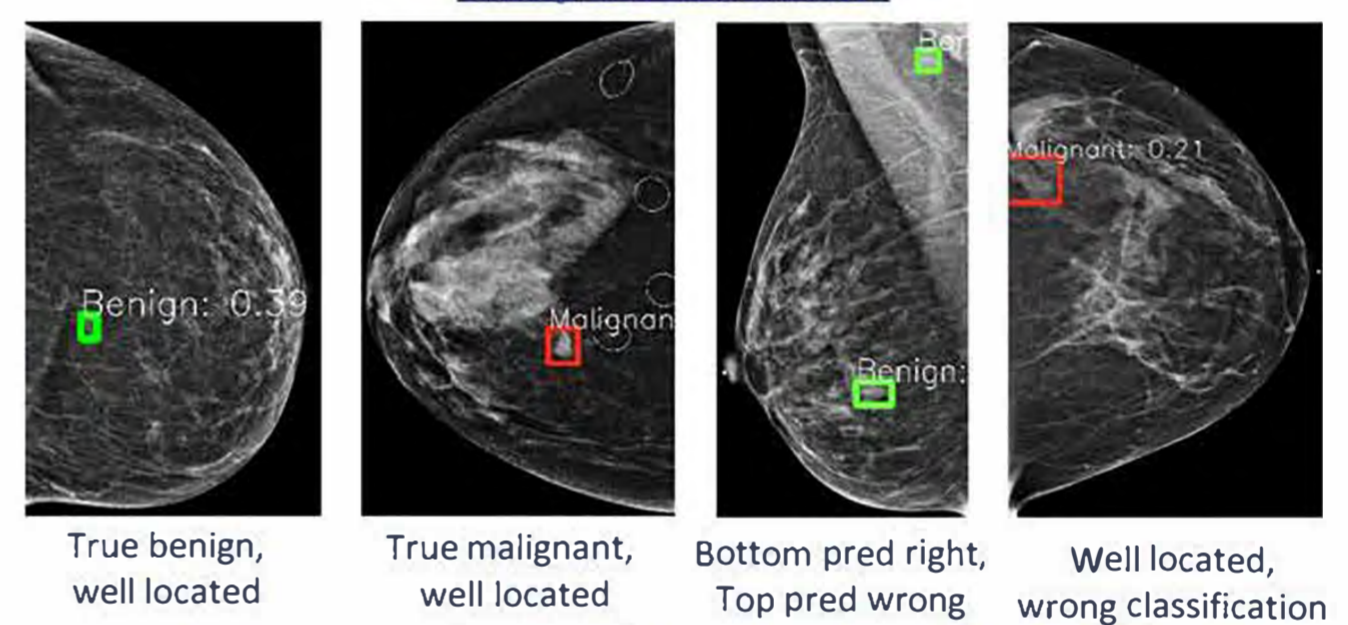
Architecture of Mask-RCNN



Results

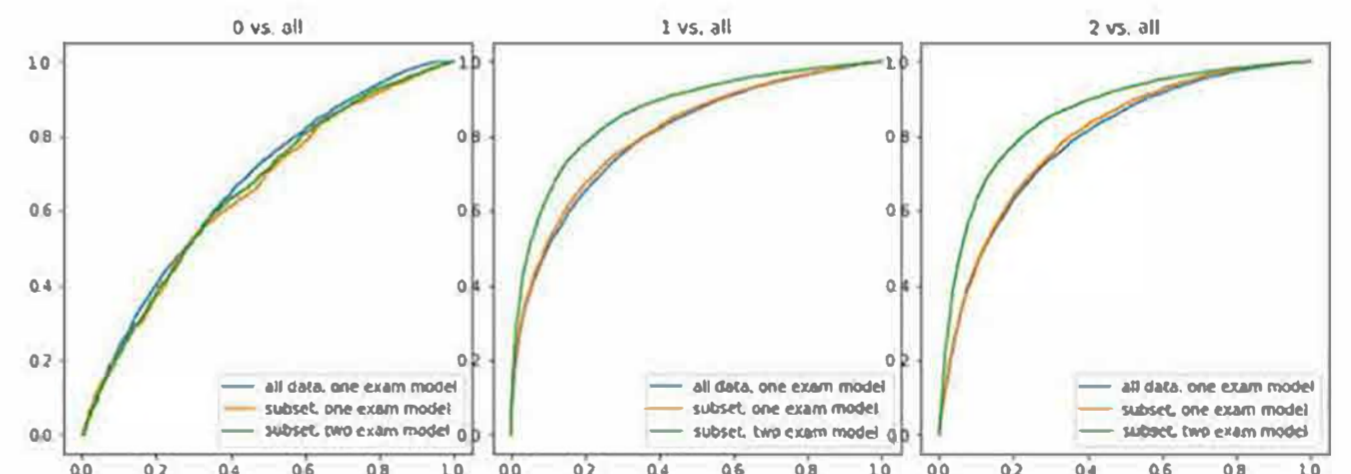


Sample Predictions

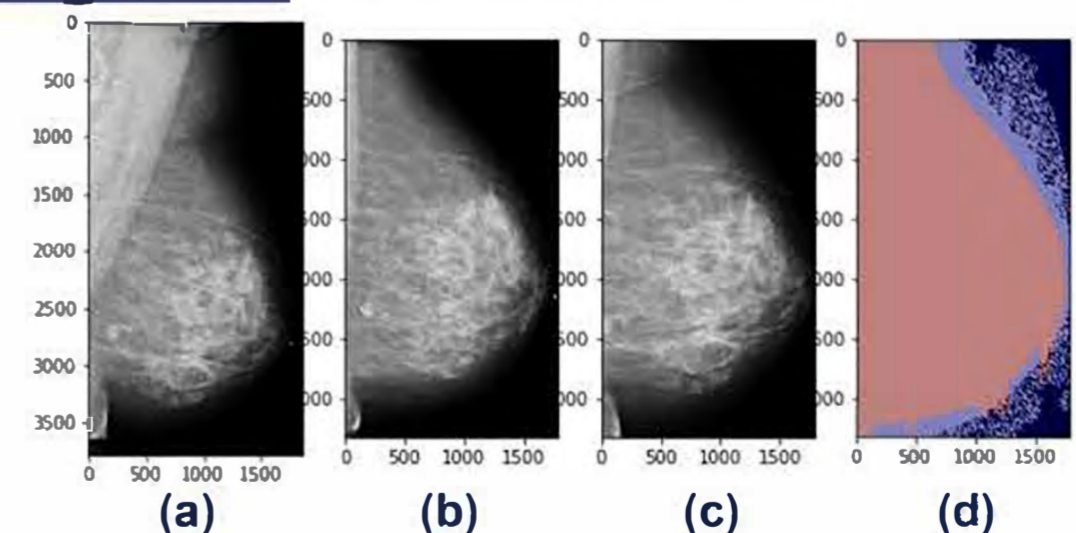


7. Incorporating Prior Exam Information

- **Baseline:** Concatenate representation of each exam after pooling layer (BI-RADS, 0=Incomplete, 1=Negative/Normal, 2=Benign)



- **Image registration:**



(a,b) Mammograms of single patient taken at different times. Not aligned. (c) Registered first image, affine transformation which optimizes mutual information to the second image is applied. (d) Overlap of the second and third images. Now the downscaled spatial representation before pooling should roughly be aligned.

- **Improved model:** Register pair of images, concatenate the representation of each exam before pooling layer, add additional convolutional layer. Test AUC improves as follows.

Model	MAC AUC	0 vs. all (Not cancer)	1 vs. all (Cancer)	2 vs. all (Unknown)
One exam network	0.743	0.708	0.798	0.725
Two exam network	0.763	0.726	0.821	0.745

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