Predict Cardiomegaly with Chest Radiograph

Shenghong Wang (06406581), Yu Qing Zhou (05860662)

Introduction

Problem to solve: Currently, chest radiography is used globally to diagnose chest diseases like cardiomegaly, but many patients do not have access to it due to limited medical resources. To support global population health initiative, we want to help patients automatically diagnose their cardiomegaly disease with their chest radiographs.

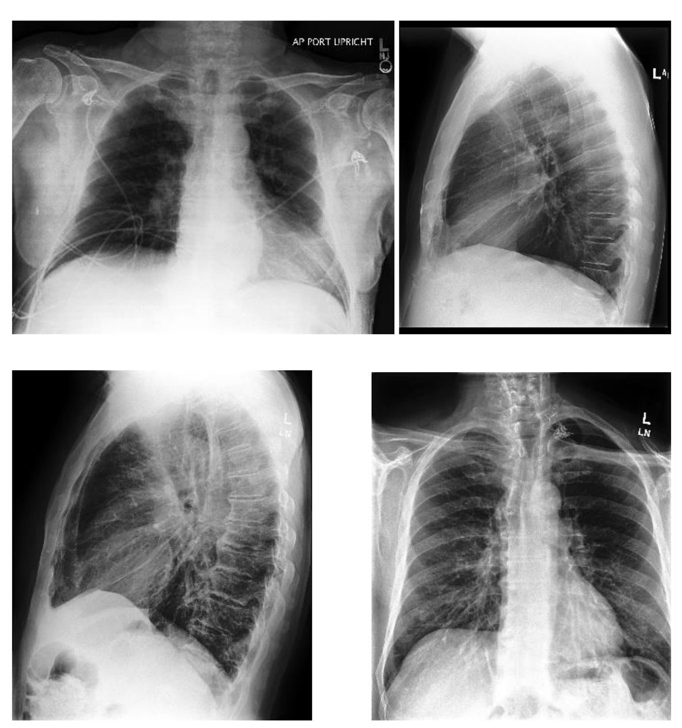
Dataset: we use the CheXpert dataset from Stanford's Machine Learning Group.

Method: we use ResNet 50 as our backbone and augment its performance with an attention-guided approach that combines both global and local information in the radiographs.

Result: the attention mechanism improves the performance of classification by 5.6% on the validation set and 30% on the test set.

CheXpert Dataset

Class	# images
Positive	27,000
Negative	11,116
Uncertain	8,087
No label	177,211

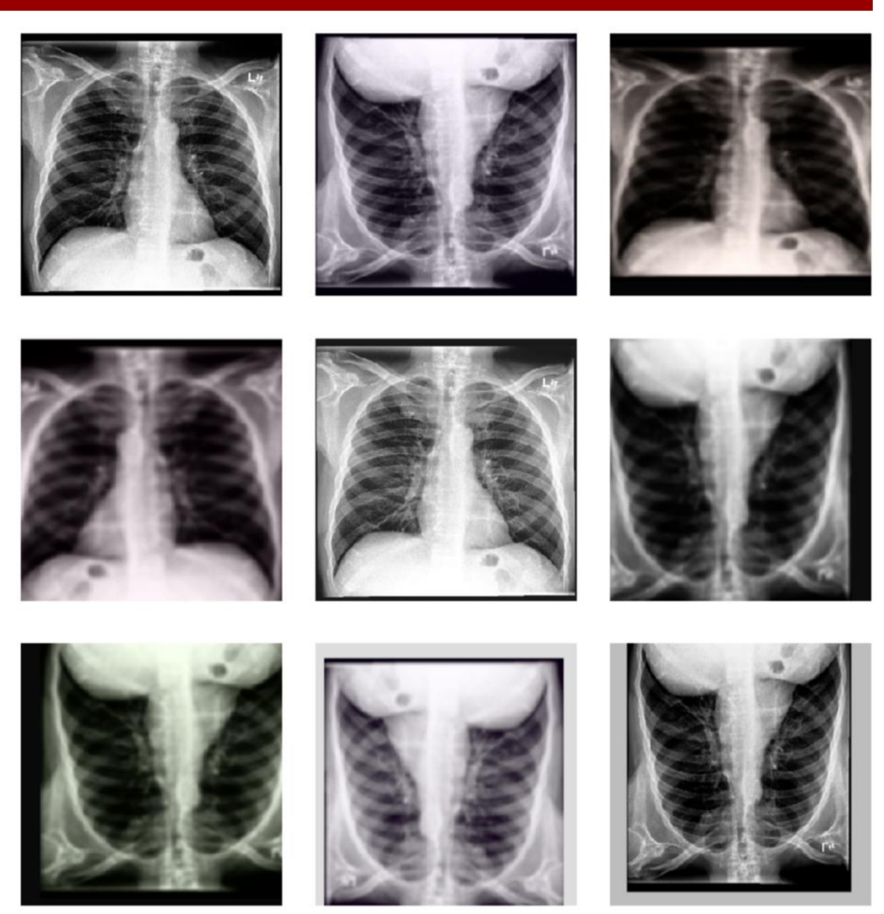


- Collected from Stanford hospital from 2002 and 2017
- Classification labels
- More positive images than negative ones in the training and validation sets

Data Preprocessing

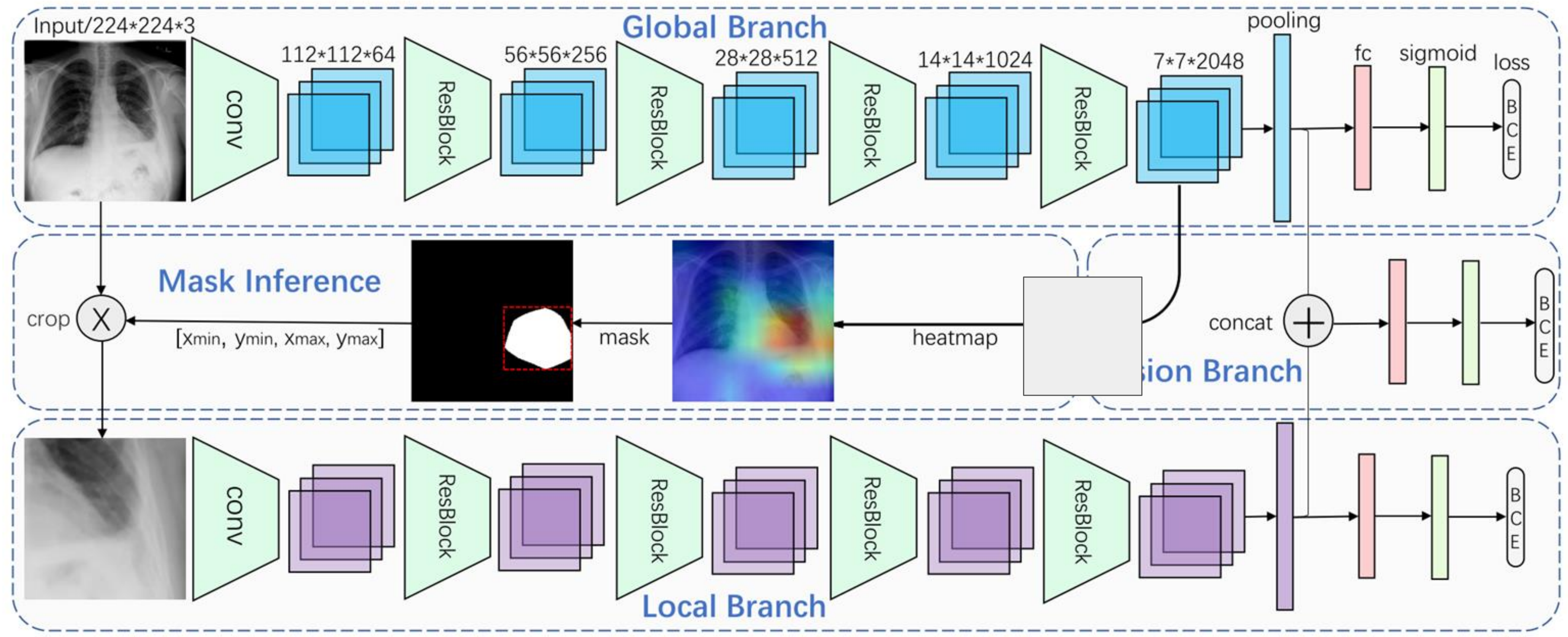
Crop and resize each image to a square shape and size 224x224.

Introduce random shift to change the position of chest and heart in the input images.



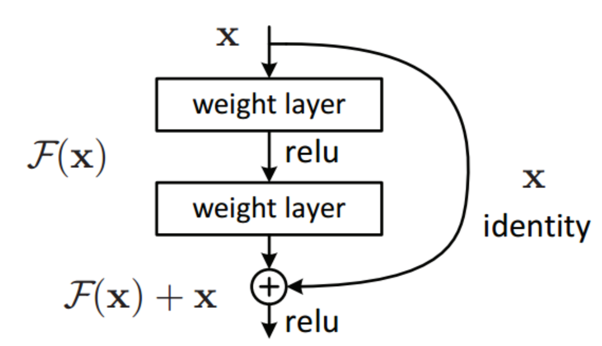
More Data augmentation:
- random brightness;
- random contrast;
- random blurriness;
- random flip;
- random shift
- center and crop;
- standardization;

Algorithm



ResNet50 Backbone

Global branch is a **ResNet50** pre-trained on ImageNet. It's fine-tuned using original X-rays image dataset.



Local Attention Area

Step 1: The output of the final convolution layer and the weight of the fully-connected layer are used to generate heatmap where we set our attention:

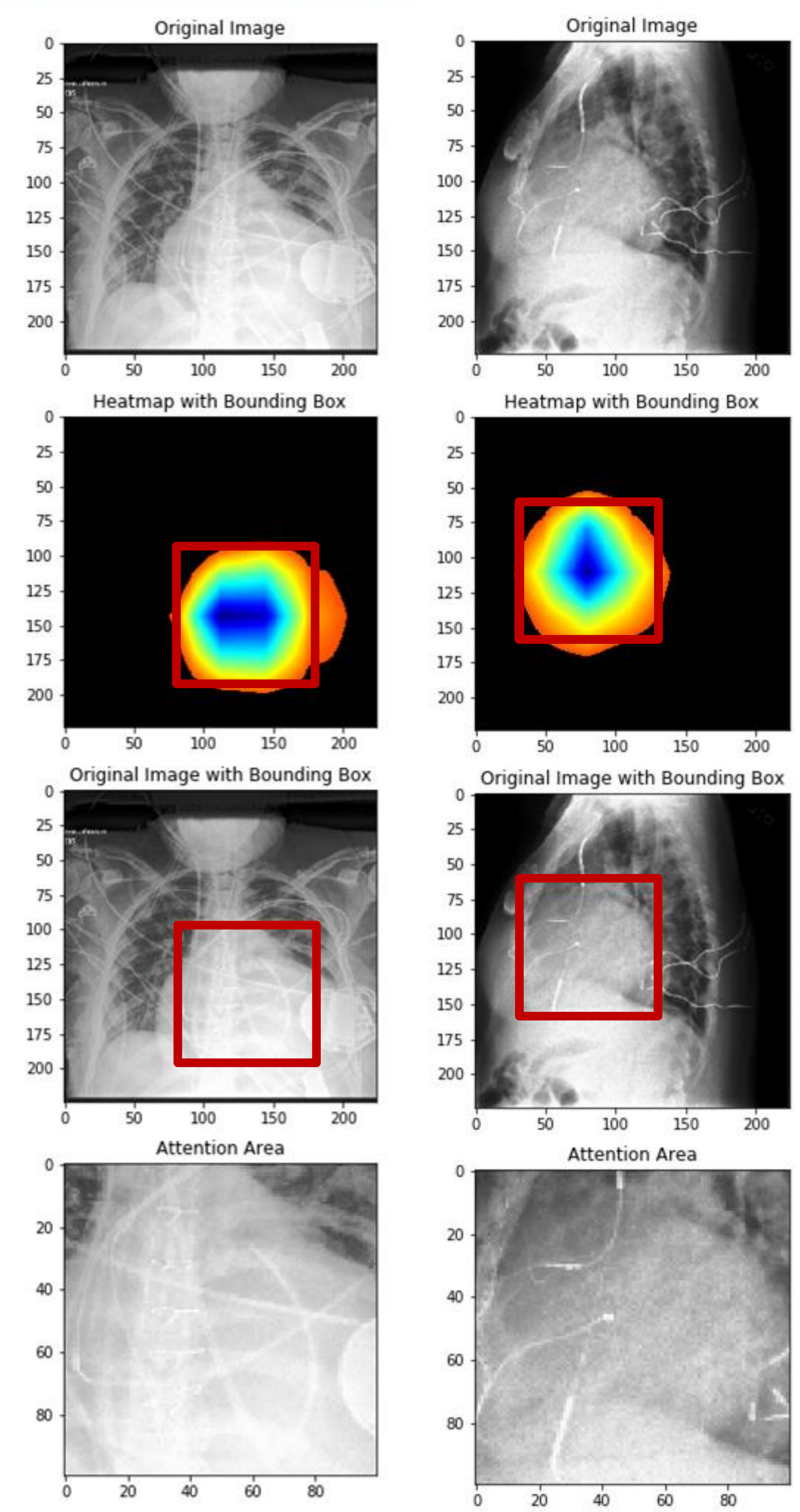
a) We first compute the class activation map, then resize it to 224×224 as the heatmap

b) We find the contour with the maximum value in the heatmap and crop it out as our local Attention area.

Step 2: The Attention area is resized to 224×224 and fed as input to another ResNet50 backbone, so we fine-tuned this local network using local areas

Final Fusion Network

The final pooling output of both global and local branch are concatenated together as the input of the fusion branch



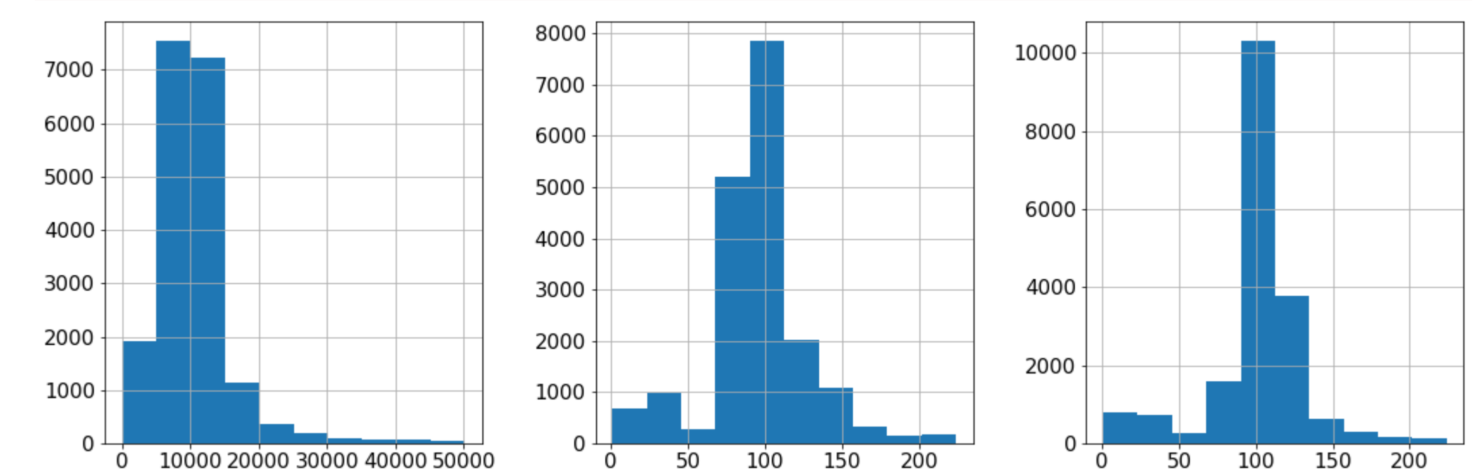
Reference:
[1] Jeremy Irvin, Pranav Rajpurkar, Michael Ko, Yifan Yu, SilvianaCiurea-Ilcus, Chris Chute, Henrik Marklund, Behzad Haghgoo, Robyn Ball, Katie Shpanskaya, Jayne Seekins, David A. Mong, Safwan S. Halabi, Jesse K. Sandberg, Ricky Jones, David B. Larson, Curtis P. Langlotz, Bhavik N. Patel, Matthew P. Lungren,and Andrew Y. Ng. CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison. 2019.
[2] Qingji Guan, Yaping Huang, Zhun Zhong, Zhedong Zheng, Liang Zheng, and Yi Yang. Diagnose like a Radiologist: Attention Guided Convolutional Neural Network for Thorax Disease Classification. 1:1–10, 2018.
[3] Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba. Learning Deep Features for Discriminative Localization. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2016-Decem:2921–2929, 2016.

Result

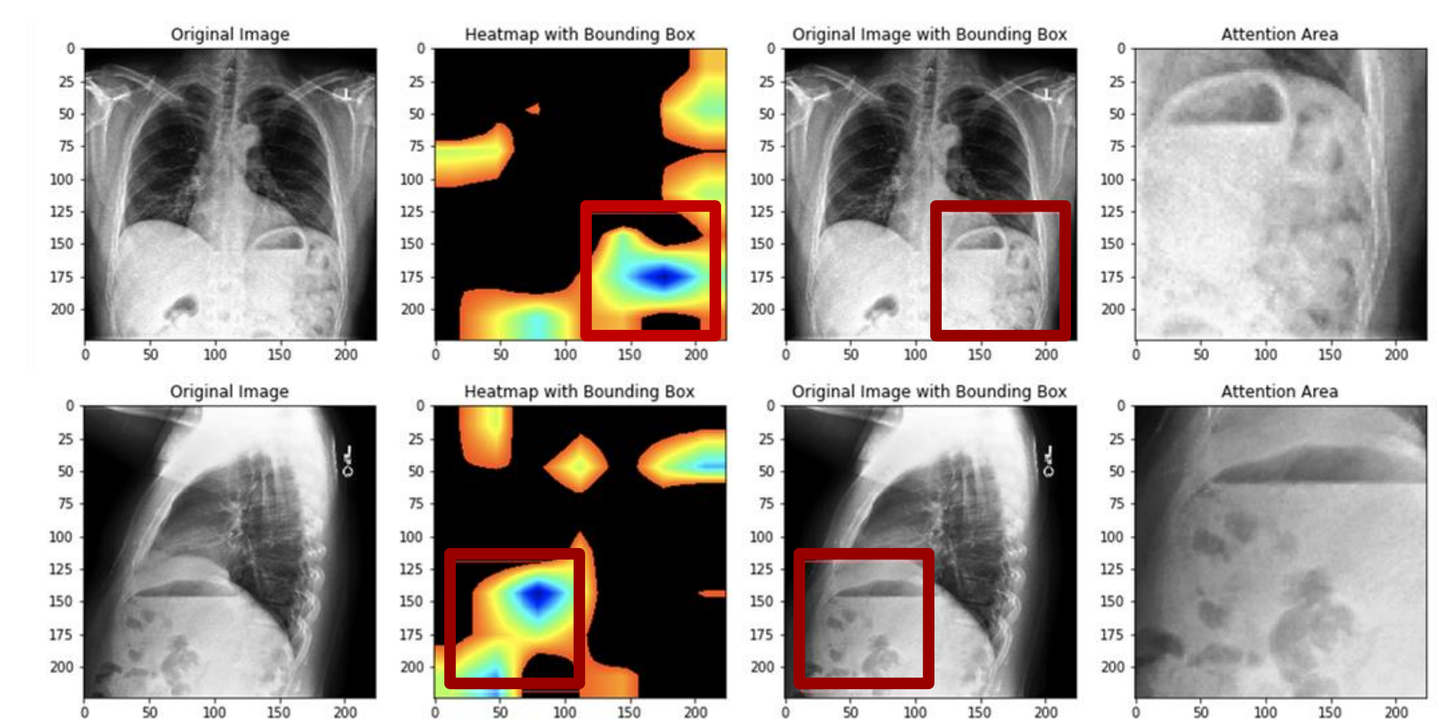
Confusion Matrix

Model	Valid Precision	Valid Recall	Valid F1	Test Precision	Test Recall	Test F1
Global Branch	0.801	0.912	0.853	0.316	1.00	0.481
Local Branch	0.750	0.612	0.674	0.515	0.618	0.562
Attention-based*	0.890	0.911	**0.901**	0.504	0.838	**0.630**

Analysis



Bounding box area(left), width(middle), height(right) distribution



Cases where the global branch predicts wrong and the attention-augmented branch predicted correctly

- The global branch picked the wrong features and overfitted;
- The local branch adds a second look at the attentive area and improves the precision of the model;
- Fusion branch aggregates the information from both branch together and combine their advantages.

Conclusion

From our work, we find that the attention-based mechanism augment ResNet's performance on classification and improves the F1 score of cardiomegaly prediction on both our validation and test sets.

For next steps, we want to improves the accuracy of selecting local attention areas from chest radiographs, which will make the model better at detecting the illness. We also want to try the same technique on other illness classes in the CheXpert dataset.