Pneumothorax Detection and Localization in X-Ray Images Given Richer Annotation Information

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Outline

- Background
- Model Architecture and Design
- Data
- Experiments
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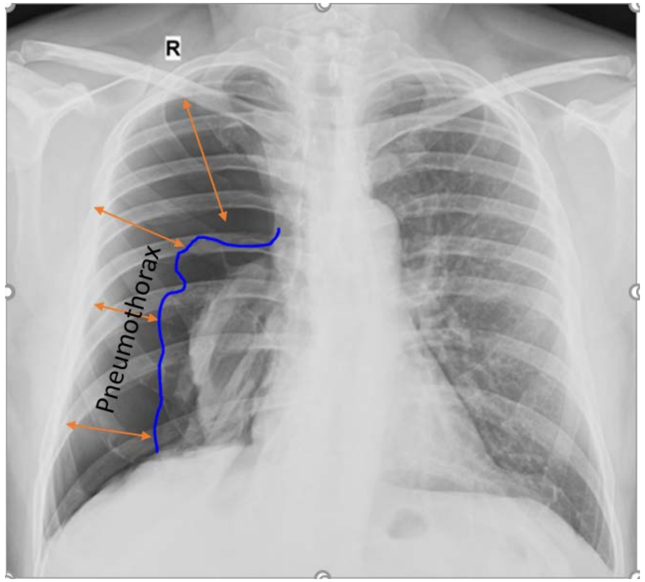
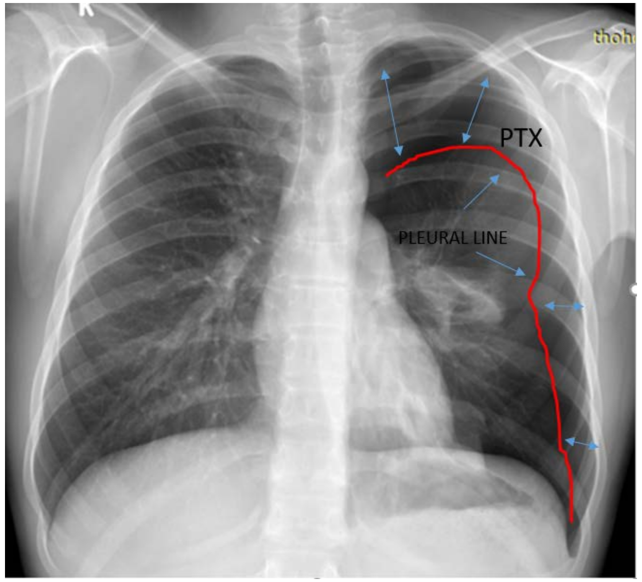
- Conclusions

Pneumothorax

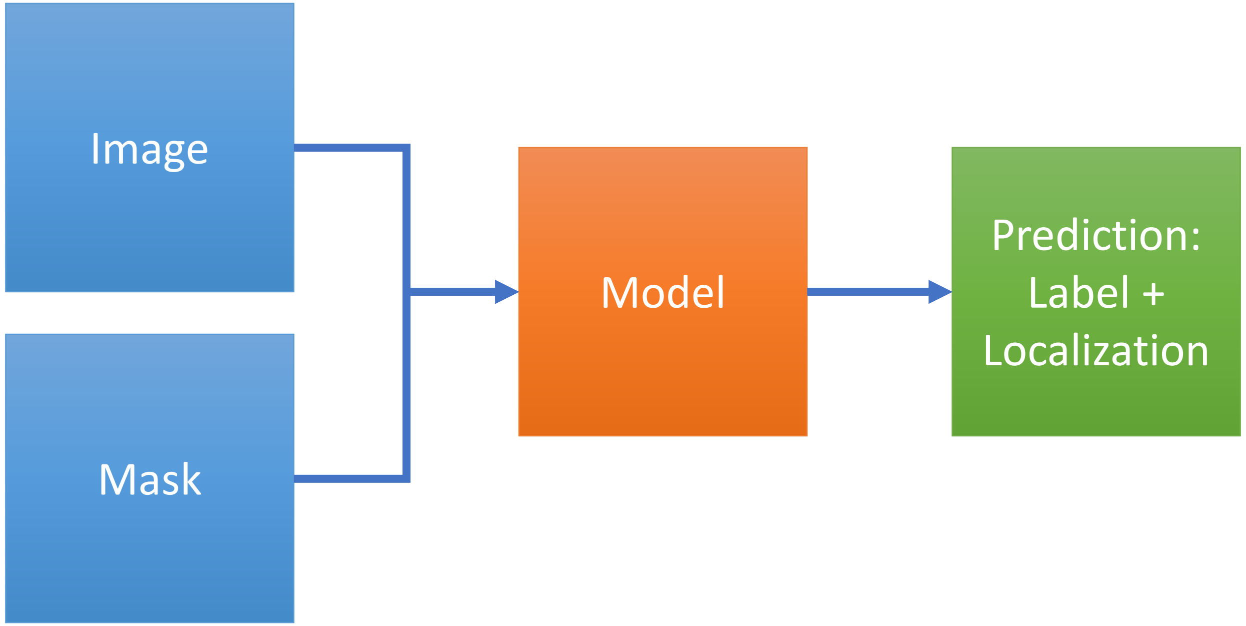
- Pneumothorax refers to collection of air in the pleural cavity.
- Large Pneumothorax especially those of the constantly enlarging type (tension pneumothorax) causing compression of mediastinal structures can be life-threatening
- Chest radiography is the first line of investigation- shows the outer margin of the visceral pleura (and lung) separated from the parietal pleura (and chest wall) by a lucent gas space devoid of pulmonary vessels.





Problem Statement

- How can we improve the performance of a classifier if masks pertaining to regions of interest are available in addition to an image level label?



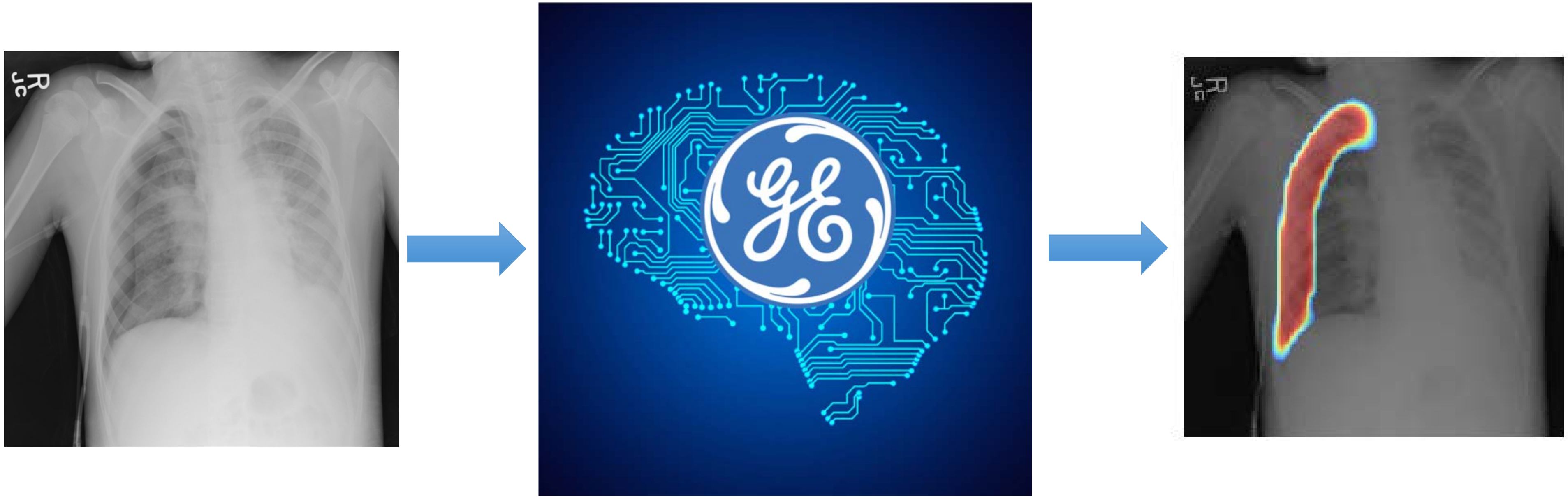
Related Work

- Most of the published literatures are improving the performance of a classifier by using more data.
- They focus to solve large data problem
- Li et. al (Google) proposed a semi-supervised method to recognize and localize thoracic diseases using bounding box

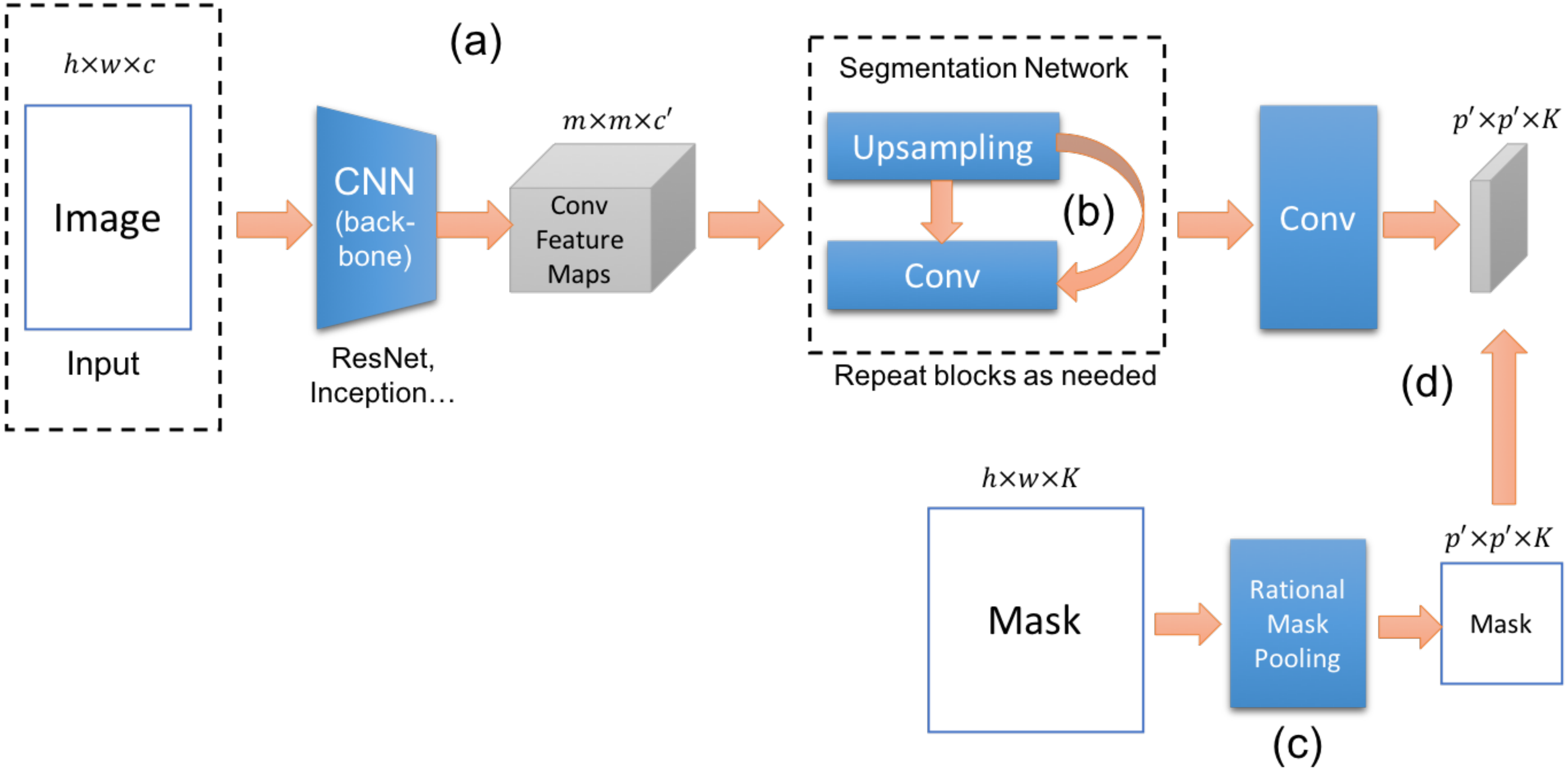
Li et. al, Thoracic Disease Identification and Localization with Limited Supervision, [arXiv: 1711.06373](https://arxiv.org/abs/1711.06373).

Contributions

- Use mask as input of classifier to improve the classification accuracy
- Generate high resolution localization maps



Model Architecture -- ClaSegNet



Model Design

- Backbone CNN outputs shared feature maps
  - - ResNet
  - - Inception
  - - …
- Loss function

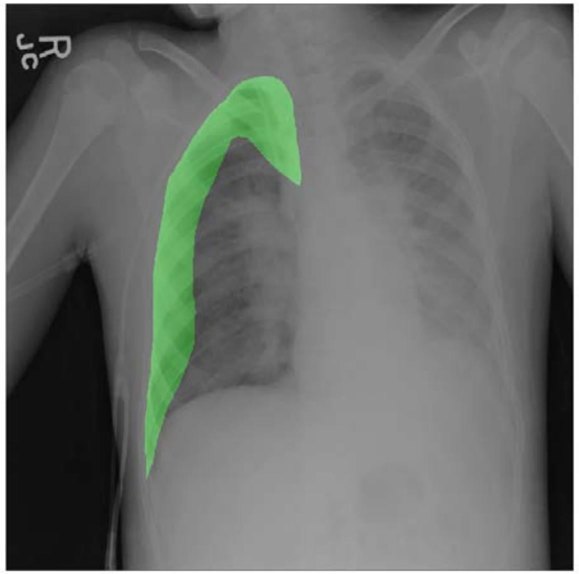
$$Lossmask = -\sum_{i} log\left(p(y_k|x_i, mask_i^k)\right)$$

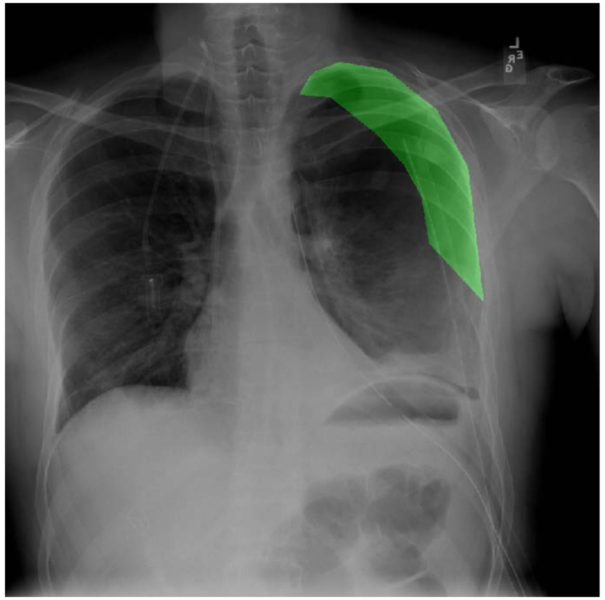
$$p(y|x_i, mask_i^k) = \prod_{j\in N} p_{ij}^k \cdot \prod_{j\in M\setminus \mathrm{N}} (1 - p_{ij}^k)$$

where $p(y|x_i, mask_i^k)$ is the probability of an image i being positive for class k, M the total area in image i and N the region covered by the mask.

Data and Annotations

NIH Data (# images)	Train (80%)	Val (10%)	Test (10%)
Pneumothorax	722	90	91
Non-pneumothorax	722	90	91
Total	1444	180	182





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Experiments

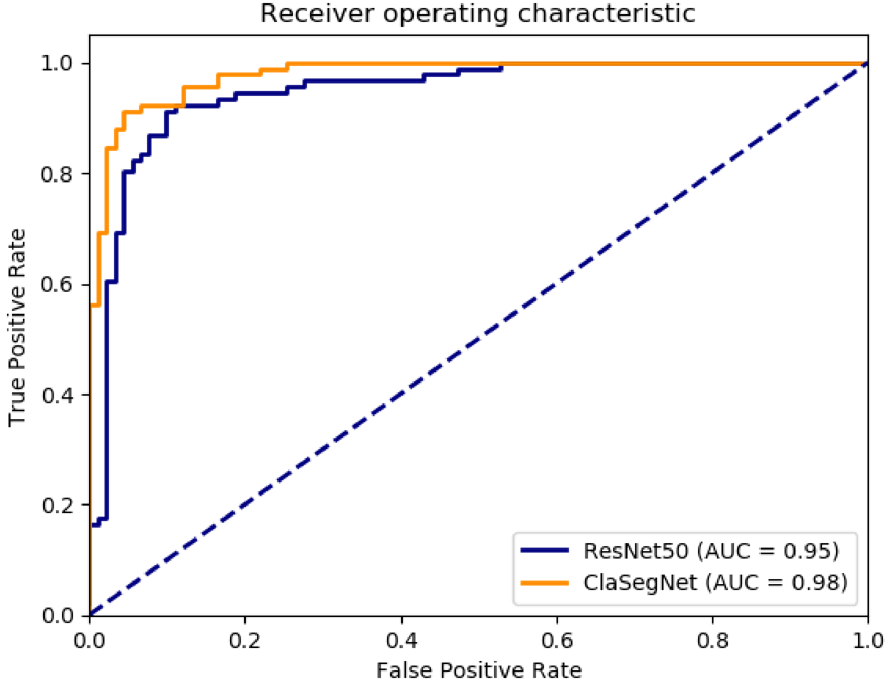
- Training
  1. Input image size is 512 x 512
  2. Normalized input image to [0, 1]
  3. Data augmentation (rotation, shift and horizontal flip)
  4. Initial learning rate is 0.0001
  5. Adam optimizer + learning rate decay
  6. Early-stopping
  7. Pre-trained backbone network
- Inferencing
  1. Input image size is 512 x 512
  2. Normalized input image to [0, 1]
  3. No data augmentation

Results

Model	val Accuracy	val Precision	val Recall	val AUC	val Dice
ResNet50	0.894	0.899	0.889	0.941	-
ClaSegNet	0.95	0.966	0.933	0.98	0.518

Model	test Accuracy	test Precision	test Recall	test AUC	test Dice
ResNet50	0.896	0.875	0.923	0.945	-
ClaSegNet	0.923	0.953	0.89	0.979	0.5

Test ROC

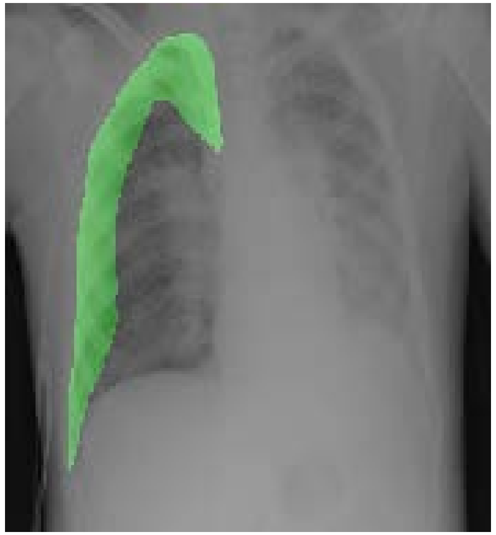


ResNet50		Predictions	
		nonPTX	PTX
Ground Truth	nonPTX	77	14
	PTX	8	83

ClaSegNet		Predictions	
		nonPTX	PTX
Ground Truth	nonPTX	87	4
	PTX	10	81

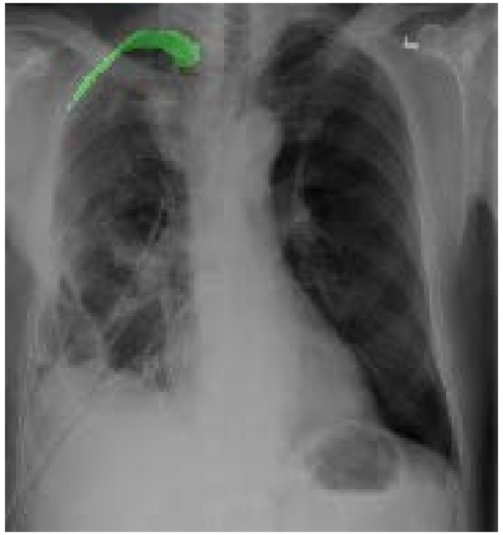
Localization maps -- TP

ground truth



prediction: 1.000

ground truth



prediction: 0.966

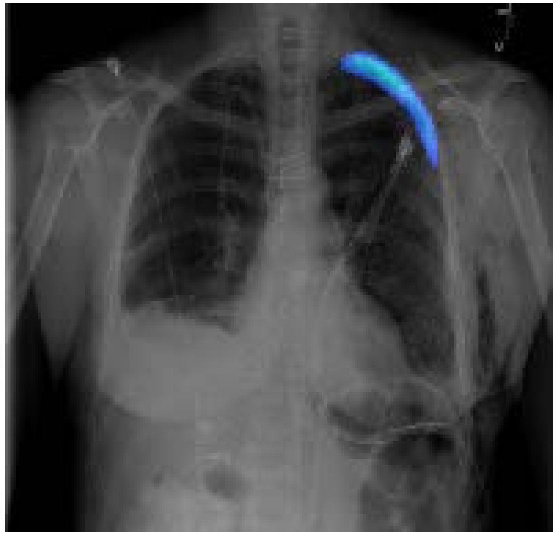
Localization maps -- FN

ground truth

prediction: 0.269

ground truth

prediction: 0.392

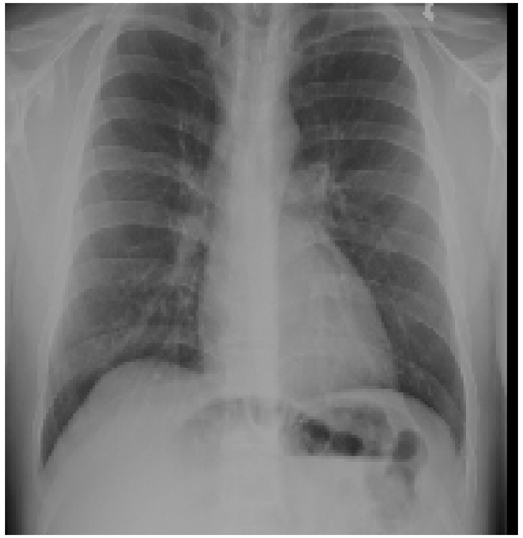


Localization maps -- FP

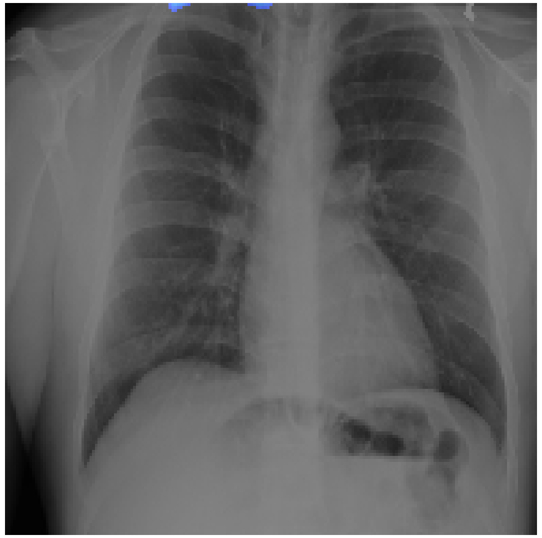
ground truth

prediction: 0.615

ground truth

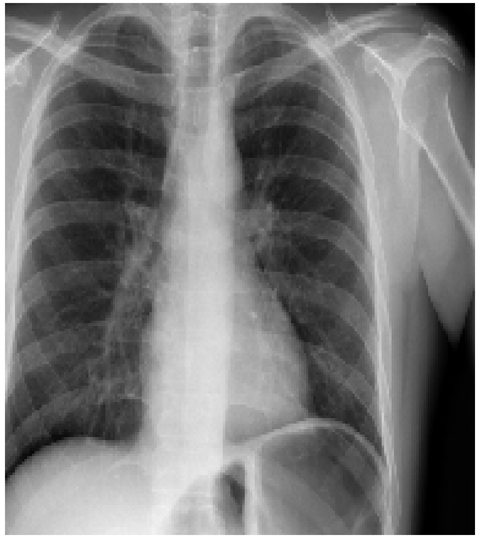


prediction: 0.526

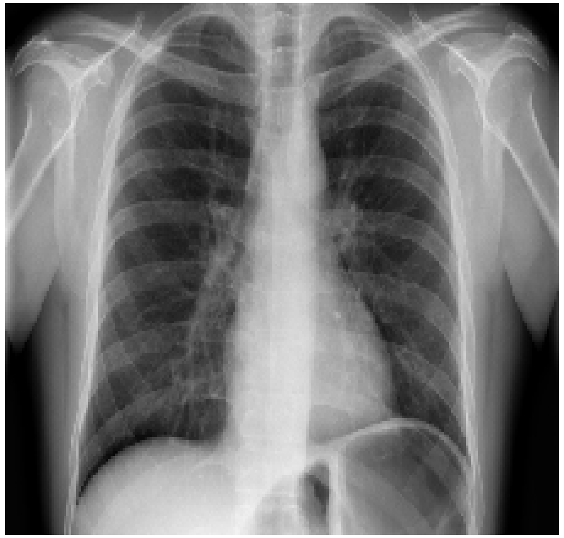


Localization maps -- TN

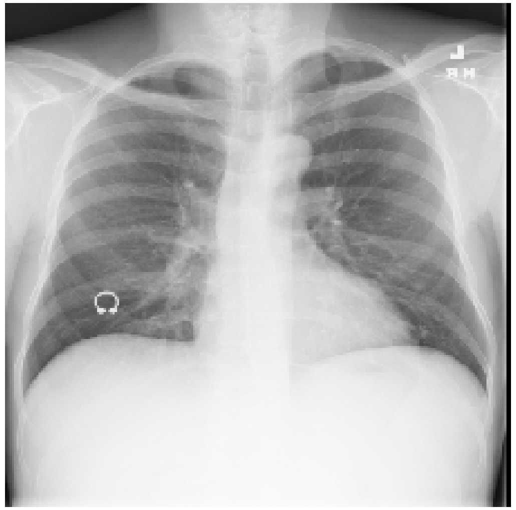
ground truth



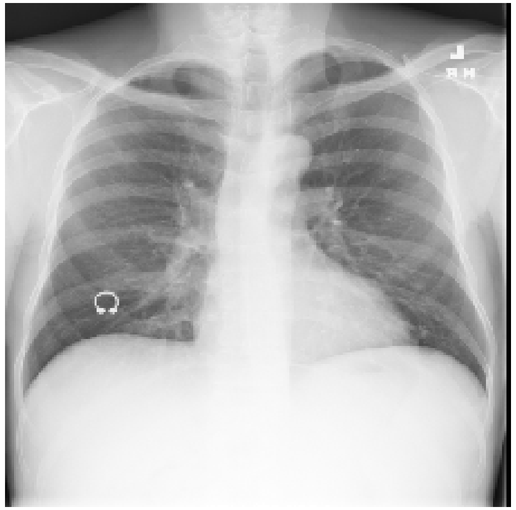
prediction: 0.021



ground truth



prediction: 0.008



Conclusions

- Utilizing richer annotation information (mask) improves the classification and localization accuracy
- Adding segmentation branch (decoder) improves the localization accuracy (resolution)

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