3011979 Intro to Deep Learning for Medical Imaging

L13: Medical imaging applications I

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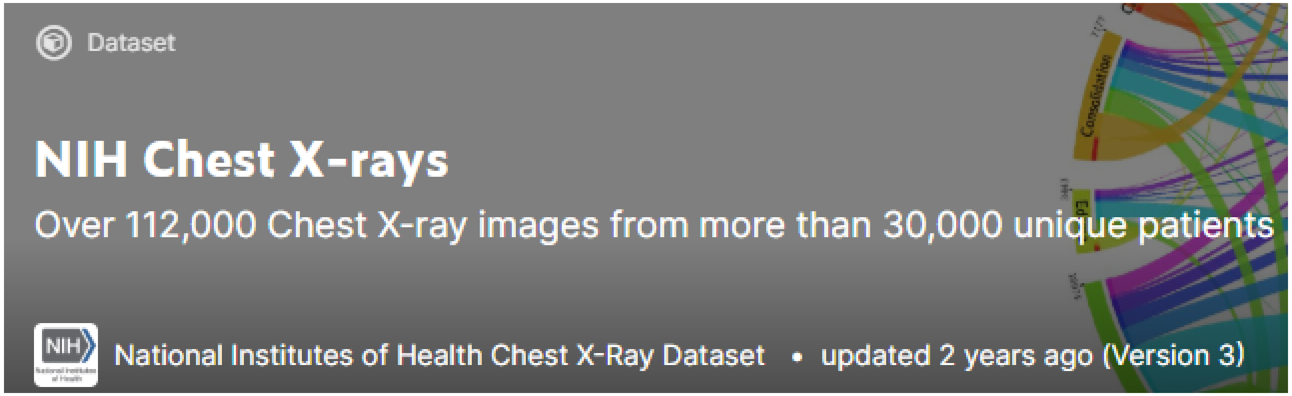
Public CXR datasets

Public CXR datasets



Pathology
Atelectasis
Cardiomegaly
Effusion
Infiltration
Mass
Nodule
Pneumonia
Pneumothorax
Consolidation
Edema
Emphysema
Fibrosis
Pleural Thickening
Hernia

Dataset	Source Institution	Disease Labeling	# Images	# Reports	# Patients
Open-I	Indiana Network for Patient Care	Expert	8,121	3,996	3,996
Chest-Xray8	National Institutes of Health	Automatic (DNorm + MetaMap)	108,948	0	32,717
CheXpert	Stanford Hospital	Automatic (CheXpert labeler)	224,316	0	65,240
PadChest	Hospital Universitario de San Juan	Expert + Automatic (Neural network)	160,868	206,222	67,625
MIMIC-CXR	Beth Israel Deacones Medical Center	Automatic (CheXpert labeler)	473,057	206,563	63,478

- First dataset contain only image + 14-class label
- Newer datasets include radiologist report
  - Labels are extracted from reports by computer

NIH Chest14 dataset

Dataset

NIH Chest X-rays

Over 112,000 Chest X-ray images from more than 30,000 unique patients

National Institutes of Health Chest X-Ray Dataset • updated 3 years ago (Version 3)

779

Data Tasks (1) Code (213) Discussion (17) Activity Metadata Download (42 GB) New Notebook

Usability 7.4 License CC0: Public Domain Tags computer science, health, software, biology, health conditions and 1 more

Description

NIH Chest X-ray Dataset

National Institutes of Health Chest X-Ray Dataset

Chest X-ray exams are one of the most frequent and cost-effective medical imaging examinations available. However, clinical diagnosis of a chest X-ray can be challenging and sometimes more difficult than diagnosis via chest CT imaging. The lack of large publicly available datasets with annotations means it is still very difficult, if not impossible, to achieve clinically relevant computer-aided detection and diagnosis (CAD) in real world medical sites with chest X-rays. One major hurdle in creating large X-ray image datasets is the lack resources for labeling so many images. Prior to the release of this dataset, Openi was the largest publicly available source of chest X-ray images with 4,143 images available.

NIH Chest14 on Google Cloud

Cloud Healthcare API > Documentation > Resources

Rate and review

NIH Chest X-ray dataset

Send feedback

The NIH Chest X-ray dataset consists of 100,000 de-identified images of chest x-rays. The images are in PNG format.

The data is provided by the NIH Clinical Center and is available through the NIH download site: https://nihcc.app.box.com/v/ChestXray-NIHCC

You can also access the data via Google Cloud (GCP), as described in Google Cloud data access.

License and attribution

There are no restrictions on the use of the NIH chest x-ray images. However, the dataset has the following attribution requirements:

- Provide a link to the NIH download site: https://nihcc.app.box.com/v/ChestXray-NIHCC
- Include a citation to the CVPR 2017 paper:

  > Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, Ronald Summers, ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases, IEEE CVPR, pp. 3462-3471, 2017

- Acknowledge that the NIH Clinical Center is the data provider

MIMIC-CXR dataset

About
MIMIC-CXR
Getting Access
Downloading
Cloud
Acknowledgements
Data
Tutorials
GitHub
Help
Edit This Page

MIMIC-CXR

MIMIC-CXR contains 227,835 imaging studies for 64,588 patients presenting to the Beth Israel Deaconess Medical Center Emergency Department between 2011 - 2016. A total of 377,110 images are available in the dataset. Each imaging study can contain one or more images, usually a frontal view and a lateral view. Studies are made available with a semi-structured free-text radiology report that describes the radiological findings of the images, written by a practicing radiologist contemporaneously during routine clinical care. All images and reports have been de-identified to protect patient privacy.

MIMIC-CXR v2.0.0

The current version of the database is v2.0.0. When referencing this version, we recommend using the full title: MIMIC-CXR v2.0.0.

MIMIC-CXR v2.0.0 is the first release of the images in their native format, DICOM, and the first release of the free-text radiology reports associated with these images. All data has been de-identified prior to release to protect patient privacy.

Past versions

MIMIC-CXR v1.0.0

MIMIC-CXR v1.0.0 was released on 22 January 2019. The data contains only JPG format images and 14 structured labels extracted from an NLP tool. As we have reorganized the data since the release of v1.0.0, we no longer distribute v1.0.0. The images are identical to MIMIC-CXR v2.0.0, and we will make the structured labels available again shortly.

- Provide both DICOM and JPEG
- Provide anonymized radiologist report

BIMCV (PadChest) dataset

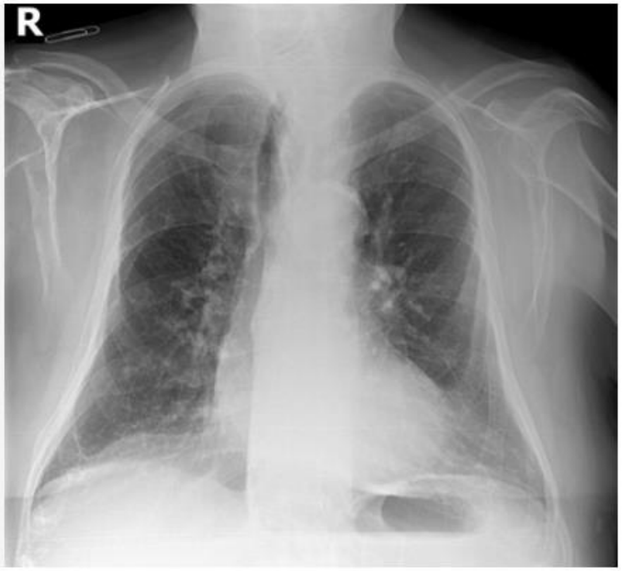
PROYECTOS

- BIMCV-COVID19
- MIDS
- DiSMed
- PADCHEST
- MIDAS
- 10K – BDBI 4 CV
- BRAIN-GIS
- CELEXTITA
- GLIOHABITATS
- HQBRAIN
- NEUROBIM-MS
- MIDL
- SHARE YOUR BRAIN

Hospital San Juan de Alicante – University of Alicante

PadChest

A large chest x-ray image dataset with multi-label annotated reports



PadChest: A large chest x-ray image dataset with multi-label annotated reports

We present a labeled large-scale, high resolution chest x-ray dataset for automated ex-ploration of medical images along with their associated reports. This dataset includes more than 160,000 images from 67,000 patients that were interpreted and reported by radiologists at Hospital San Juan (Spain) from 2009 to 2017, covering six different position views and additional information on image acquisition and patient demography.

The reports were labeled with 174 different radiographic findings, 19 differential diagnoses and 104 anatomic locations organized as a hierarchical taxonomy mapped to standard Unified Medical Language System (UMLS) terminology. A 27% of the reports were

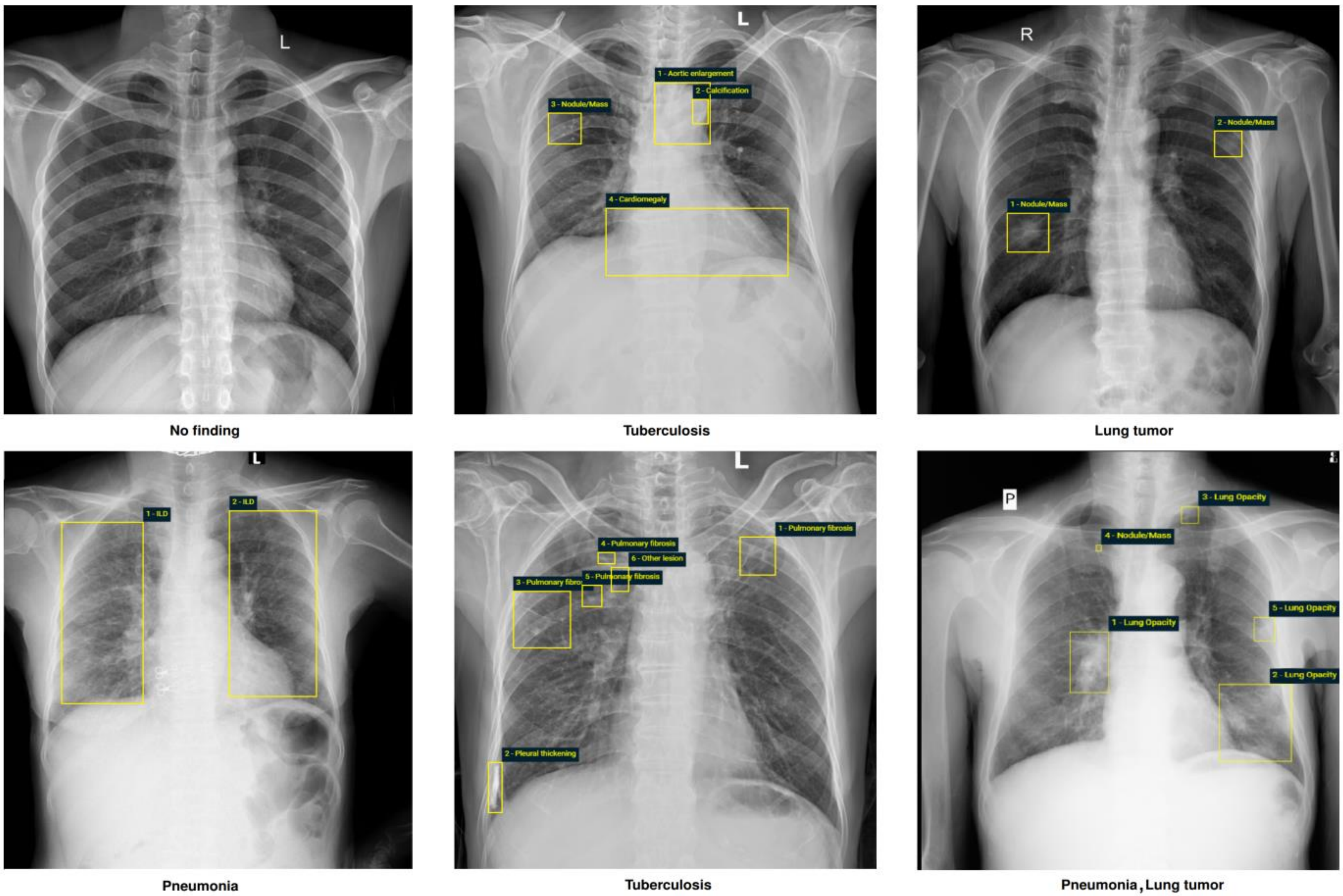
Read paper
(from Medical Image Analysis)

Read preprint
(from arxiv.org)

Download complete dataset
1.02 TB

- Provide extracted labels (reports written in Spanish)

VinDR-CXR dataset



- 15,000 CXR with multi-doctor bounding box annotations

TB CXR dataset

Datasets: Tuberculosis Chest X-ray Datasets.

Author: Rajaraman S, Jaeger S, Antani SK

Abstract:

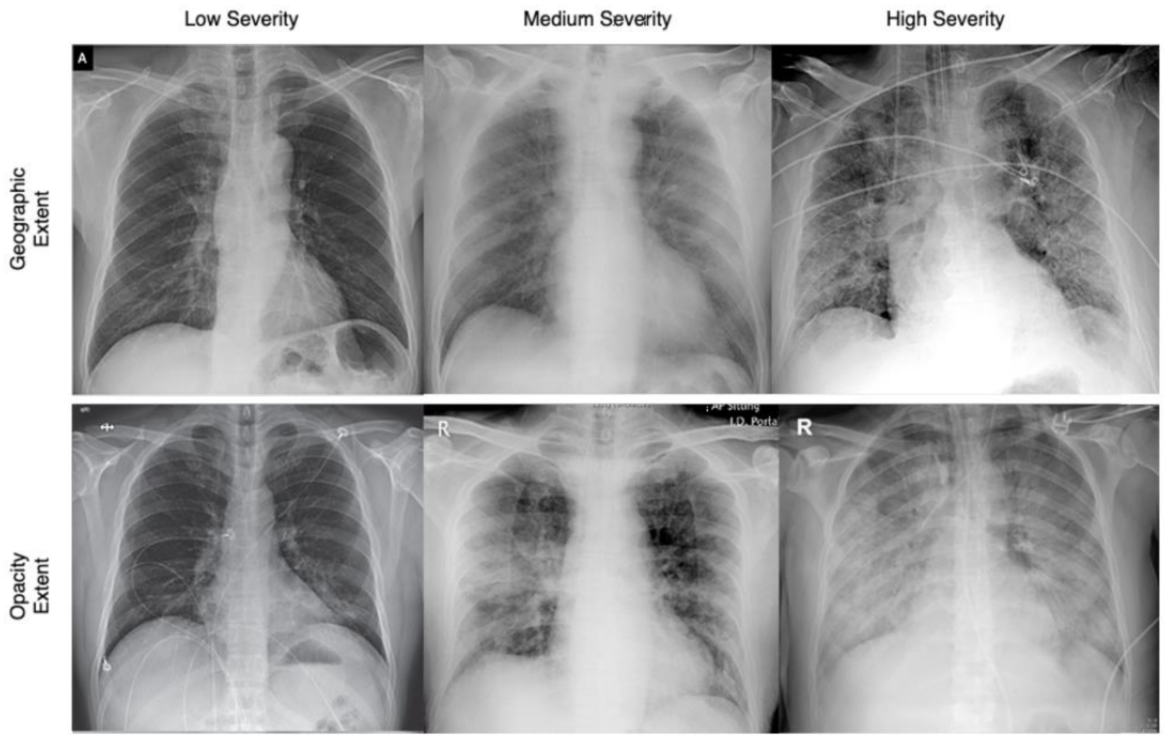
The following de-identified chest X-ray (CXR) image data sets are available to the research community along with findings and consensus radiologist annotations. Both sets contain normal as well as abnormal CXRs with the latter containing TB-consistent manifestations. For additional information about image datasets and annotations please refer to these papers [1] and [2]. The use and sharing of these deidentified images have been reviewed and exempted by the Ethics boards.

Montgomery County CXR Set: The images in this data set have been acquired from the TB Control Program of the Department of Health and Human Services of Montgomery County, MD, USA. This set contains 138 posterior-anterior CXRs of which 80 are normal and 58 are abnormal with manifestations that are consistent with TB. All images are de-identified and available along with left and right PA-view lung masks in PNG format. The data set also includes consensus annotations from two radiologists for 1024 × 1024 resized images and radiology readings. Download Link

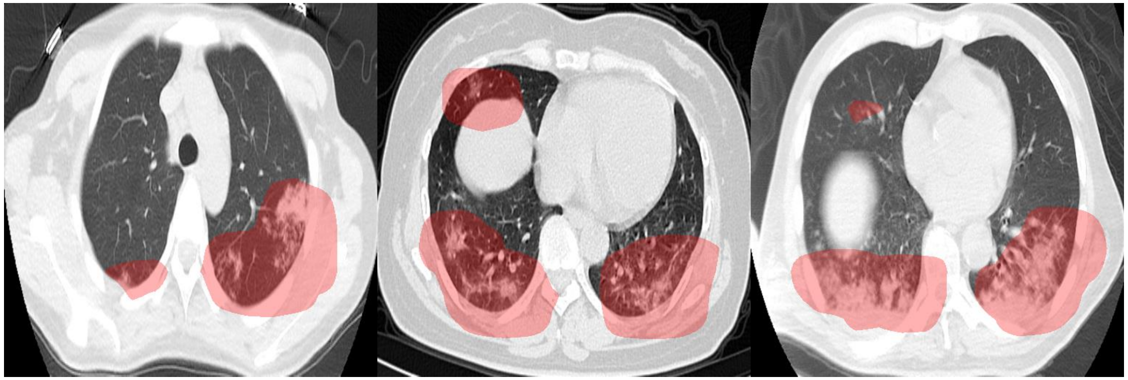
Shenzhen Hospital CXR Set: The CXR images in this data set have been collected and provided by Shenzhen No.3 Hospital in Shenzhen, Guangdong providence, China. The images are in PNG format. There are 326 normal and 336 abnormal CXRs, respectively, showing various TB-consistent manifestations. The data set also includes consensus annotations for a subset (N = 68) from two radiologists for 1024 × 1024 resized images and radiology readings. Download Link

- Include lung masks

COVID-Net datasets



396 CXR images with graded severity scores



200k CT slices from 4,000 COVID-19 patients from 15 countries

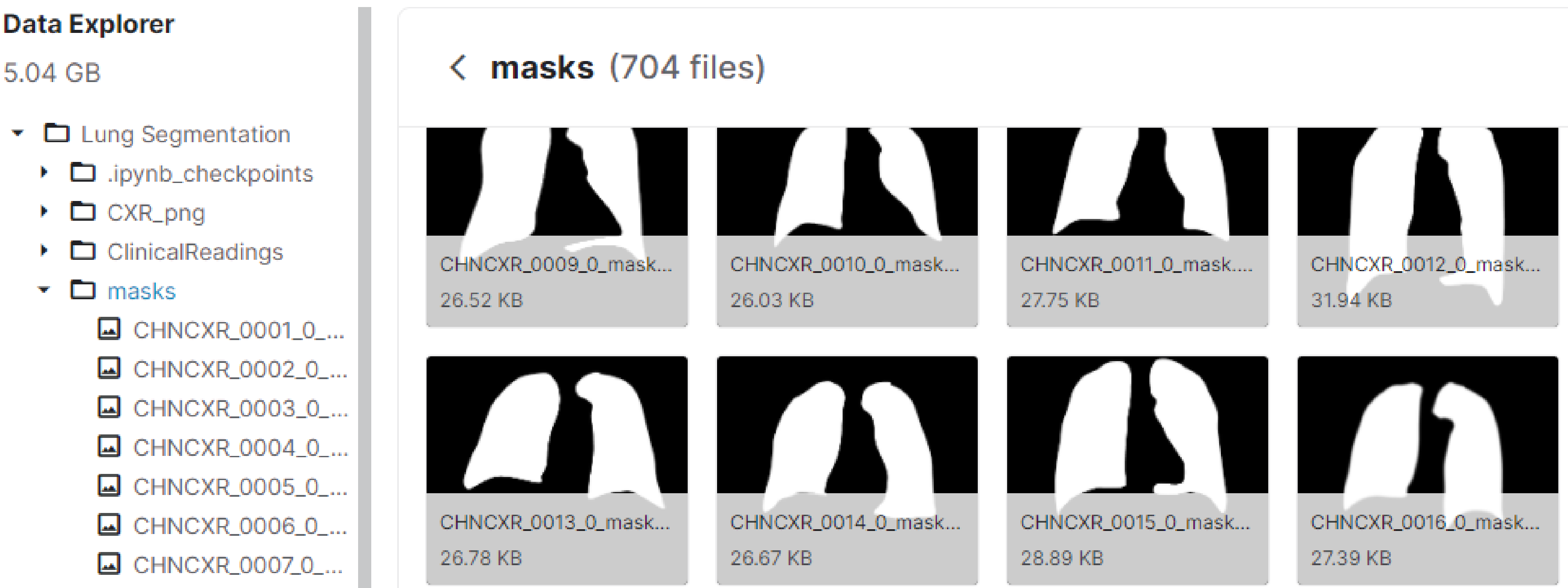
COVID-Net datasets

Quick Links

1. COVIDNet-CXR models (COVID-19 detection using chest x-rays): https://github.com/lindawangg/COVID-Net/blob/master/docs/models.md
2. COVIDNet-CT models (COVID-19 detection using chest CT scans): https://github.com/haydengunraj/COVIDNet-CT/blob/master/docs/models.md
3. COVIDNet-CXR-S models (COVID-19 airspace severity grading using chest x-rays): https://github.com/lindawangg/COVID-Net/blob/master/docs/models.md
4. COVIDNet-S models (COVID-19 lung severity assessment using chest x-rays): https://github.com/lindawangg/COVID-Net/blob/master/docs/models.md
5. COVIDx-CXR dataset: https://github.com/lindawangg/COVID-Net/blob/master/docs/COVIDx.md
6. COVIDx-CT dataset: https://github.com/haydengunraj/COVIDNet-CT/blob/master/docs/dataset.md
7. COVIDx-S dataset: https://github.com/lindawangg/COVID-Net/tree/master/annotations
8. COVIDNet-P inference for pneumonia: https://github.com/lindawangg/COVID-Net/blob/master/docs/covidnet_pneumonia.md
9. CancerNet-SCa models for skin cancer detection: https://github.com/jamesrenhoulee/CancerNet-SCa/blob/main/docs/models.md

Training, inference, and evaluation scripts for COVIDNet-CXR, COVIDNet-CT, COVIDNet-S, and CancerNet-SCa models are available at the respective repos

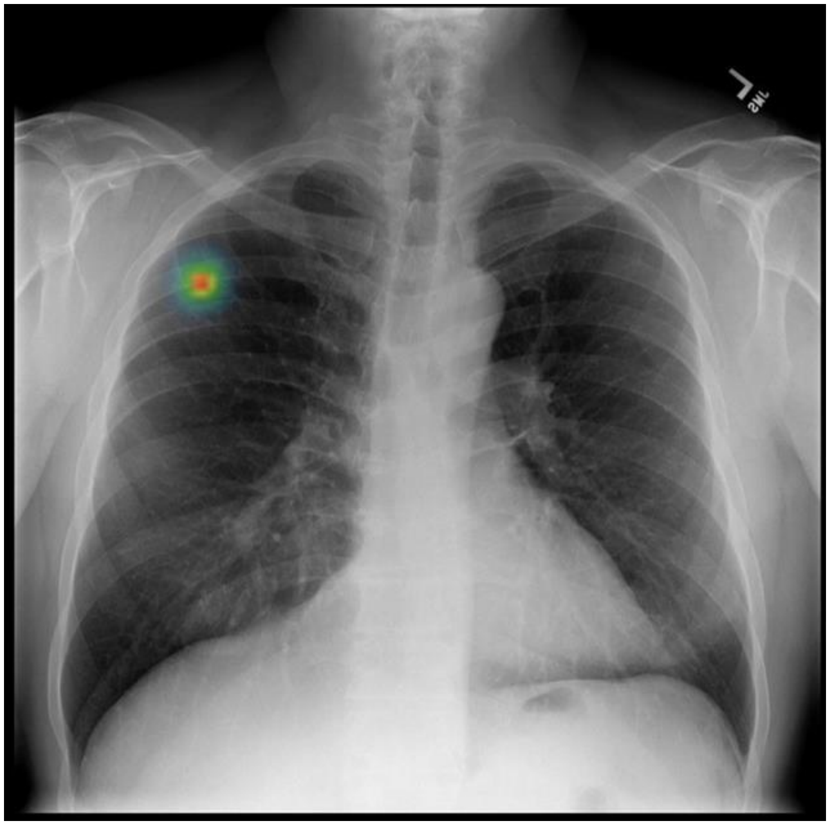
Lung segmentation dataset



Explainability of CXR classification

Nodule detection

Lunit INSIGHT for Chest Radiography



Original Research
Thoracic Imaging

Free Access

Development and Validation of Deep Learning–based Automatic Detection Algorithm for Malignant Pulmonary Nodules on Chest Radiographs

Ju Gang Nam*, Sunggyun Park*, Eui Jin Hwang, Jong Hyuk Lee, Kwang-Nam Jin, Kun Young Lim, Thienkai Huy Vu, Jae Ho Sohn, Sangheum Hwang, Jin Mo Goo, Chang Min Park

* J.G.N. and S.P. contributed equally to this work.

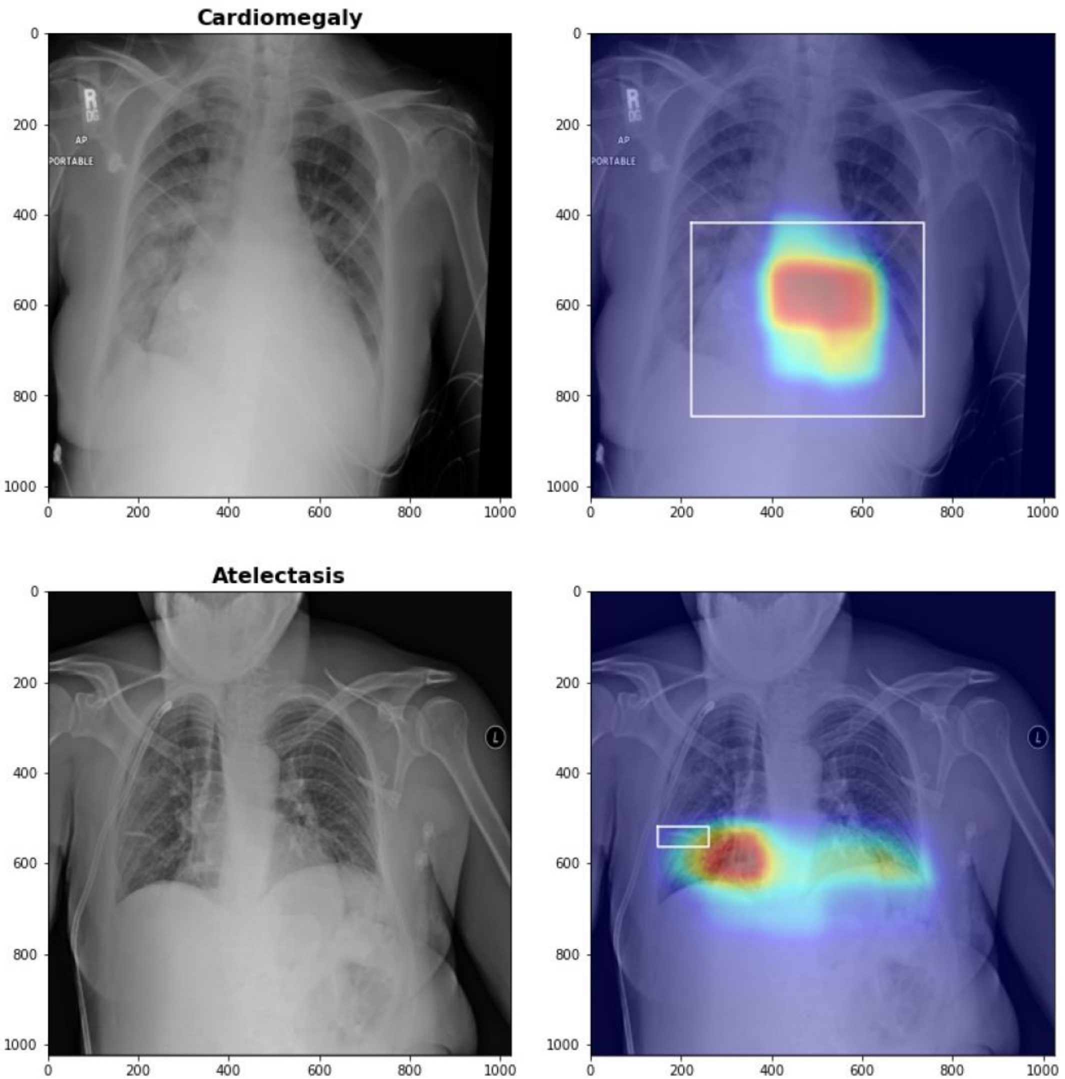
Author Affiliations

Published Online: Sep 25 2018 | https://doi.org/10.1148/radiol.2018180237

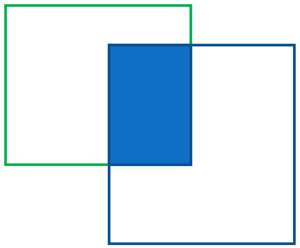
- 43,292 CXR images from 34,676 patients
- Nodule location annotated by 13 radiologists
- Model trained with annotated nodule locations
- Data not released

- In most situations, we have only image + label

Intersection over union metric



$$\mathrm{IoU} = \frac{|A \cap B|}{|A \cup B|}$$



- IoU = 1 only if the heatmap is exactly equal to the bounding box

- Heatmap is continuous
  - Consider top k percentiles

- Dice coefficient = $\frac{2 * |A \cap B|}{|A| + |B|}$

Image from hackermoon.com

Dice loss function

Heatmap

$$|A| = \begin{bmatrix} 0.01 & 0.03 & 0.02 & 0.02 \\ 0.05 & 0.12 & 0.09 & 0.07 \\ 0.89 & 0.85 & 0.88 & 0.91 \\ 0.99 & 0.97 & 0.95 & 0.97 \end{bmatrix}^{2\ (optional)} \xrightarrow{\text{sum}} 7.82$$

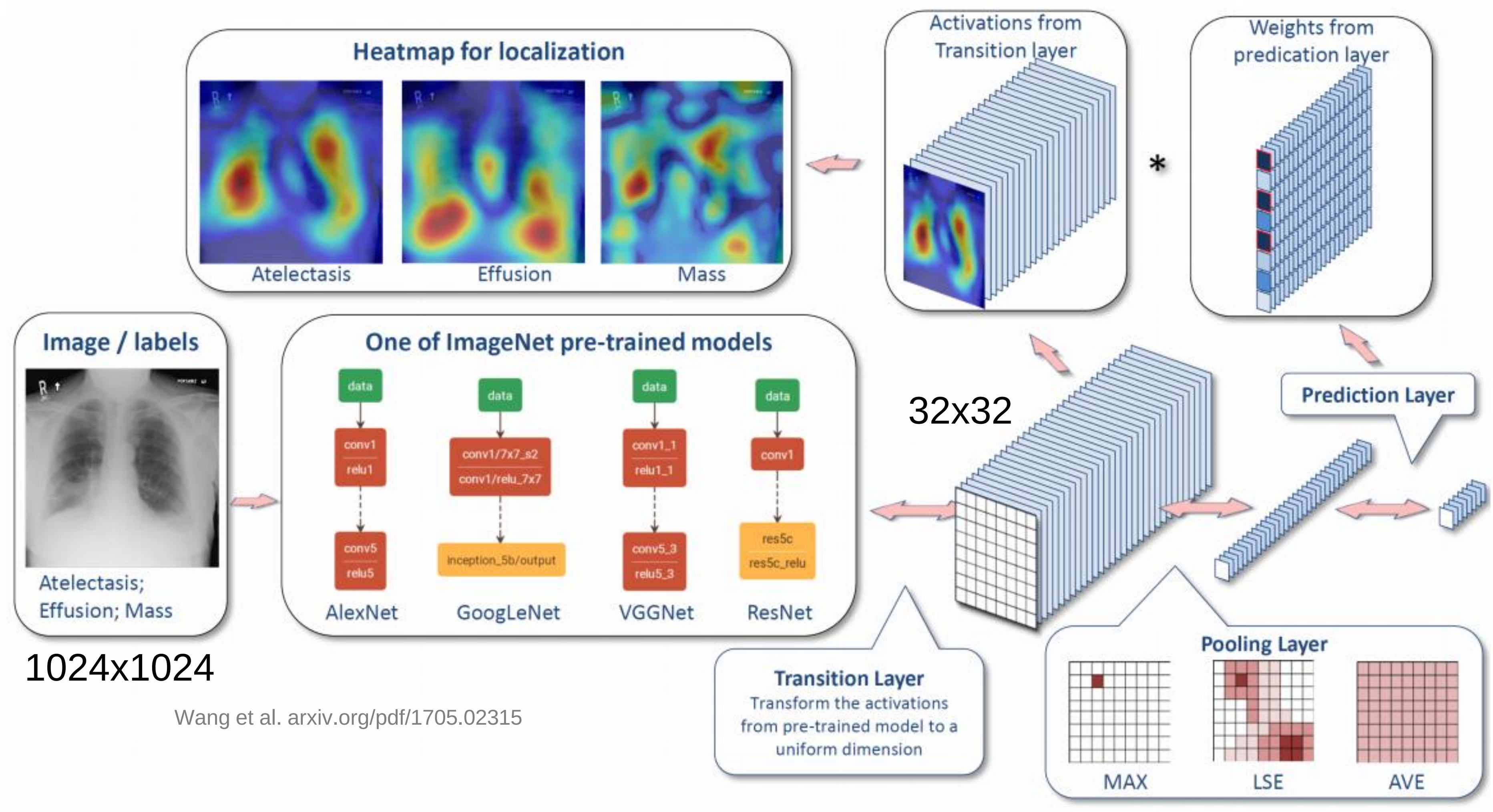
Bounding box
in the form of
binary mask

$$|B| = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix}^{2\ (optional)} \xrightarrow{\text{sum}} 8$$

Image from www.jeremyjordan.me/semantic-segmentation/

- Dice loss $= 1 - \dfrac{2\sum A_{i,j}B_{i,j}}{\sum {A_{i,j}}^2 + \sum {B_{i,j}}^2}$
- Dice loss is small if A and B are similar

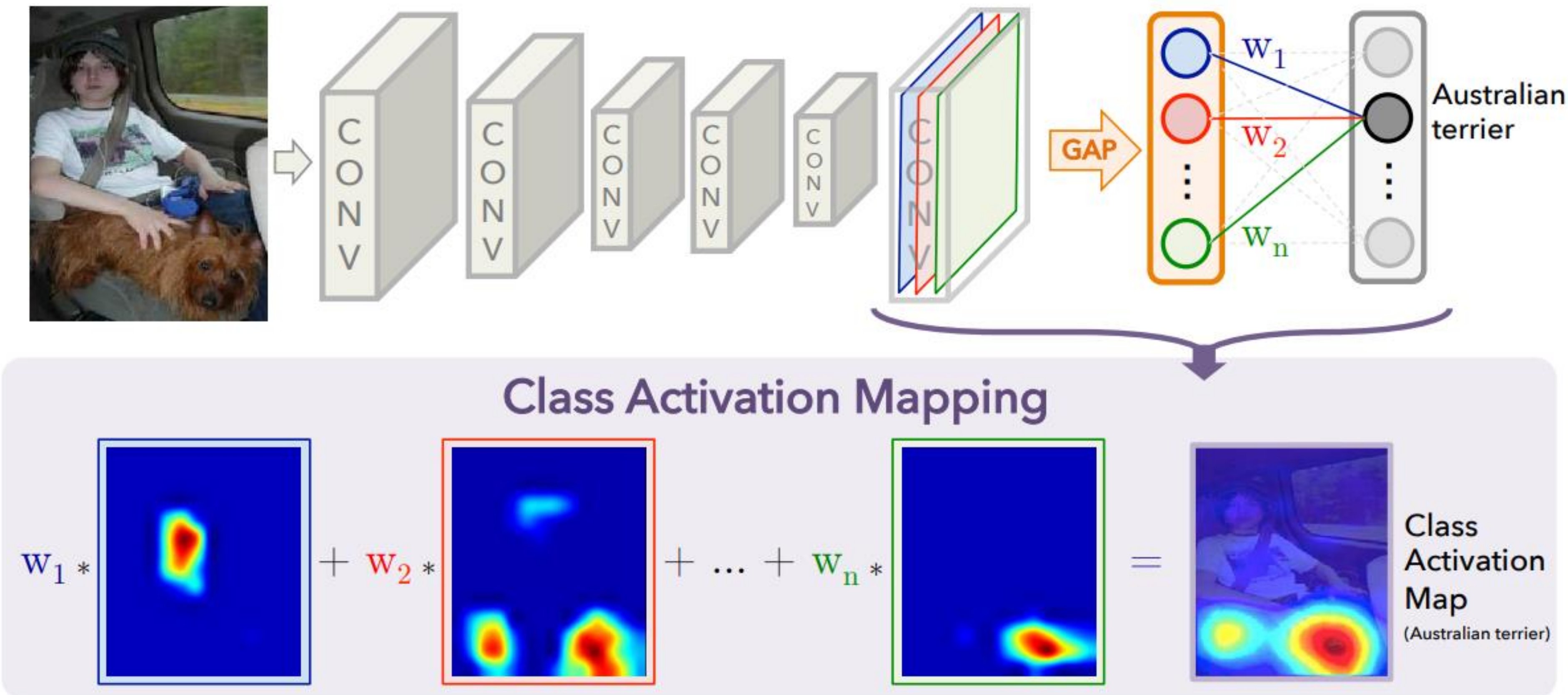
What can we do without annotation?



Wang et al. arxiv.org/pdf/1705.02315

- Use heatmaps in the last convolutional layer

Class activation map (CAM)



Zhou et al. “Learning Deep Features for Discriminative Localization” CVPR (2016)

- Convolutional layers preserve location information
  - Heatmaps in the last layer can be up-sampled to match the input image
  - Assign weight to each heatmap (channel) based on the output class

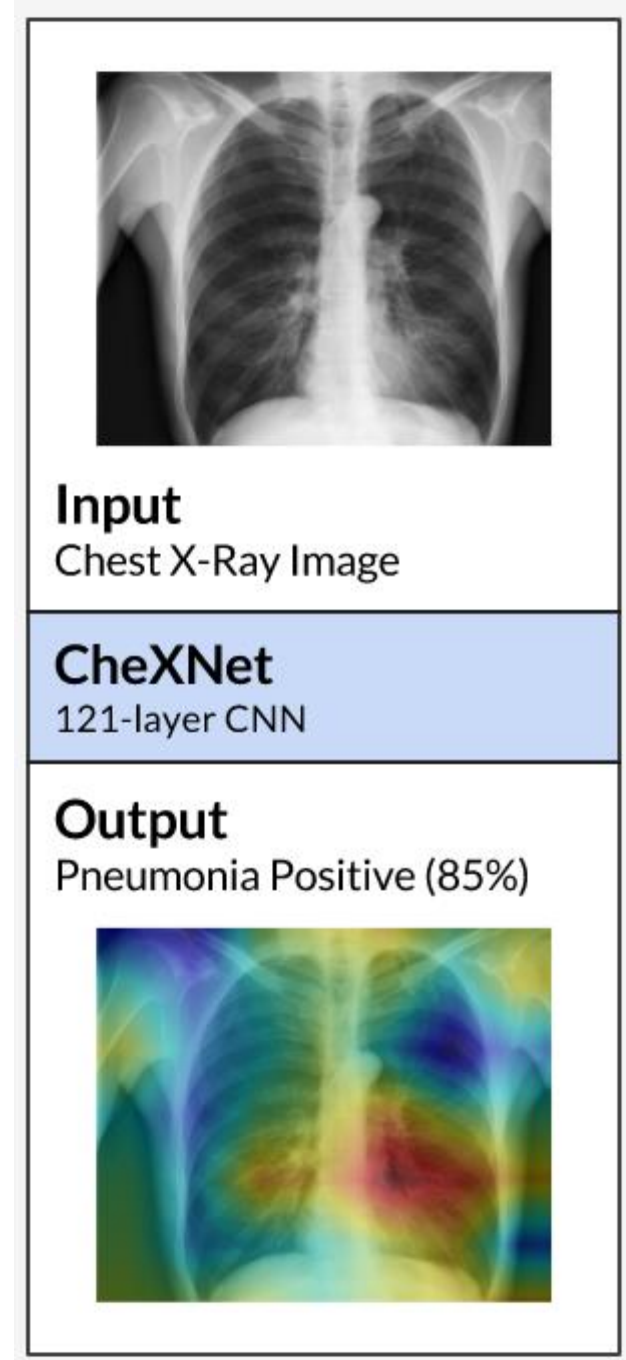
CAM as explanation

Stanford ML Group

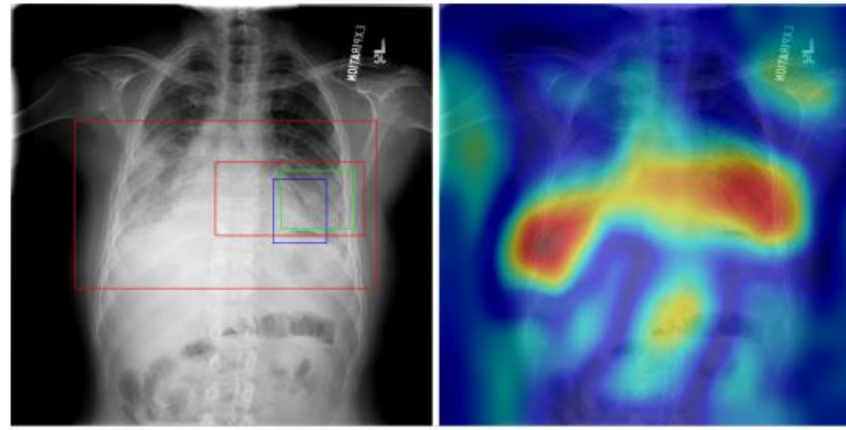
CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning

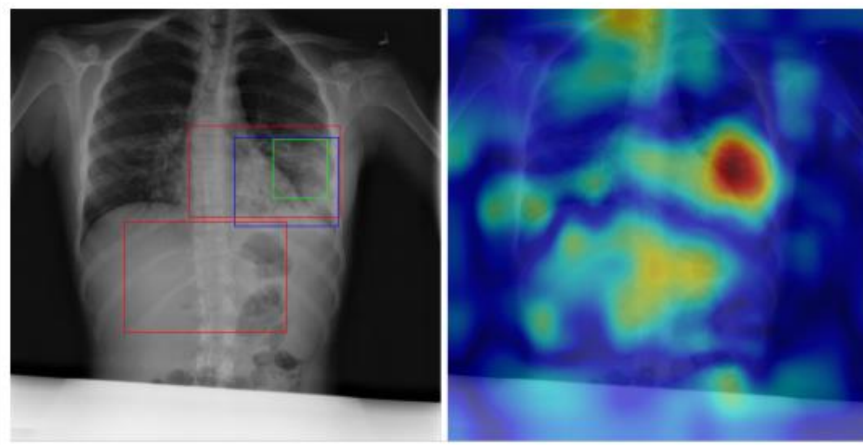
Pranav Rajpurkar*, Jeremy Irvin*, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren, Andrew Y. Ng

	F1 Score (95% CI)
Radiologist 1	0.383 (0.309, 0.453)
Radiologist 2	0.356 (0.282, 0.428)
Radiologist 3	0.365 (0.291, 0.435)
Radiologist 4	0.442 (0.390, 0.492)
Radiologist Avg.	0.387 (0.330, 0.442)
CheXNet	0.435 (0.387, 0.481)



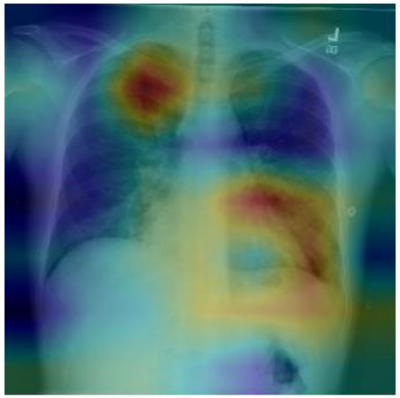
First CAM for CXR from ResNet

Radiology report	Keyword	Localization Result
findings: frontal lateral chest x-ray performed in expiration. left apical pneumothorax visible. small pneumothorax visible along the left heart border and left hemidiaphragm. pleural thickening, mass right chest. the mediastinum cannot be evaluated in the expiration. bony structures intact. impression: left post biopsy pneumothorax.	Mass; Pneumothorax	

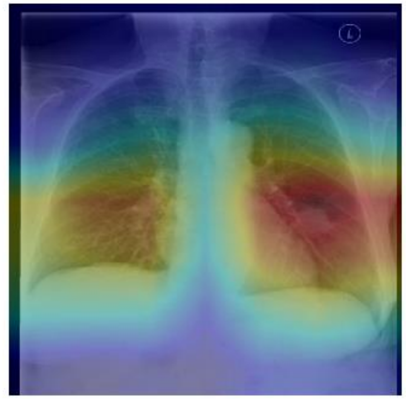
Radiology report	Keyword	Localization Result
findings: unchanged left lower lung field infiltrate/air bronchograms. unchanged right perihilar infiltrate with obscuration of the right heart border. no evidence of new infiltrate. no evidence of pneumothorax the cardiac and mediastinal contours are stable. impression: 1. no evidence pneumothorax. 2. unchanged left lower lobe and left lingular consolidation/bronchiectasis. 3. unchanged right middle lobe infiltrate	Pneumonia; Infiltration	

Wang et al. arxiv.org/pdf/1705.02315

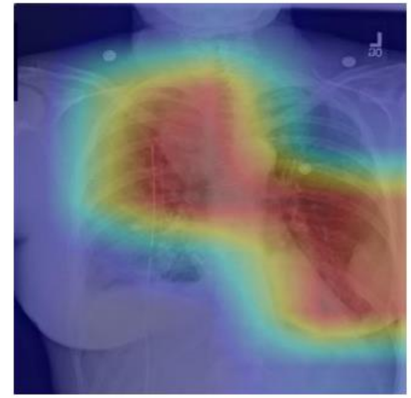
Slightly better CAM from DenseNet model



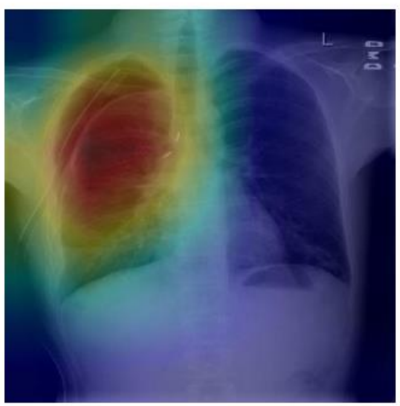
(a) Patient with multifocal community acquired pneumonia. The model correctly detects the airspace disease in the left lower and right upper lobes to arrive at the pneumonia diagnosis.



(b) Patient with a left lung nodule. The model identifies the left lower lobe lung nodule and correctly classifies the pathology.



(c) Patient with primary lung malignancy and two large masses, one in the left lower lobe and one in the right upper lobe adjacent to the mediastinum. The model correctly identifies both masses in the X-ray.



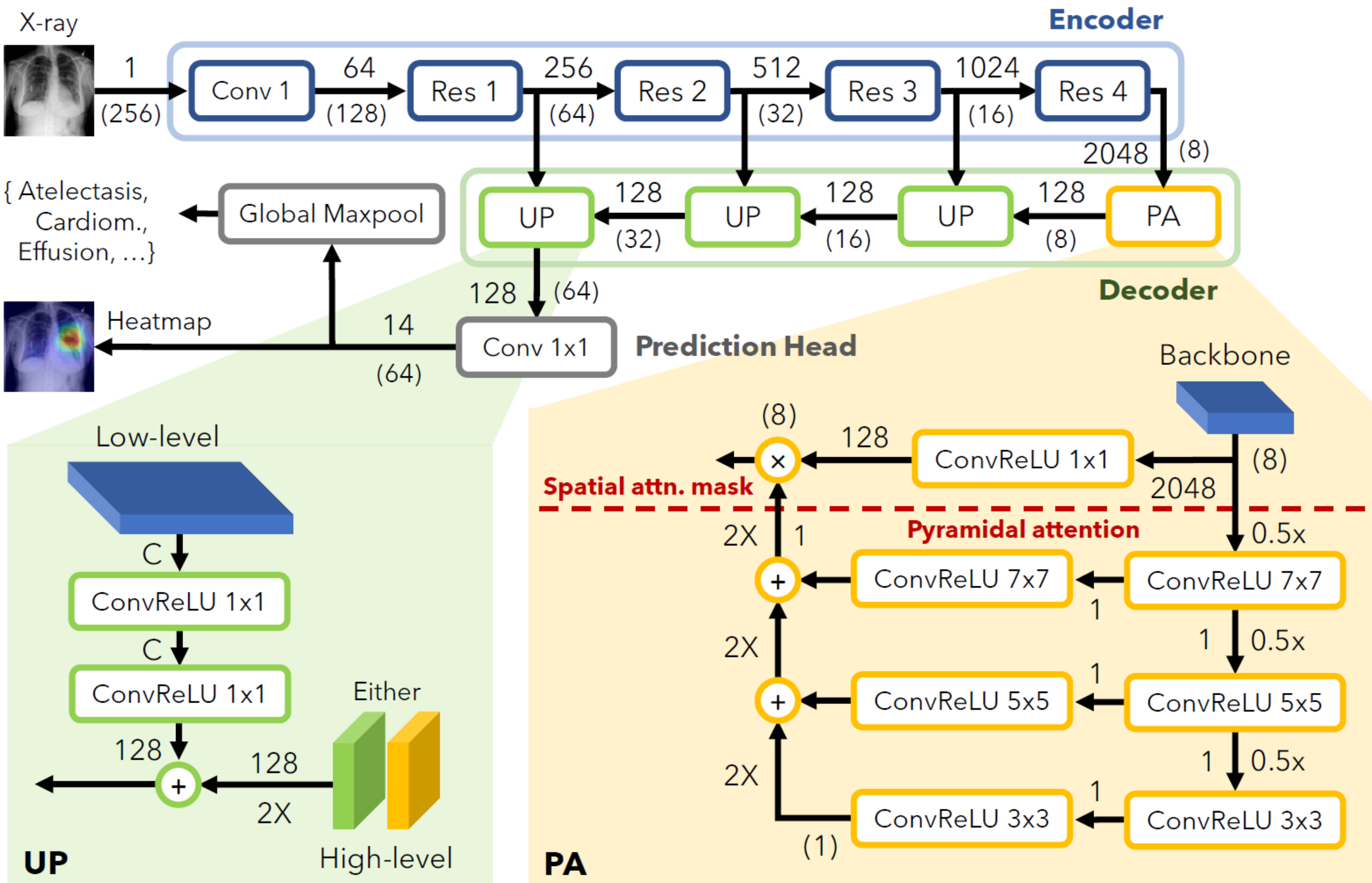
(d) Patient with a right-sided pneumothroax and chest tube. The model detects the abnormal lung to correctly predict the presence of pneumothorax (collapsed lung).

(e) Patient with a large right pleural effusion (fluid in the pleural space). The model correctly labels the effusion and focuses on the right lower chest.

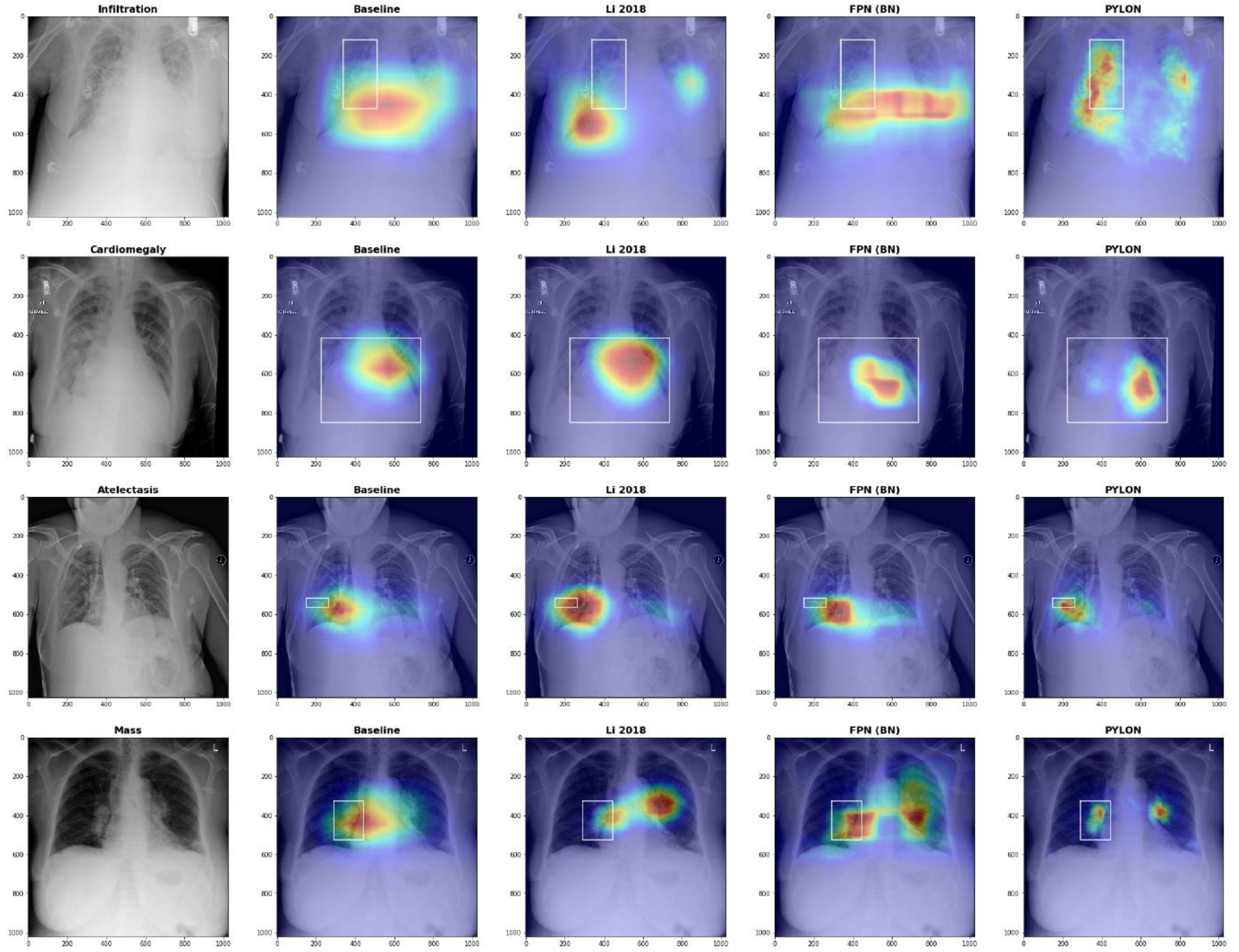
(f) Patient with congestive heart failure and cardiomegaly (enlarged heart). The model correctly identifies the enlarged cardiac silhouette.

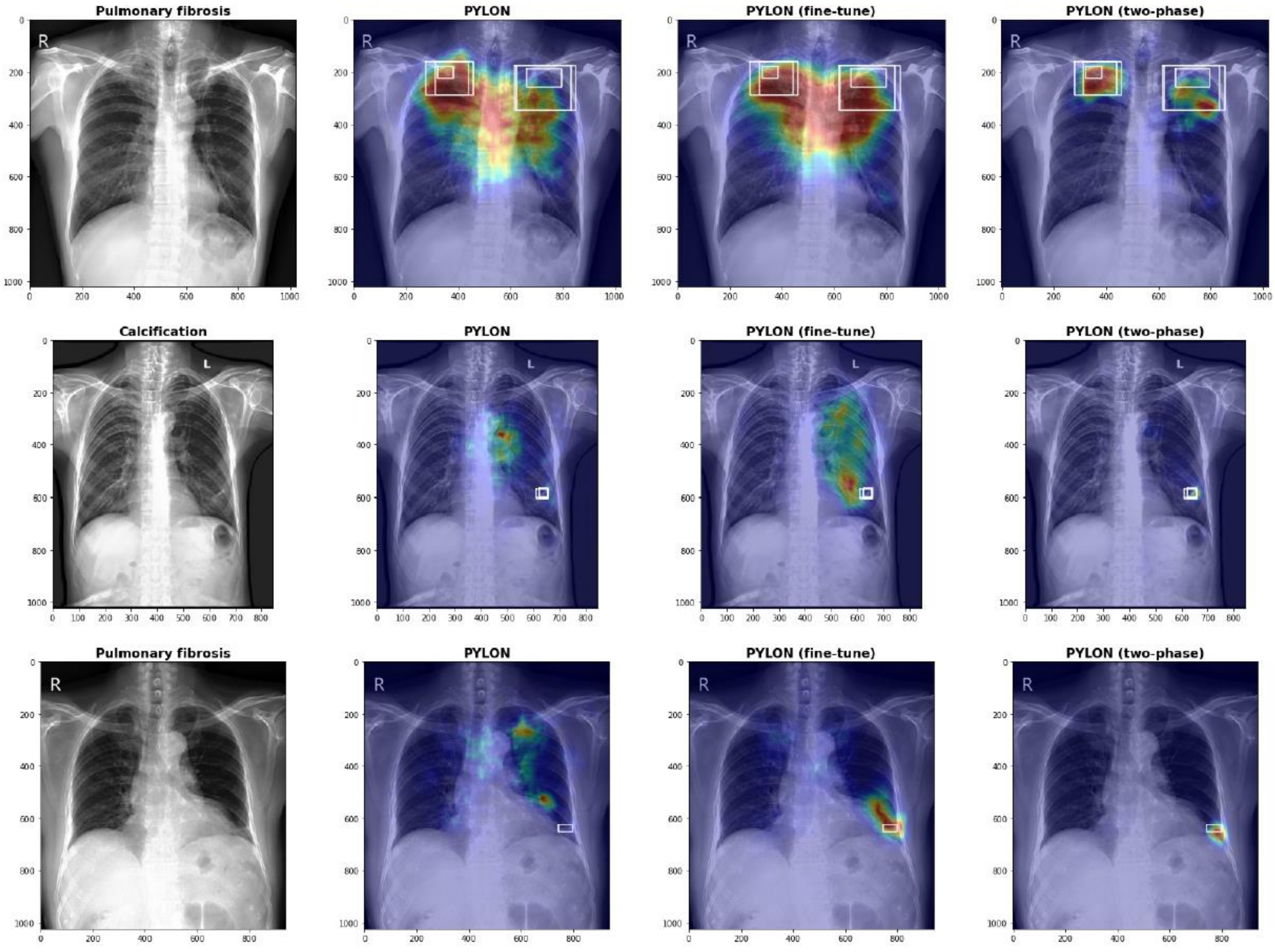
Rajpurkar et al. arxiv.org/pdf/1711.05225

An alternative approach for better CAM



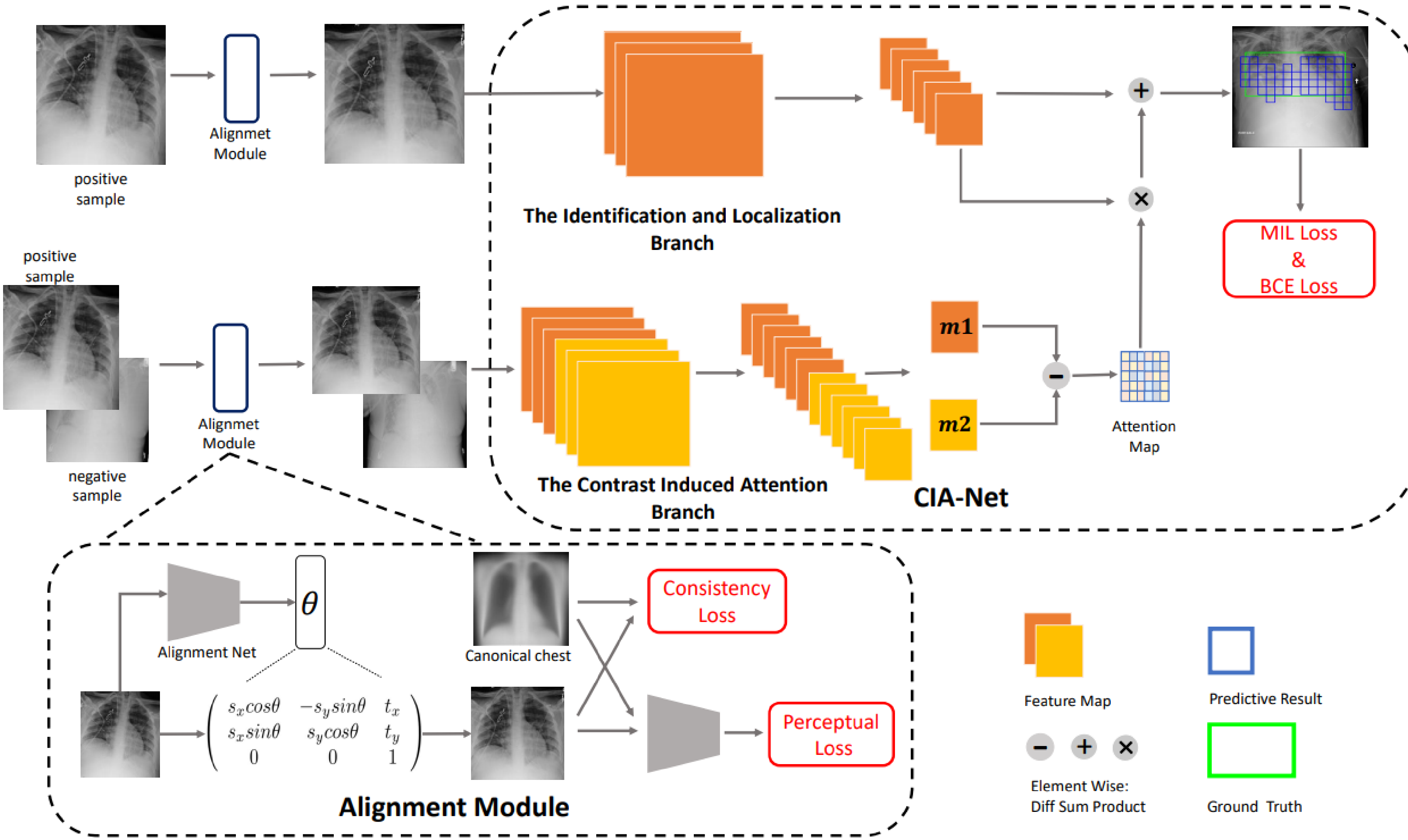
Preechakul et al. Under review at Nature Communications


Infiltration
Baseline
Li 2018
FPN (BN)
PYLON
Cardiomegaly
Baseline
Li 2018
FPN (BN)
PYLON
Atelectasis
Baseline
Li 2018
FPN (BN)
PYLON
Mass
Baseline
Li 2018
FPN (BN)
PYLON


Pulmonary fibrosis
PYLON
PYLON (fine-tune)
PYLON (two-phase)
Calcification
PYLON
PYLON (fine-tune)
PYLON (two-phase)
Pulmonary fibrosis
PYLON
PYLON (fine-tune)
PYLON (two-phase)

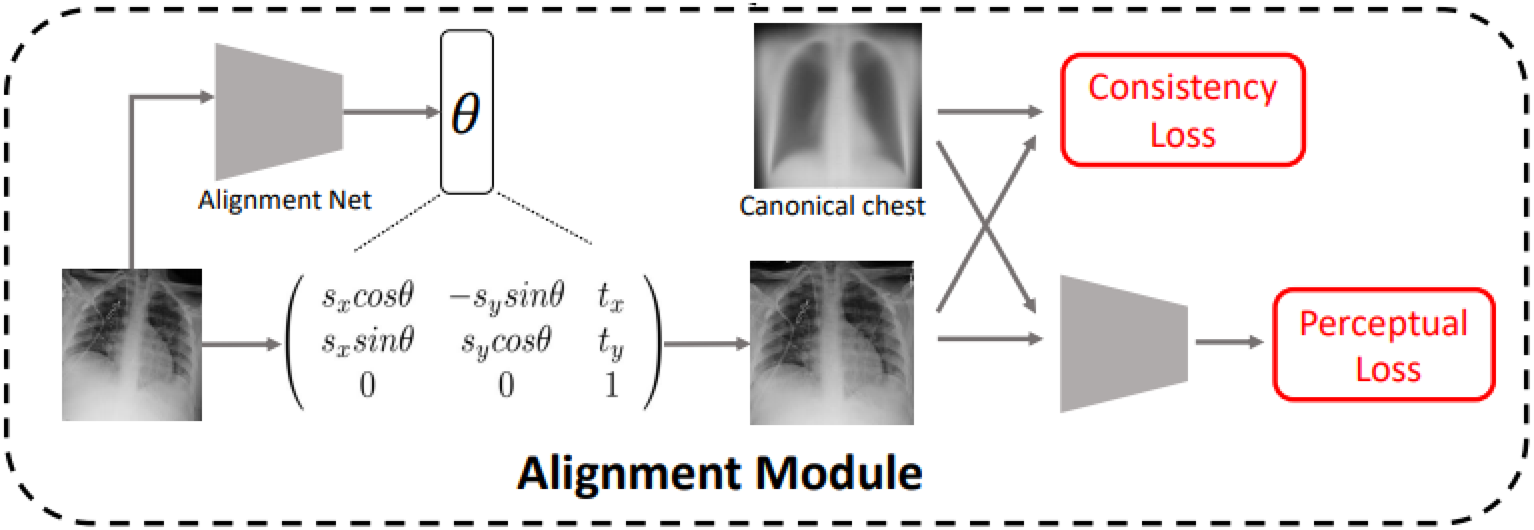
Some medical imaging applications

Network with CXR alignment



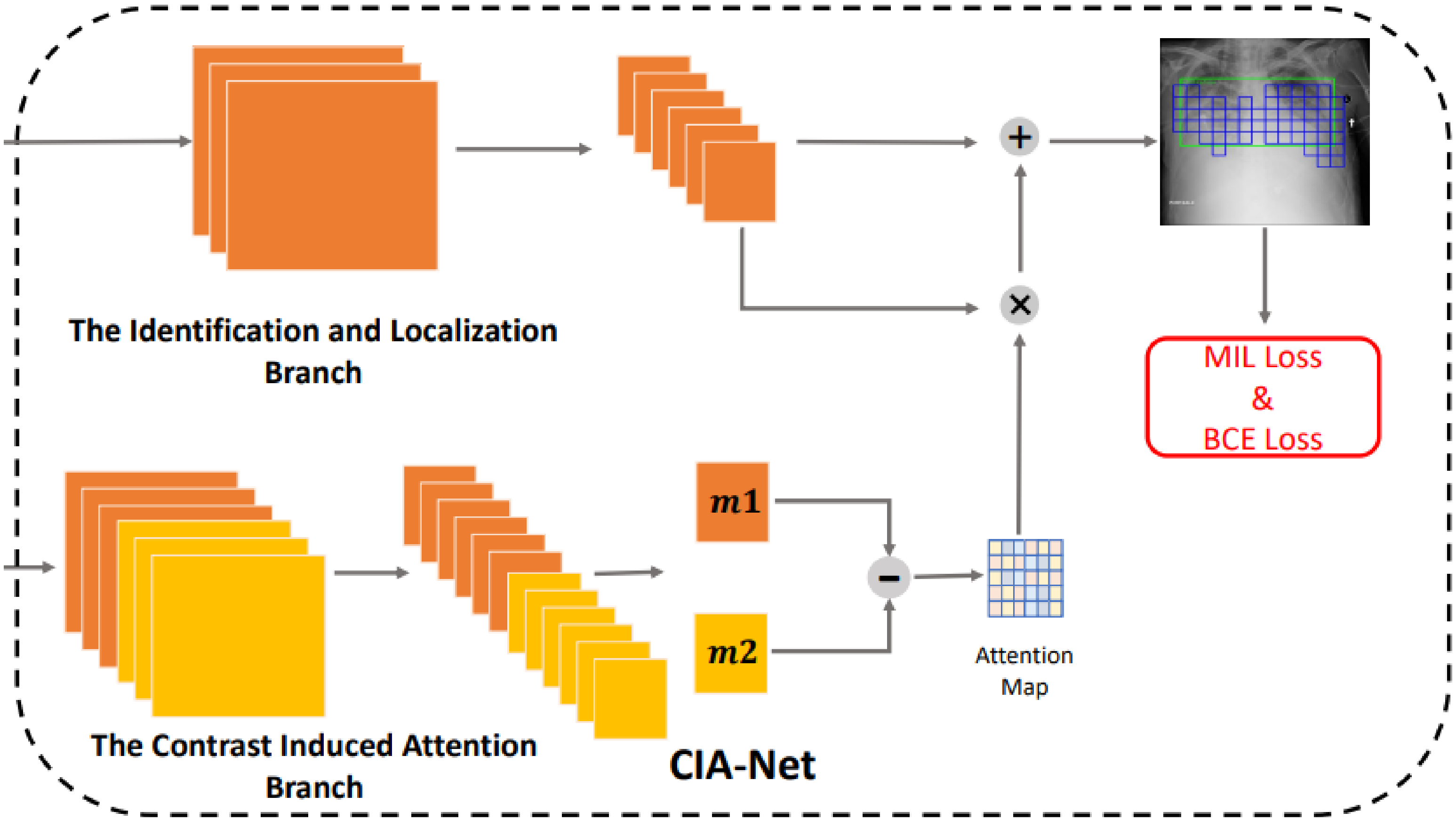
Liu et al. "Align, Attend and Locate: Chest X-ray Diagnosis via Contrast Induced Attention Network with Limited Supervision" ICCV 2019

Alignment with no annotation



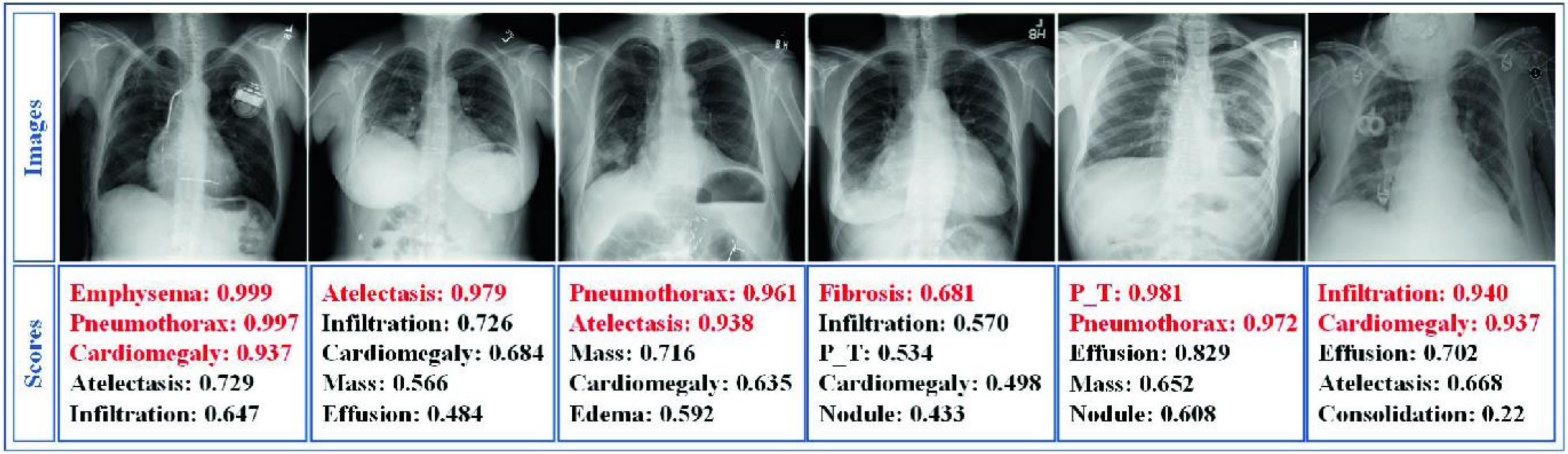
- **Consistency loss** = Euclidean distance between pixels in aligned image vs in reference image
- **Perceptual loss** = Euclidean distance between outputs of neural network when aligned image or reference image was used as input
  - The pixel values need not be the same if the neural network still produce the same output

Use of multiple main loss functions



- MIL loss is for image-level classification
- BCE loss is for pixel-level classification
  - Only for images with bounding box annotation

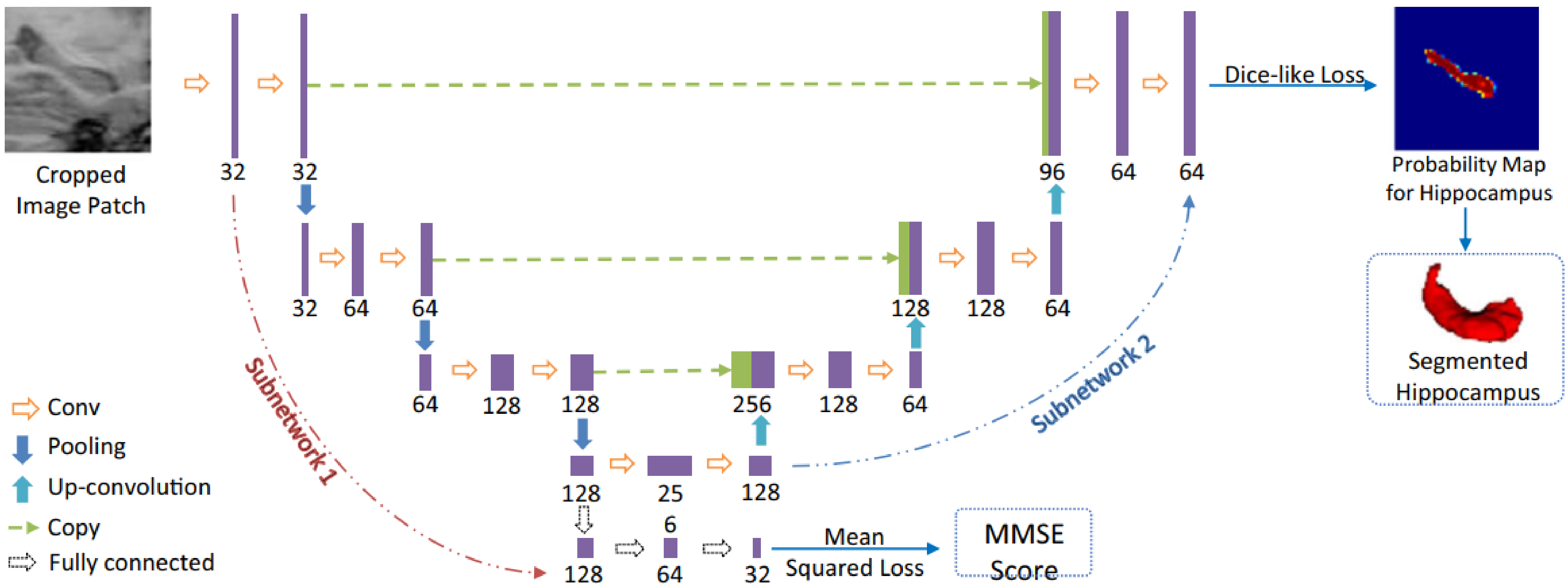
Multi-label classification for CXR



Chen et al. “Multi-label Chest X-Ray Image Classification via Label Co-occurrence Learning” PRCV 2019

- Each image can be diagnosed with multiple labels
- Each label is independent from the other
- In the output layer of neural network, instead of “**softmax**” activation (which normalize prediction to probability), switch to “**sigmoid**” to allow each output head to produce its own probability in [0, 1] range

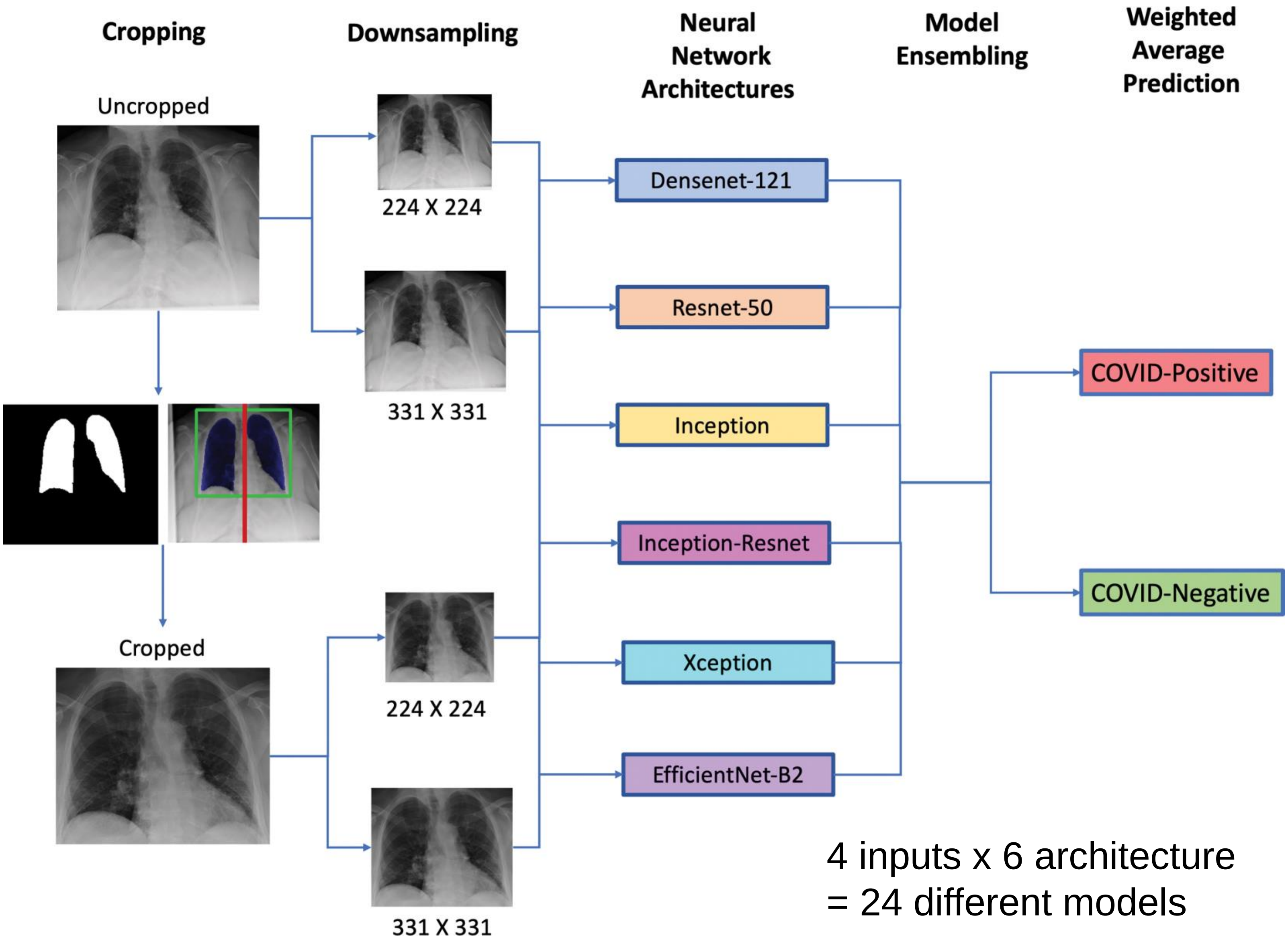
Joint segmentation and score prediction



Cao et al. Multimed Tools Appl (2017)

- U-Net with additional dense layers output for MMSE score prediction at the bottom of the convolutional network

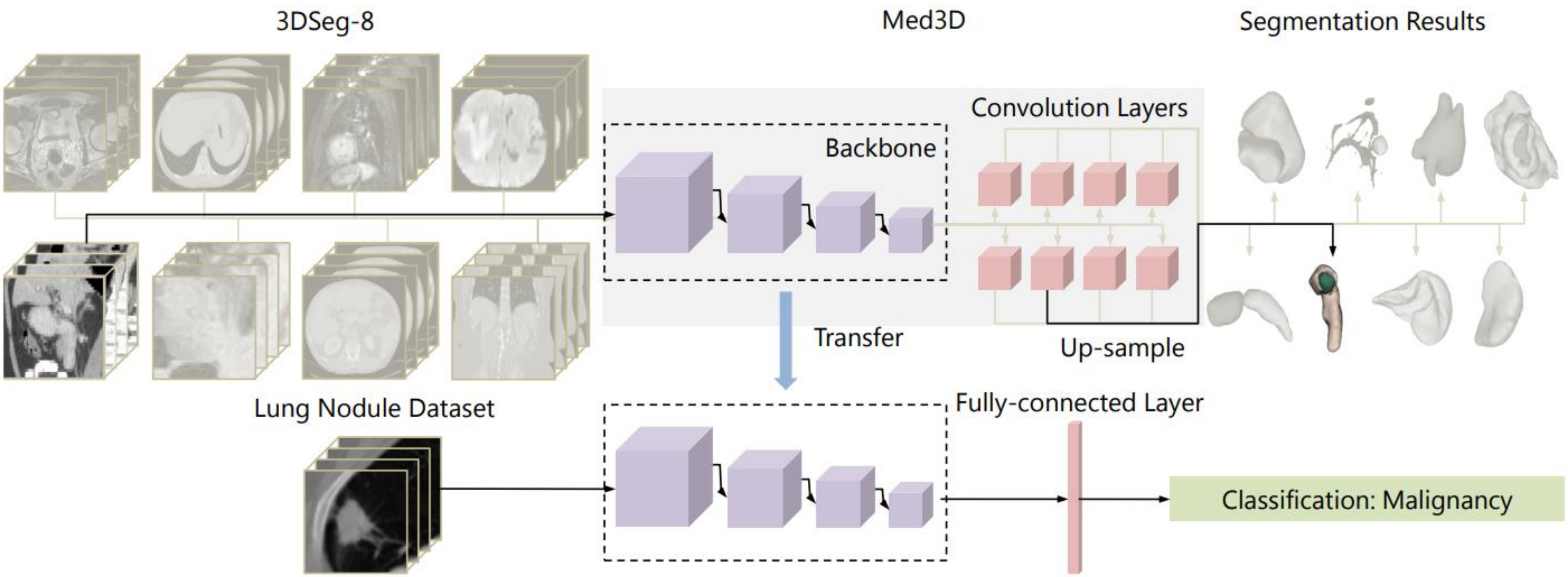
Neural network ensemble



4 inputs x 6 architecture
= 24 different models

Wehbe et al. Radiology (2020)

Aggregating datasets with shared model

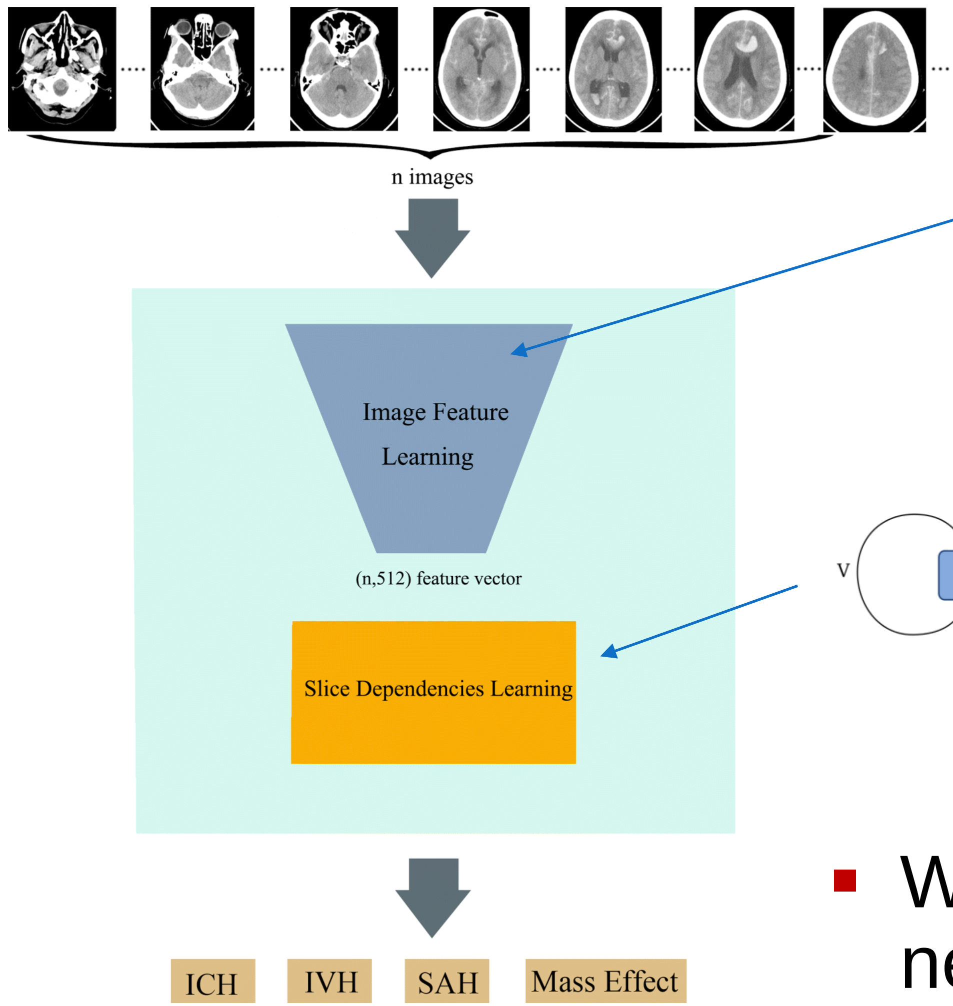


Chen et al. arxiv.org/pdf/1904.00625 (2019)

- Common convolutional layers as encoder for all tasks
- Attach separate output and train using data for each task
- Use ResNet as backbone
- Trained model weights: https://github.com/Tencent/MedicalNet

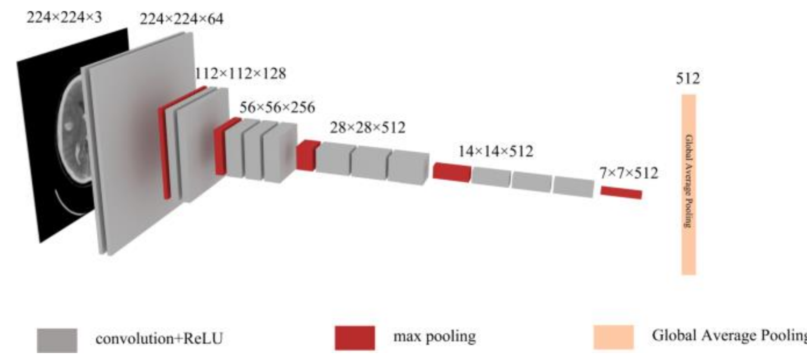
Dealing with variable multi-slices input

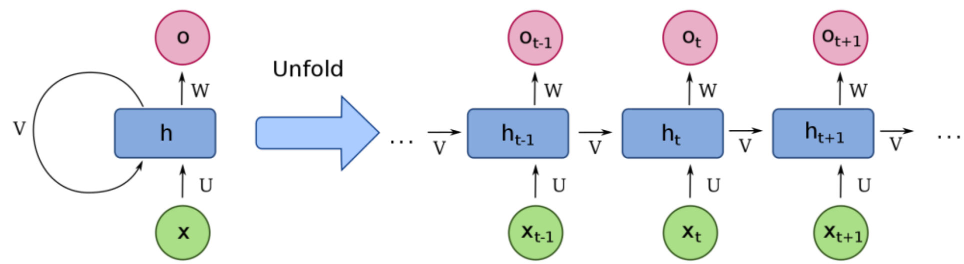
Variable number of input slices



Li et al. BMC Bioinformatics (2020)

VGG16





Recurrent Neural Network

- We will cover recurrent neural network in the next (last) lecture

Any question?