CXR Classification

[AI619] Midterm Project

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Roadmap

CXR Classification

- Overview of CXR data
  - Basics, Anatomy, Pathologies
- Commercial AI for CXR
  - Lunit, Kakao
- Open-source CXR data
  - NIH-CXR, etc.
- Midterm Project Guidelines

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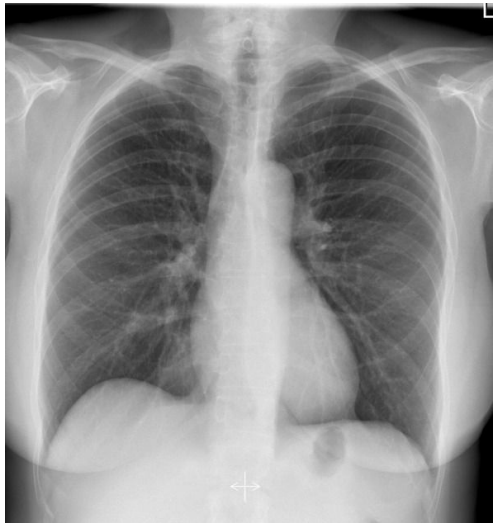
Overview of the Chest X-ray (aka ‘chest radiograph’)



Frontal view

- PA (posteroanterior)
- AP (anteroposterior)

More important

Lateral view

Chest PA vs. AP

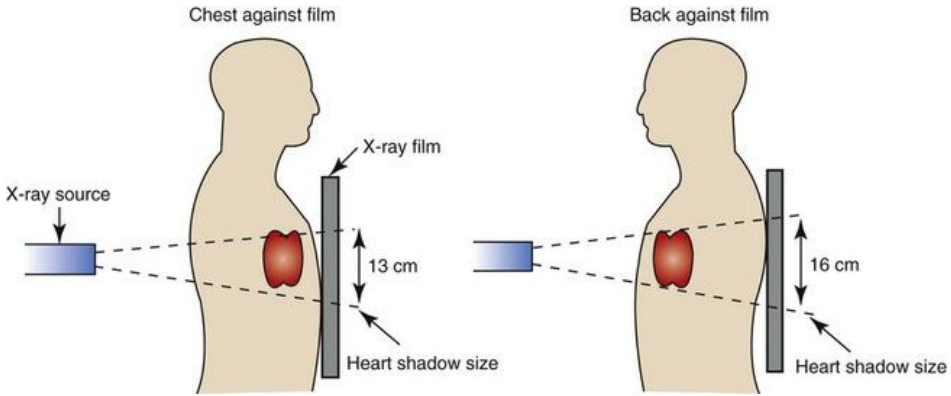


Image source: Thoracic Key
https://thoracickey.com/radiologic-examination-of-the-chest/

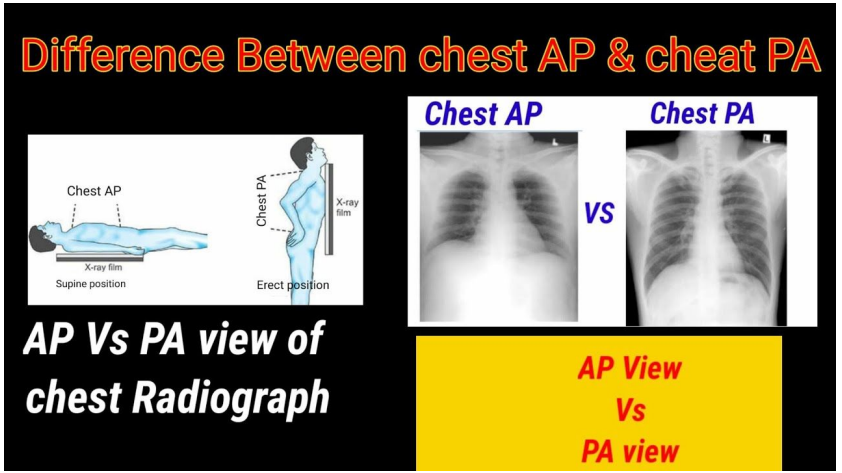
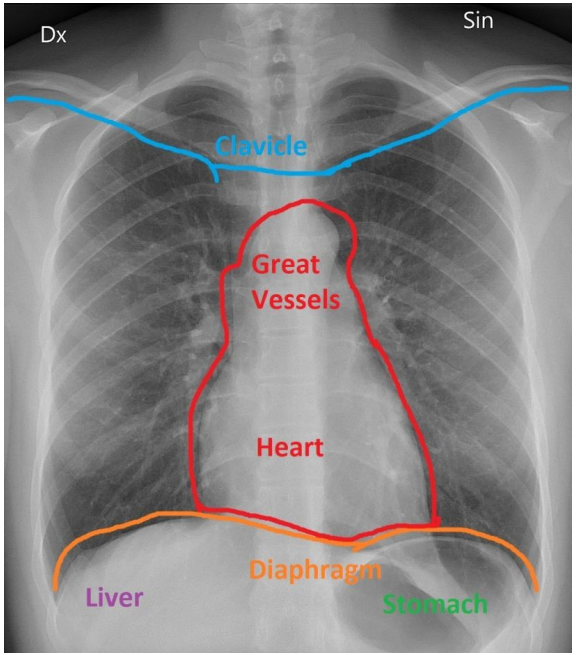


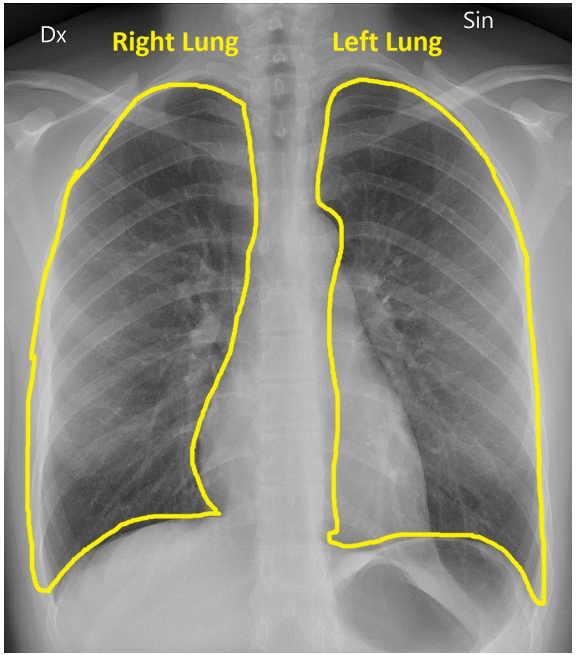
Image source: BL Kumawat
https://www.youtube.com/watch?v=eAZyNUhk25M

Image quality: PA > AP

- Heart size on the image is smaller
- Better inspiration → More air in lungs → Better contrast

CXR Anatomy





Source: Glass Box Medicine (Rachel Draelos, MD. PhD)
https://glassboxmedicine.com/2019/02/10/radiology-normal-chest-x-rays/

Examples of lesions visible on CXR

Image source: Radiopaedia
https://radiopaedia.org/cases/normal-cxr

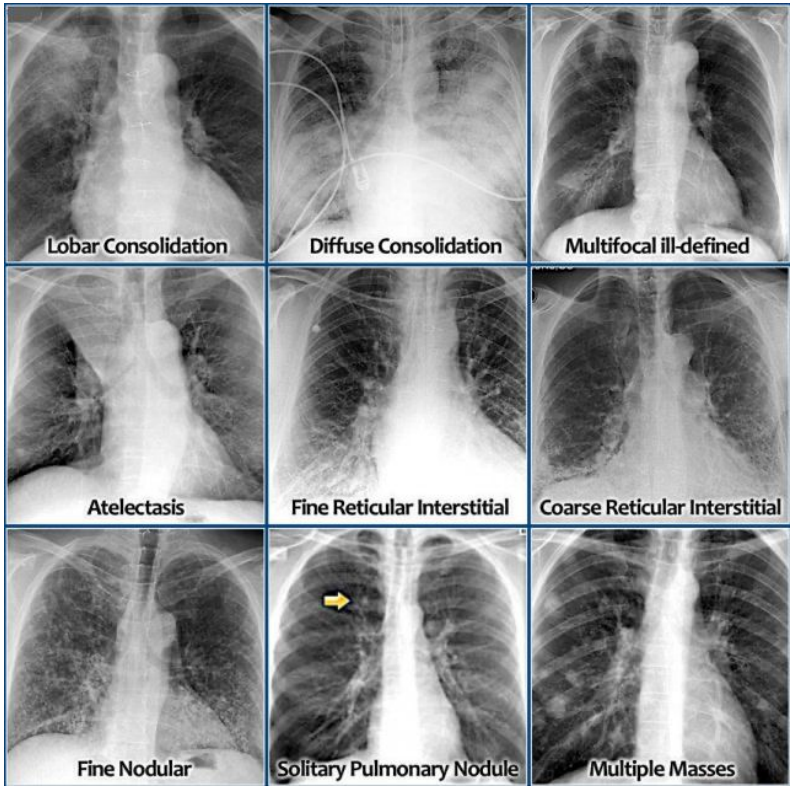


Image source: Radiology Assistant
https://radiologyassistant.nl/chest/chest-x-ray/lung-disease

Lung anatomy & pathology

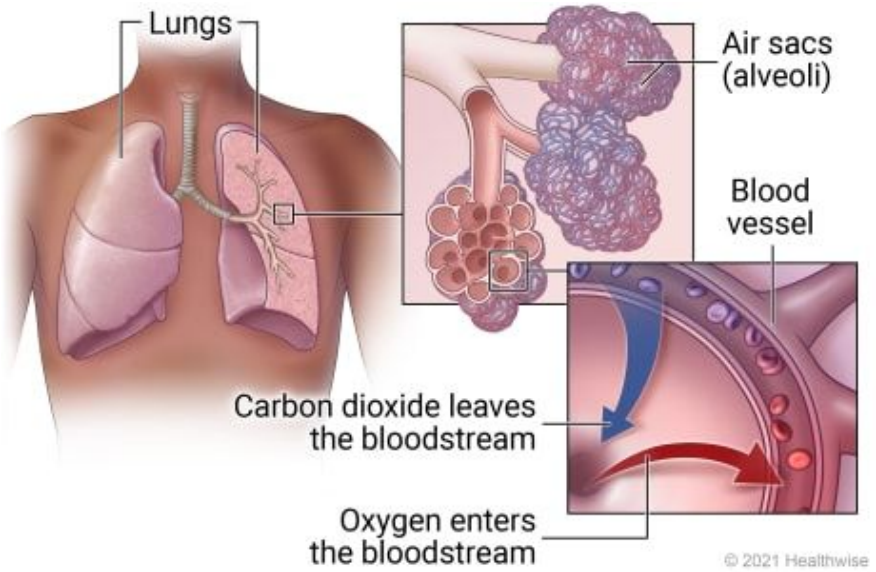


Image source: UVM Health Network
https://www.uhhospitals.org/health-information/health-and-wellness-library/article/adult-diseases-and-conditions-v0/anatomy-of-the-respiratory-system

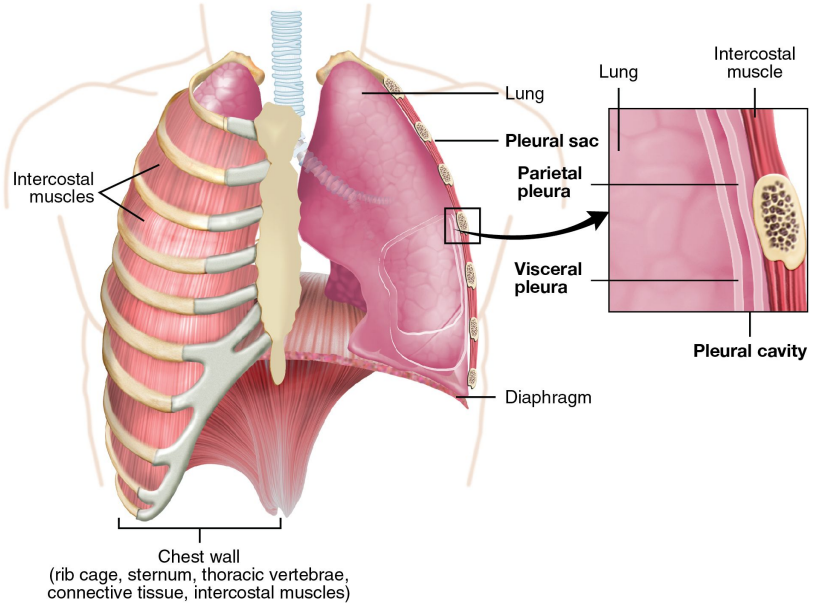


Image source: Anatomy & Physiology Connexions (through Wikipedia)
https://en.wikipedia.org/wiki/Pleural_cavity#/media/File:2313_The_Lung_Pleurea.jpg

Consolidation

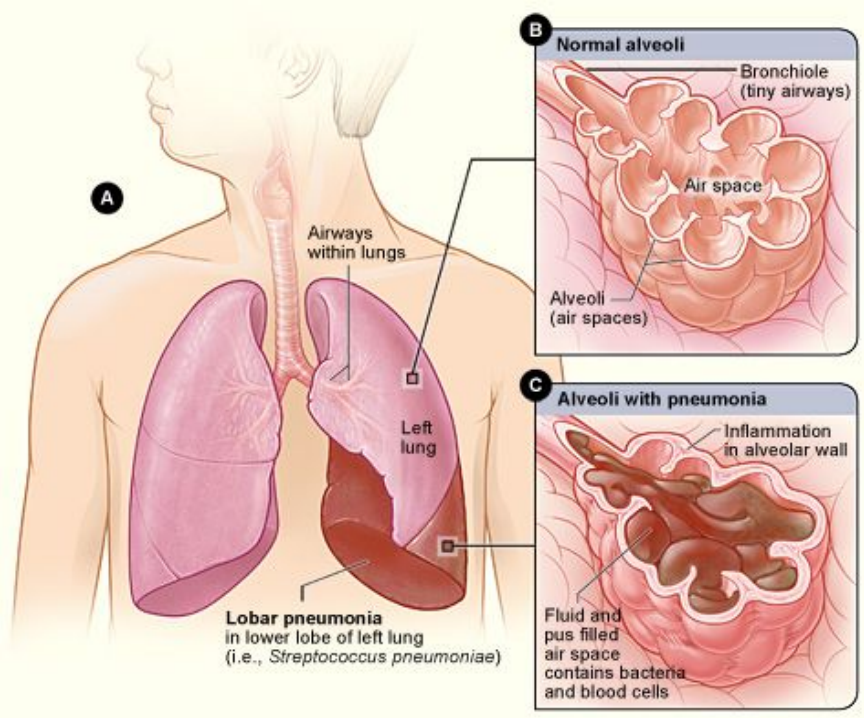


Image source: Heart, Lung and Blood Institute (through Wikipedia)
http://www.nhlbi.nih.gov/health/health-topics/topics/pnu/causes.html

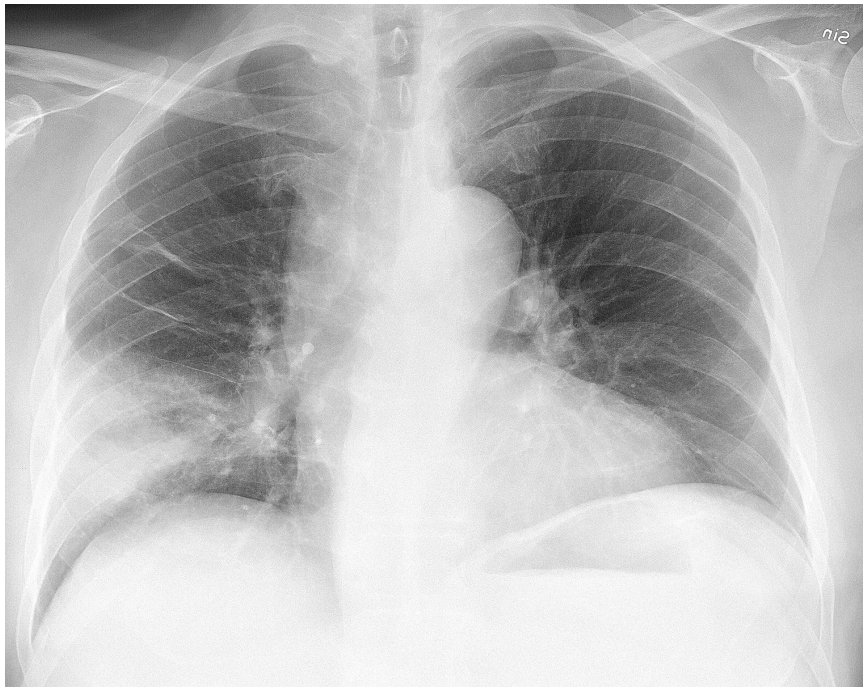
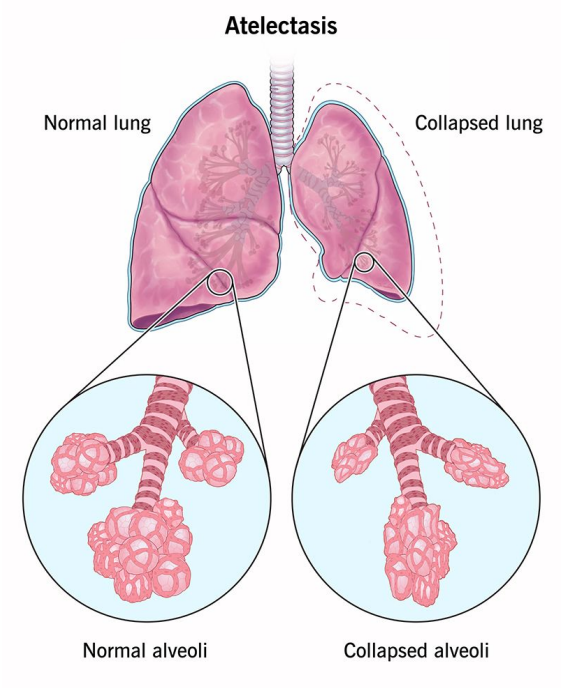


Image source: Mikael Haggstrom (through Wikipedia)
https://en.wikipedia.org/wiki/Lobar_pneumonia#/media/File:X-ray_of_lobar_pneumonia.jpg

Atelectasis



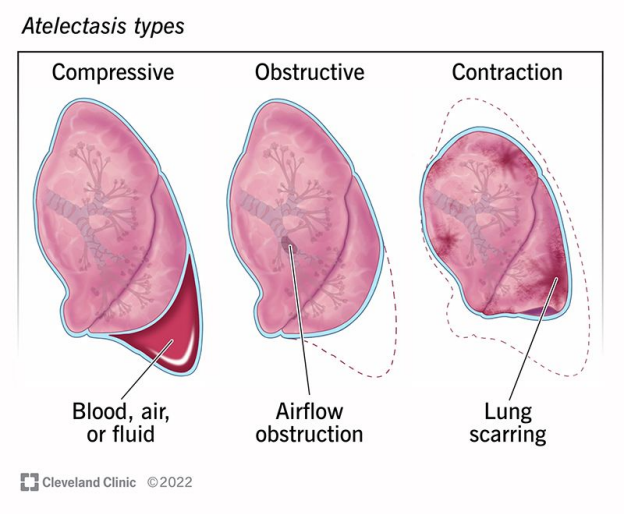


Image source: Cleveland Clinic
https://my.clevelandclinic.org/health/diseases/17699-atelectasis

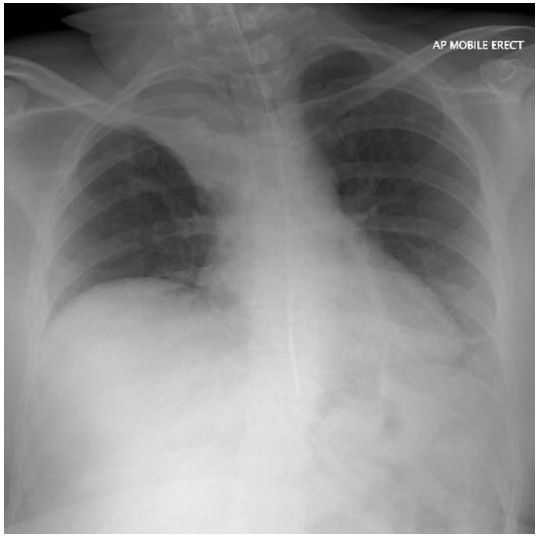


Image source: Radiopaedia
https://radiopaedia.org/articles/atelectasis-summary

Pleural Effusion

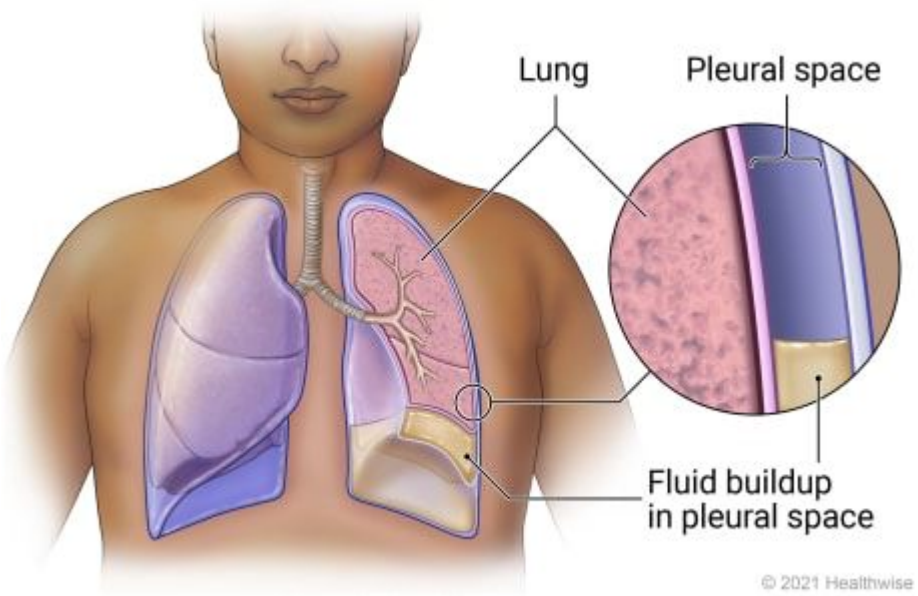


Image source: UVM Health
https://www.uvmhealth.org/healthwise/topic/tp13175

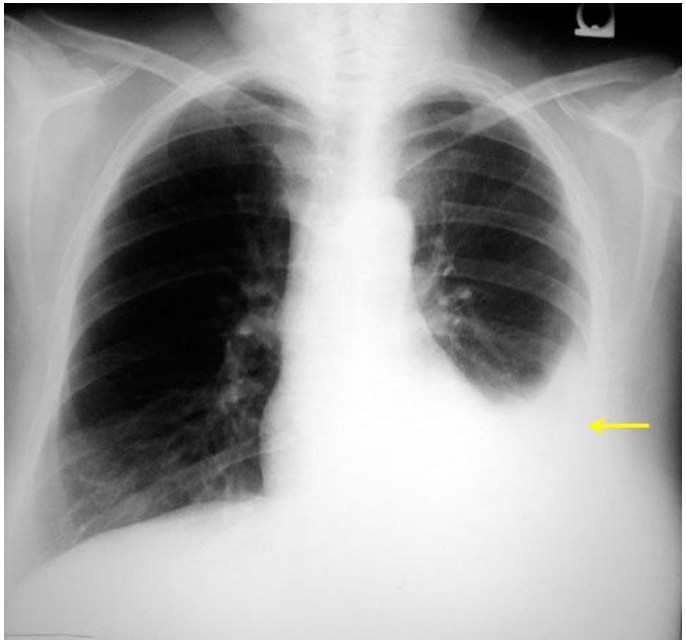


Image source: Arcot J. Chandrasekhar, MD
https://www.meddean.luc.edu/lumen/meded/radio/curriculum/medicine/pleural_effusion1.htm

Pneumothorax (Collapsed lung)

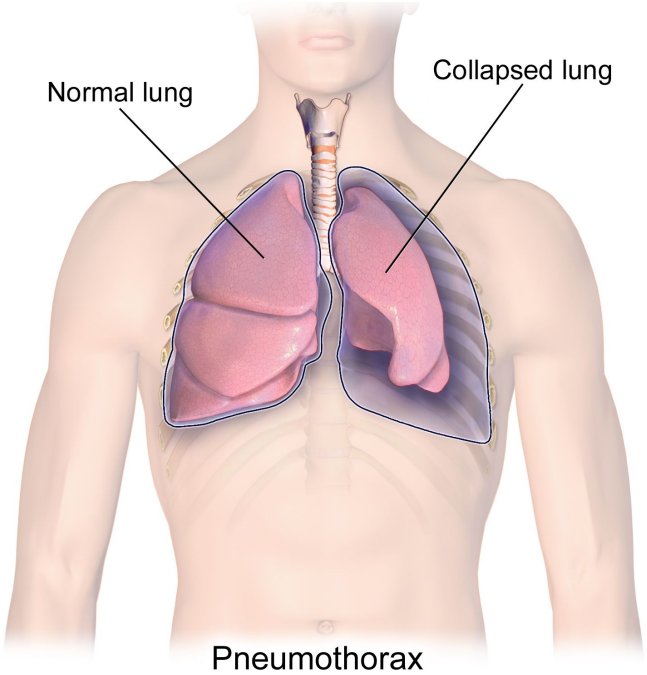


Image source: BruceBlaus
https://en.wikipedia.org/wiki/Pneumothorax#/media/File:Blausen_0742_Pneumothorax.png

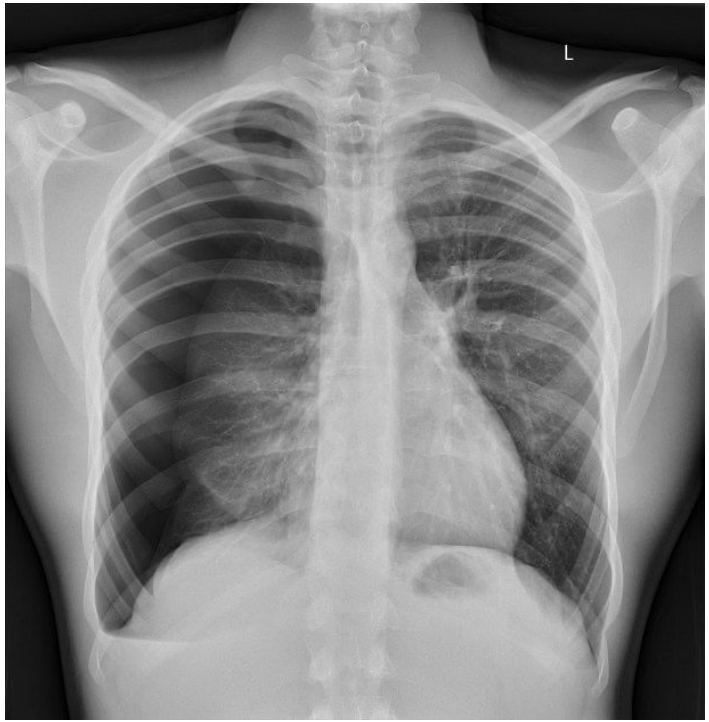


Image source: Radiopaedia
https://radiopaedia.org/articles/pneumothorax

Nodule/Mass (tumour)

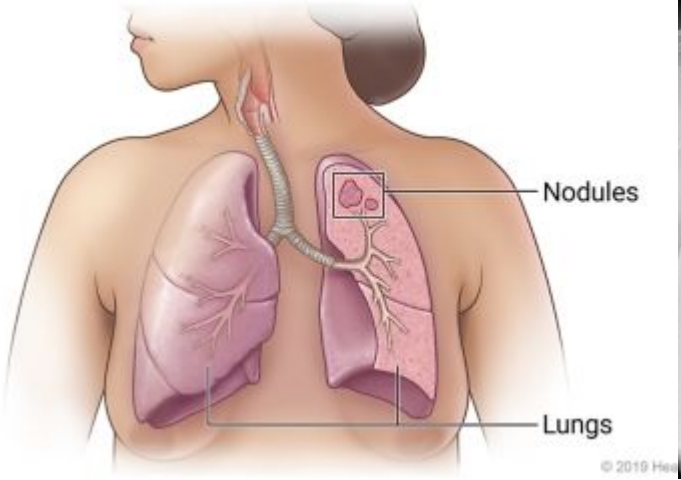


Image source: Kaiser Permanente
https://healthy.kaiserpermanente.org/health-wellness/health-encyclopedia/he.learning-about-lung-nodules.abp5538

Image source: Radiopaedia
https://radiopaedia.org/articles/solitary-pulmonary-nodule-an-approach

Image source: Radiopaedia
https://radiopaedia.org/articles/multiple-pulmonary-nodules-5-mm-differential-diagnosis

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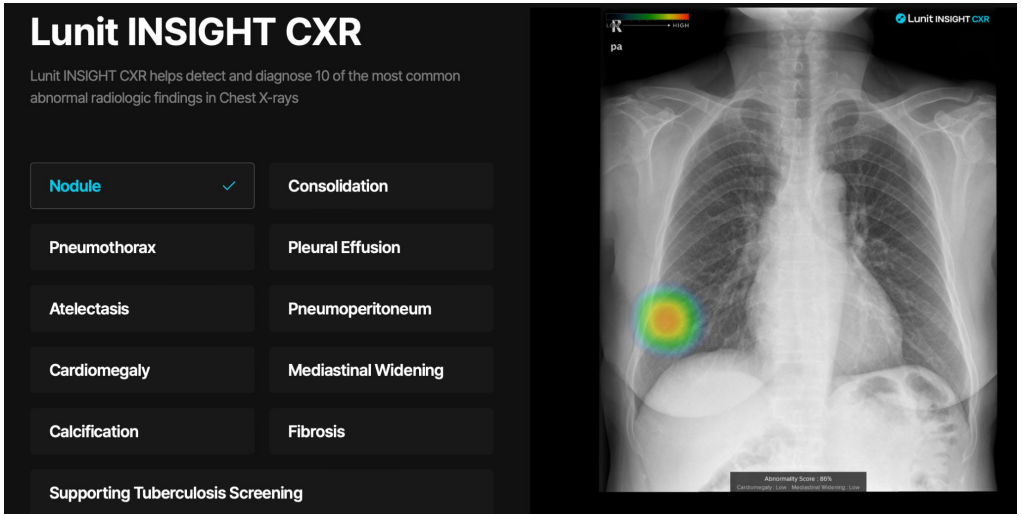
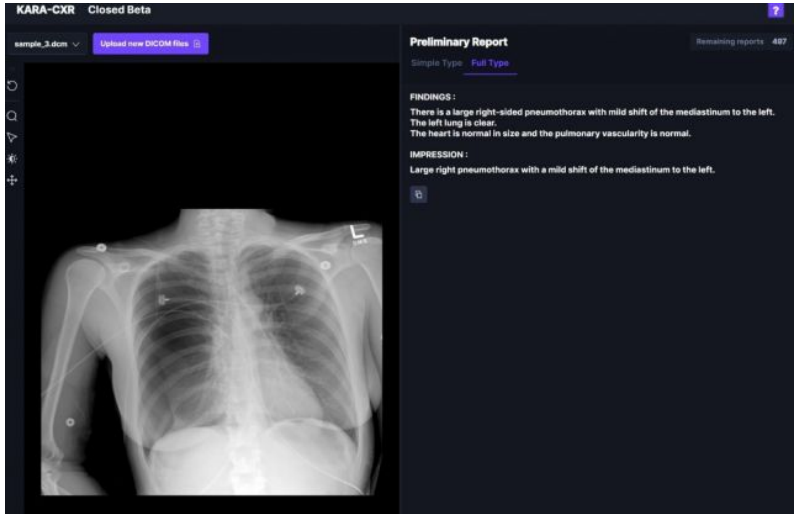
AI for CXR

Lunit Insight CXR



Detection & Localization

Kakao's Kara CXR



Natural language outputs

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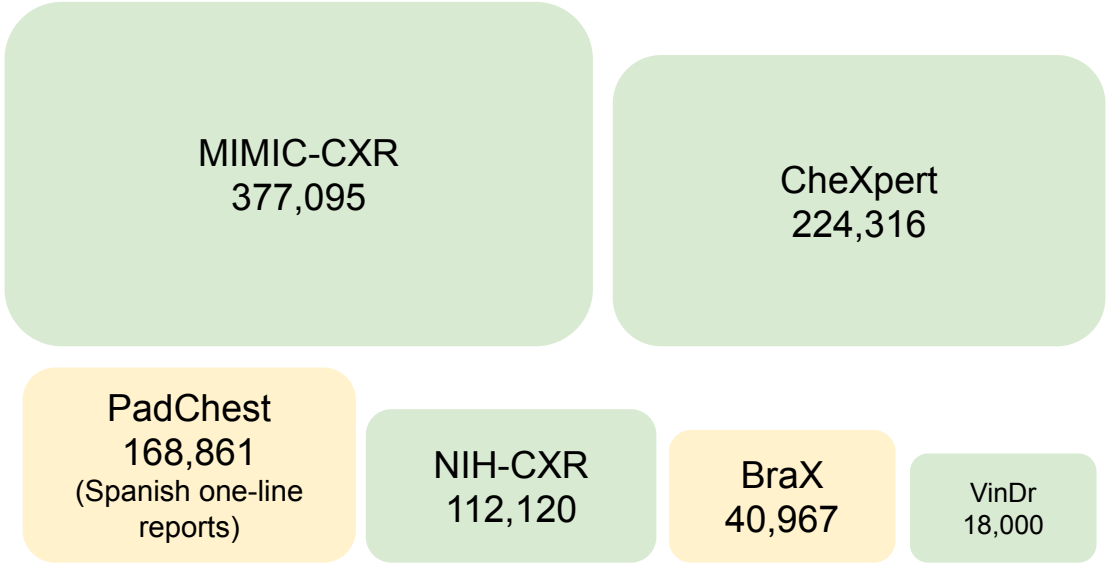
Open-source CXR datasets



DICOM files

```
Filename.........: ../input/stage_1_train_images/9f888f62-3d5b-49c5-aee2-e301c2f9604d.dcm
Storage type.....: 1.2.840.10008.5.1.4.1.1.7

Patient's name......: 9f888f62-3d5b-49c5-aee2-e301c2f9604d,
Patient id..........: 9f888f62-3d5b-49c5-aee2-e301c2f9604d
Patient's Age.......: 70
Patient's Sex.......: F
Modality............: CR
Body Part Examined..: CHEST
View Position.......: PA
Image size.......: 1024 x 1024, 122718 bytes
Pixel spacing....: ['0.168', '0.168']
```


```python
i = 1
num_to_plot = 5
for file_name in os.listdir('../input/stage_1_train_images/'):
    file_path = os.path.join('../input/stage_1_train_images/', file_name)
    dataset = pydicom.dcmread(file_path)
    show_dcm_info(dataset)
    plot_pixel_array(dataset)

    if i >= num_to_plot:
        break

    i += 1
```

Use the *pydicom* library
Useful resource:
https://www.kaggle.com/code/schlerp/getting-to-know-dicom-and-the-data

Reading in DICOM files

```
def show_dcm_info(dataset):
    print("Filename.........:", file_path)
    print("Storage type.....:", dataset.SOPClassUID)
    print()

    pat_name = dataset.PatientName
    display_name = pat_name.family_name + ", " + pat_name.given_name
    print("Patient's name......:", display_name)
    print("Patient id..........:", dataset.PatientID)
    print("Patient's Age.......:", dataset.PatientAge)
    print("Patient's Sex.......:", dataset.PatientSex)
    print("Modality............:", dataset.Modality)
    print("Body Part Examined..:", dataset.BodyPartExamined)
    print("View Position.......:", dataset.ViewPosition)

    if 'PixelData' in dataset:
        rows = int(dataset.Rows)
        cols = int(dataset.Columns)
        print("Image size.......: {rows:d} x {cols:d}, {size:d} bytes".format(
            rows=rows, cols=cols, size=len(dataset.PixelData)))
        if 'PixelSpacing' in dataset:
            print("Pixel spacing....:", dataset.PixelSpacing)
```

```
def plot_pixel_array(dataset, figsize=(10,10)):
    plt.figure(figsize=figsize)
    plt.imshow(dataset.pixel_array, cmap=plt.cm.bone)
    plt.show()
```

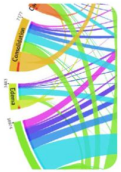
For our midterm project, use the **NIH-CXR** dataset from Kaggle

NATIONAL INSTITUTES OF HEALTH CHEST X-RAY
DATASET AND 1 COLLABORATOR · UPDATED 7 YEARS AGO

1231 | New Notebook | Download (45 GB)

NIH Chest X-rays

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



Data Card | Code (488) | Discussion (25) | Suggestions (0)

About Dataset

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.

Usability
7.35

License
CC0: Public Domain

Expected update frequency
Not specified

Tags

Computer Science | Health | Software | Biology | Health Conditions

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Midterm Project - CXR Classification

What you'll be given:

- Skeleton code for supervised training (including data loader for NIH-CXR) using a vision transformer model

Your task:

- Beat my model (which will be a basic supervised ViT) using the same architecture and training data.
- Strategy is up to you:
  - data augmentations
  - pre-training methods (e.g. DINO, MAE, I-JEPA, etc.)
  - Etc. (*get creative*)
- Please use the same model architecture and state_dict as the provided example
  - It's facebookresearch's DINO ViT-small architecture
- If you really wish to use a different model architecture, please email me :)

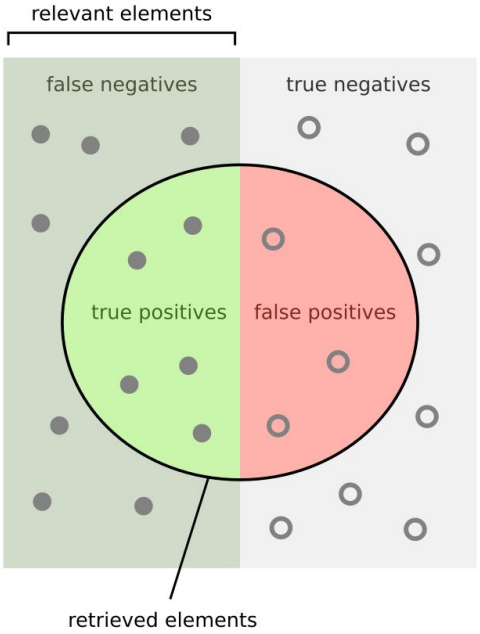
Few things of note

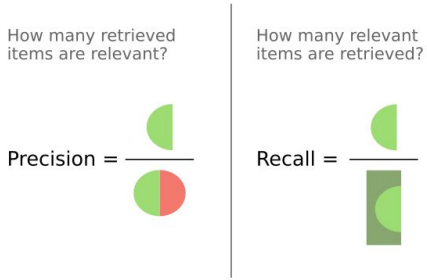
- CXR classification is a **multilabel** (not multiclass) classification
  - I.e., binary classification for each label. Different from n-way classification such as the ImageNet challenge.
  - So your output needs to be a vector with as many dimensions as target lesions
- CXR datasets are **imbalanced**
  - Dealing with this imbalance can be important for model performance
- Some lesions are harder to detect than others
  - For example, pleural effusion is easier than nodules
  - Lesions that are more easily visible for the human eye tend to be easier for machines to detect as well
- Different from natural images… as you will see
  - Lower inter-class variability (“label sharpness”)
  - Small, detailed features tend to be more important

How your model will be evaluated

F1-score for (1) Atelectasis, (2) Effusion, (3) Mass/Nodule

$$F_1 = \frac{2}{\mathrm{recall}^{-1} + \mathrm{precision}^{-1}} = 2\frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}} = \frac{2\mathrm{tp}}{2\mathrm{tp} + \mathrm{fp} + \mathrm{fn}}.$$





Contact

Contact me (Wonjun Kim) if you have any questions regarding the CXR classification project :)

wonjun@kaist.ac.kr