AXONN

Analyzing X-rays over Neural Networks

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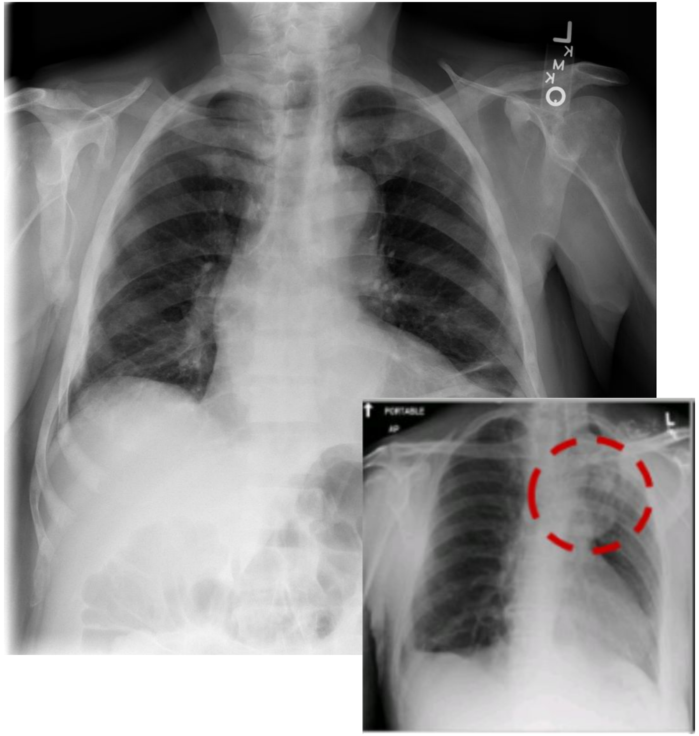
Outline

1. The 14 Pathologies
2. Exploring the Data
3. Data Management
4. The Neural Network
5. Results
6. Reflection

1. The 14 Pathologies



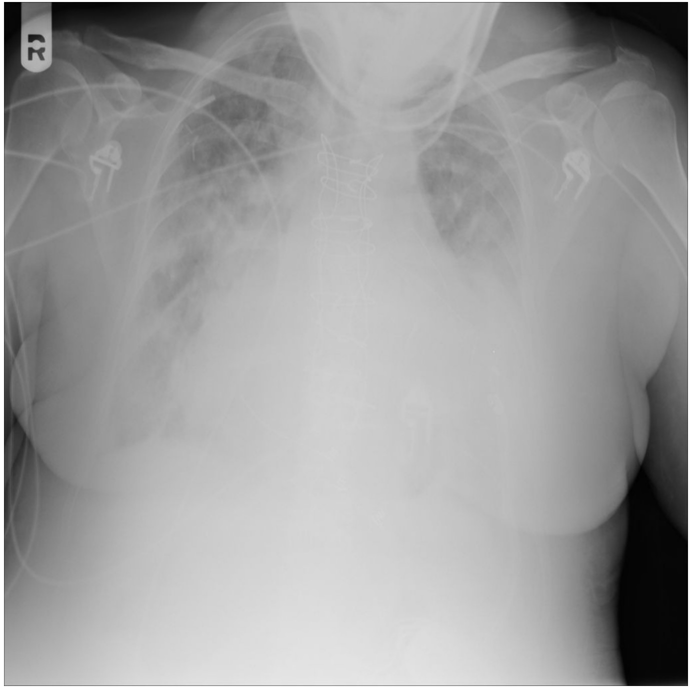
Atelectasis

Often called a **collapsed lung.**

Collapse of a part of the lung due to a decrease in the amount of air.

Findings can include:

- Volume loss and increased density.
- It is usually unilateral.
- Lung opacification and/or loss of lung volume .



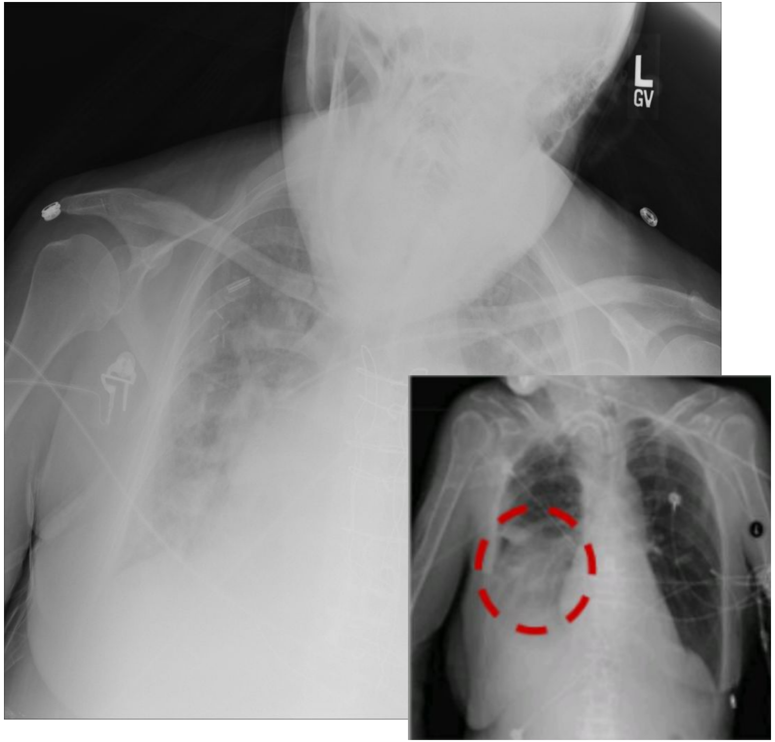
Pulmonary Consolidation

Region of lung tissue that has filled with liquid

Pneumonia is by far the most common cause of consolidation.

The key-findings on the X-ray are:

- Typically, an area of white lung is seen on a standard X-ray. Consolidated tissue is radio-opaque.
- No volume loss.

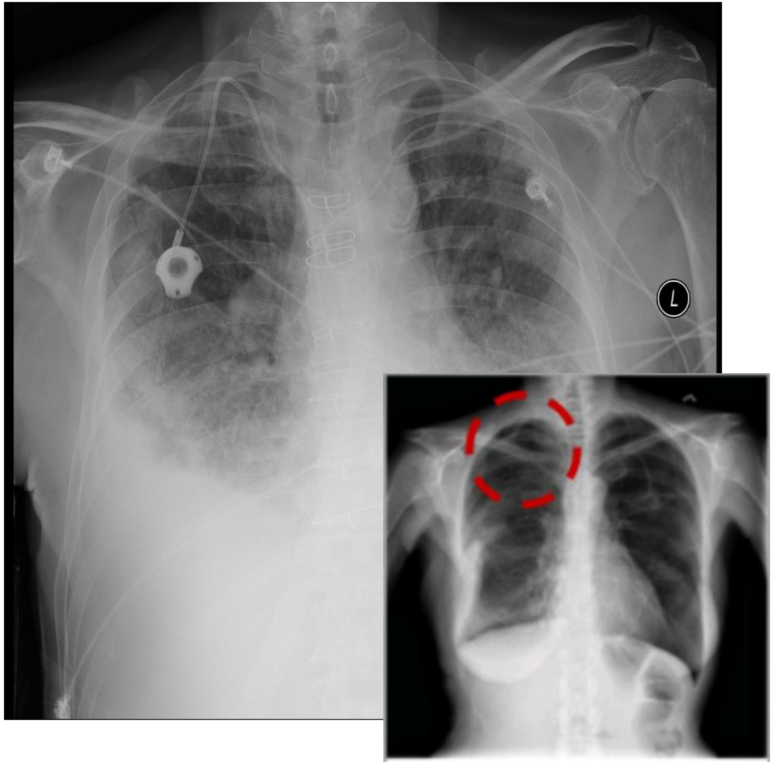


Infiltration

Substance denser than air, such as pus or blood, which lingers within the lungs.

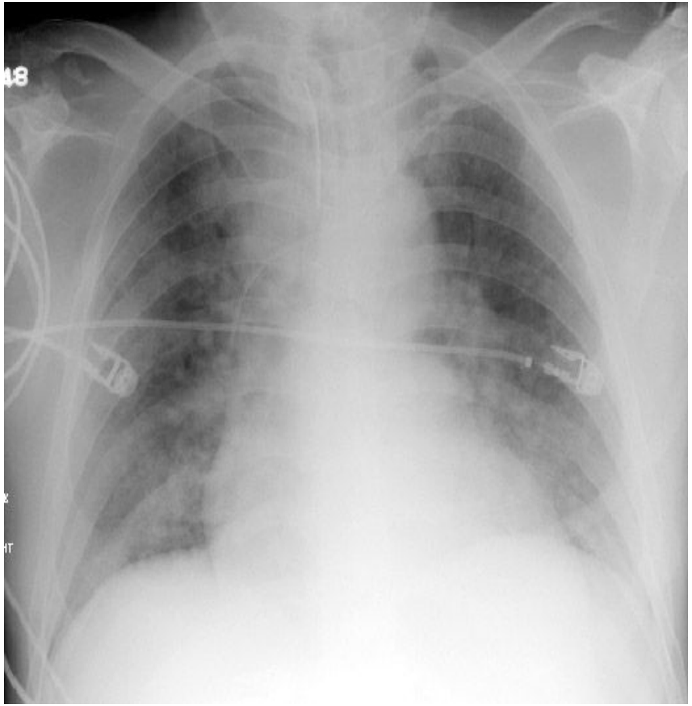
Pulmonary infiltrates are associated with pneumonia.

Pneumothorax



Presence of air within the pleural space.

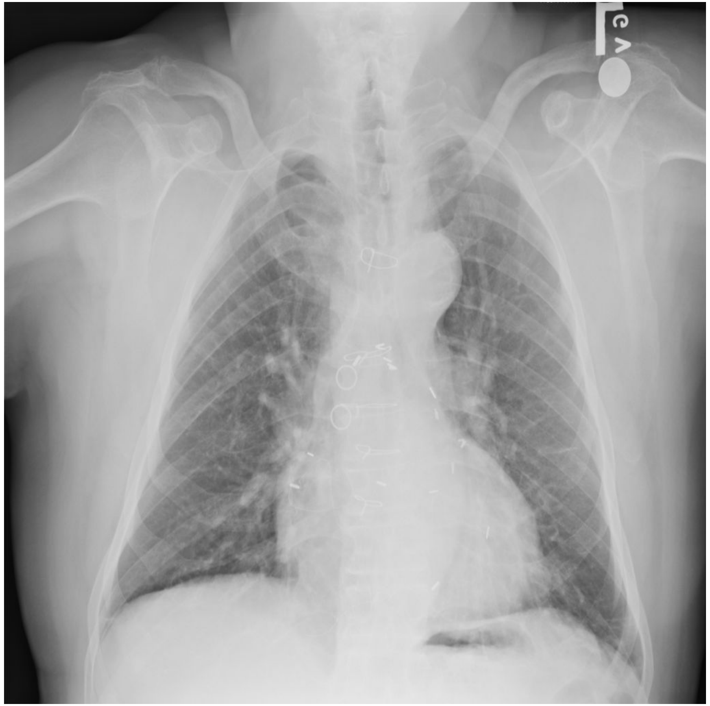
Appears as air without lung markings in the least dependant part of the chest .



Edema

Edema is caused by excess fluid in the lungs making it difficult to breathe.

X-rays shows an increased cardiac size.



Emphysema

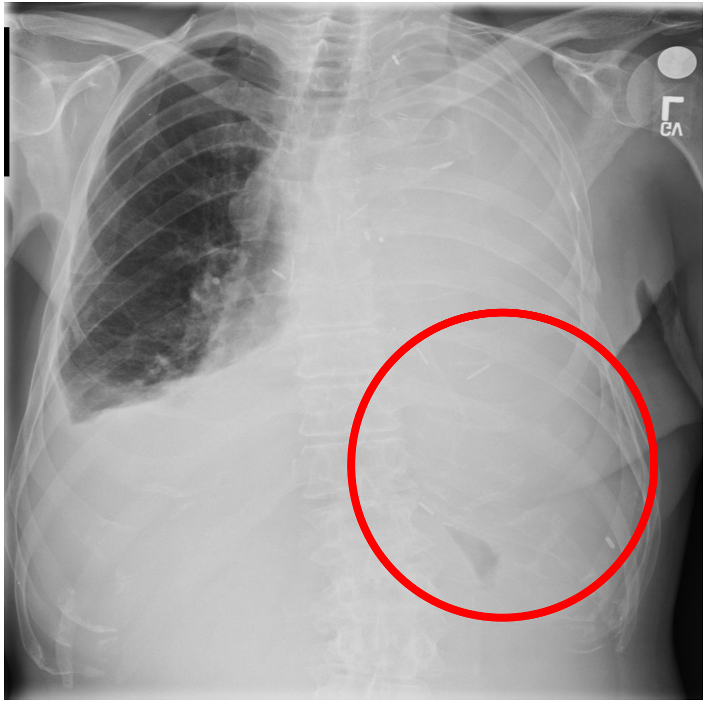
Normal lung tissue looks like a new sponge.

Emphysematous lung looks like an old used sponge, with large holes and a dramatic loss of “springy-ness” or elasticity.

Fibrosis

It causes net-like shadowing of the lung peripheries which is typically more prominent towards the lung bases

It may cause the contours of the heart to be less distinct or 'shaggy'

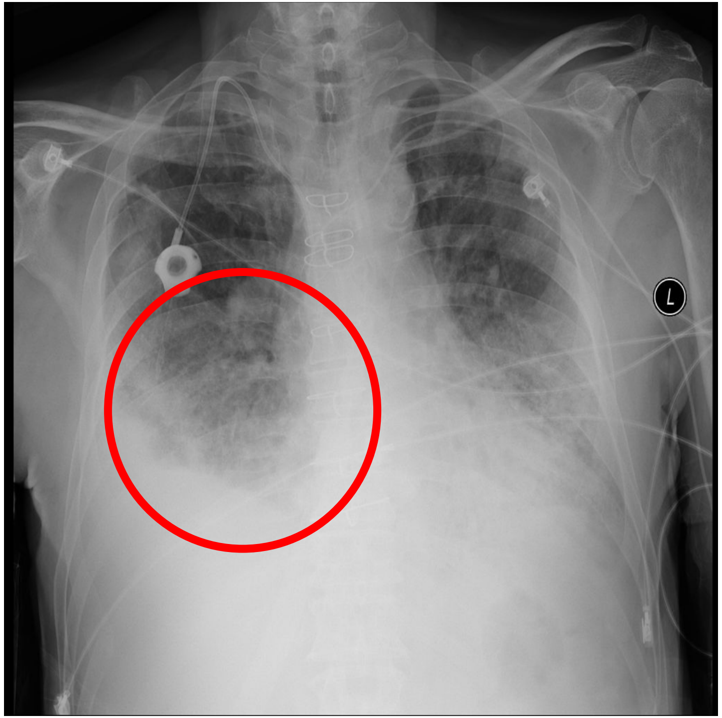


Effusion

An unusual amount of fluid around the lung.

Many medical conditions can lead to it, such as:

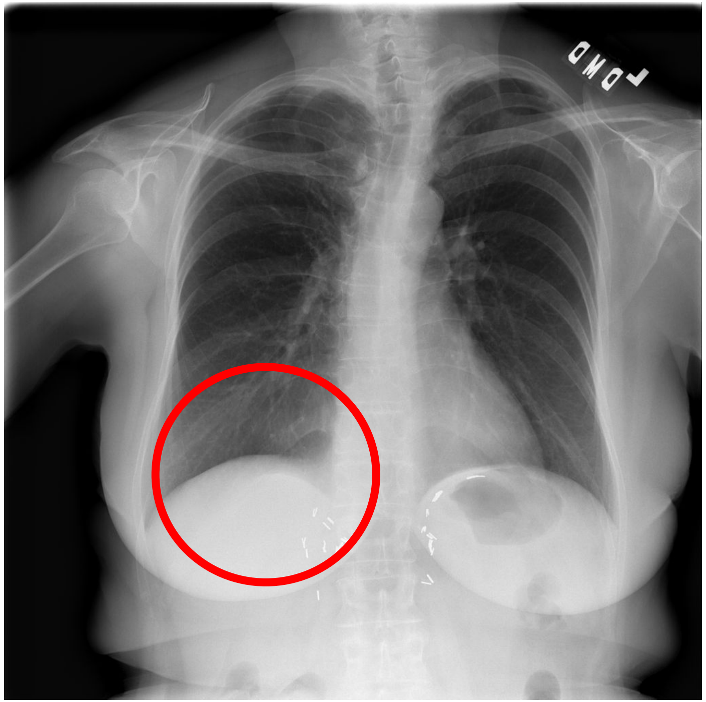
- Leakage from other organs
- Cancer
- Infections
- Autoimmune conditions
- Pulmonary embolism



Pneumonia

An inflammatory condition of the lung affecting primarily the small air sacs known as alveoli.

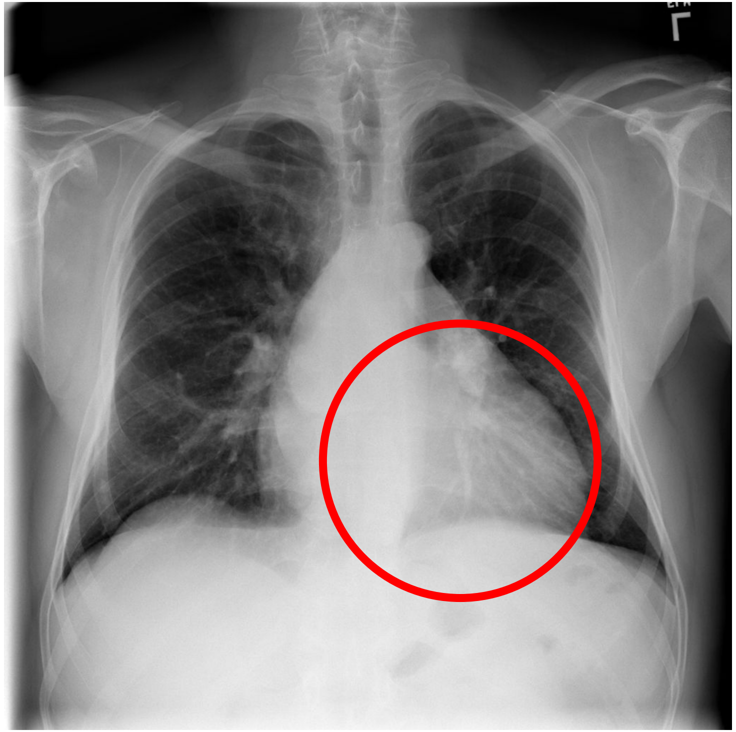
Usually caused by infection with viruses or bacteria and less commonly by other microorganisms, certain medications and conditions such as autoimmune diseases.



Pleural thickening

Extensive, often smooth scarring, thickens the pleural membrane lining the lungs and chest wall.

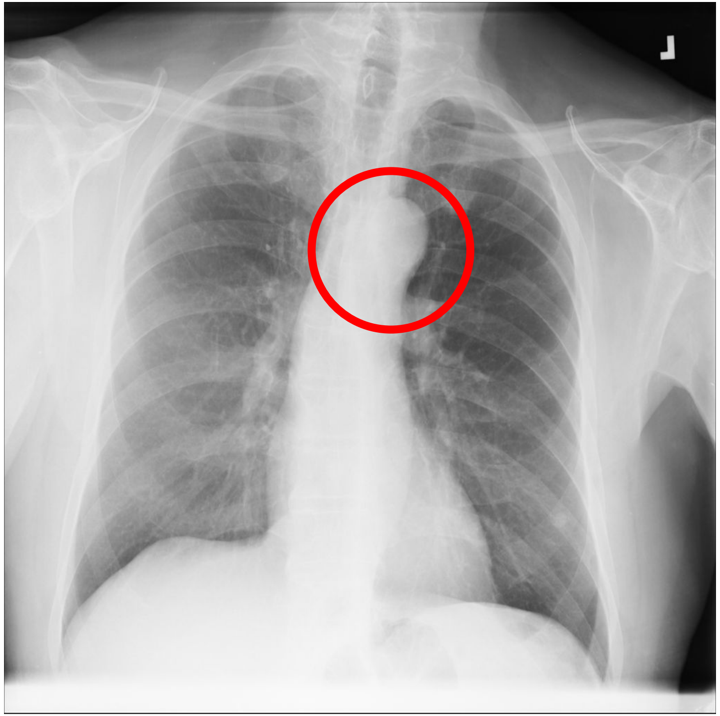
Usually caused by exposure to asbestos, other causes include infection, inflammatory disease and non-malignant pleural effusion.



Cardiomegaly

A medical condition in which the heart is enlarged.

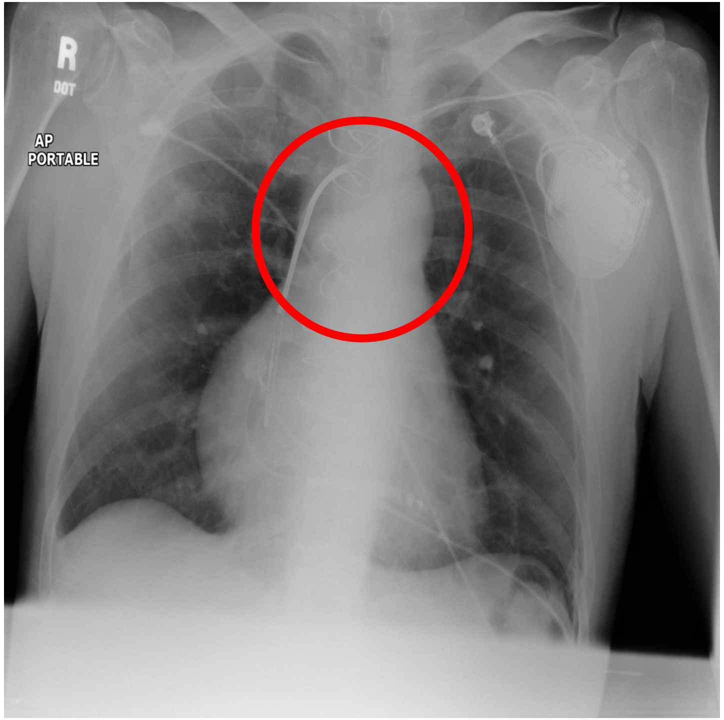
The causes of cardiomegaly may vary, however, many times this condition results from high blood pressure (hypertension) or coronary artery disease.



Nodule

A small round or oval-shaped growth in the lung. Pulmonary nodules are smaller than three centimeters in diameter.

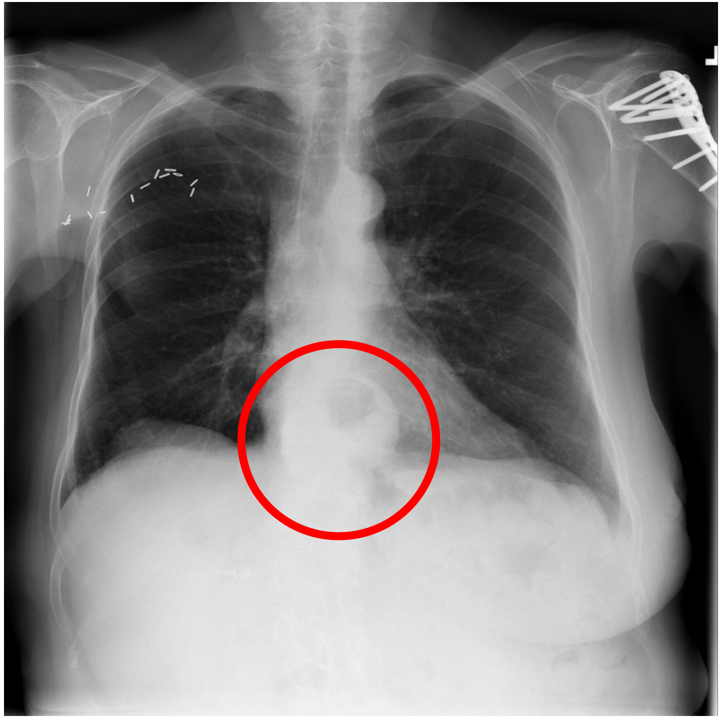
Nodules are the result of inflammation in the lung as a result of an infection or disease producing inflammation in the body.



Mass

A nodule can become mass if it is larger than three centimeters in diameter.

Causes are similar to the ones causing nodules.



Hernia

A hiatal hernia occurs when the upper part of the stomach pushes up through the diaphragm and into the chest region.

The exact cause is not known. In some people, injury or other damage may weaken muscle tissue. This makes it possible for the stomach to push through the diaphragm.

2. Exploring the Data

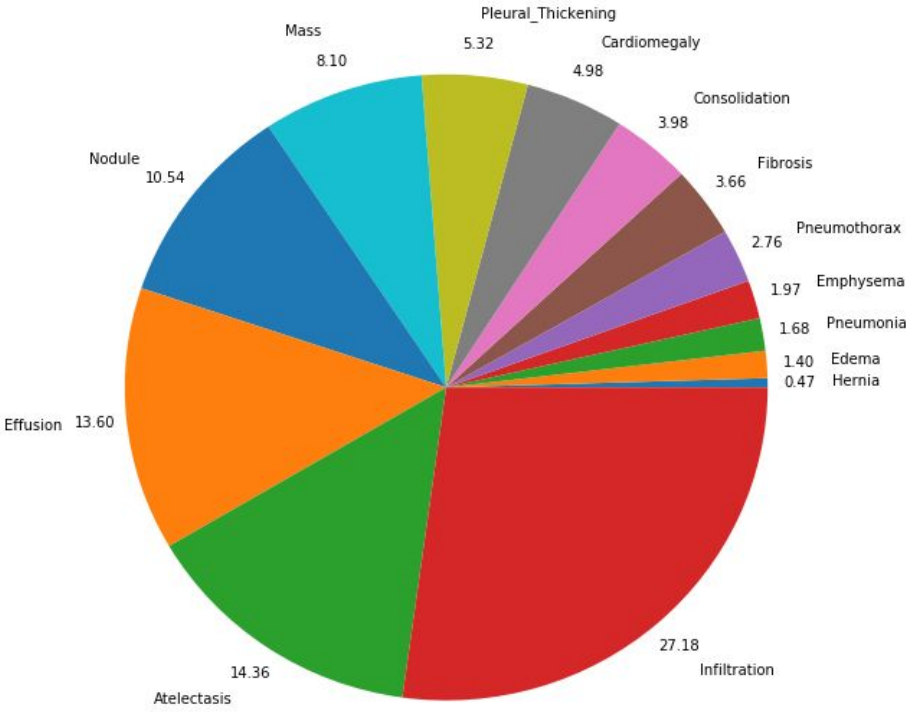


Fig. 1. Distribution of the pathologies among all the patients.

Male	47 years
Female	45 years

Average age

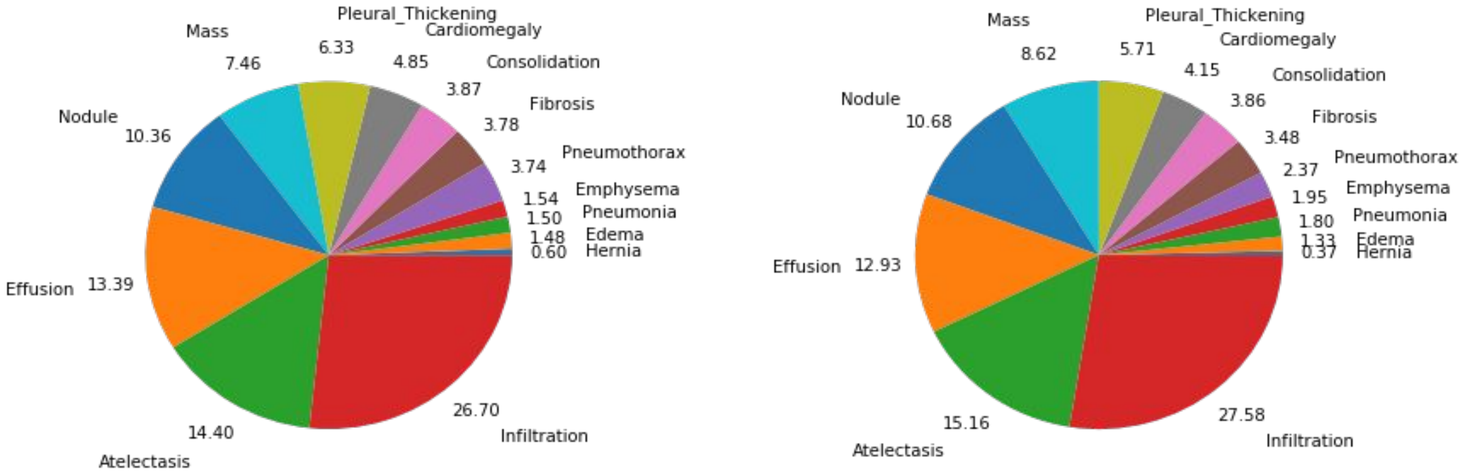


Fig. 2. Distribution of the pathologies among female patients (left) and male patients (right).

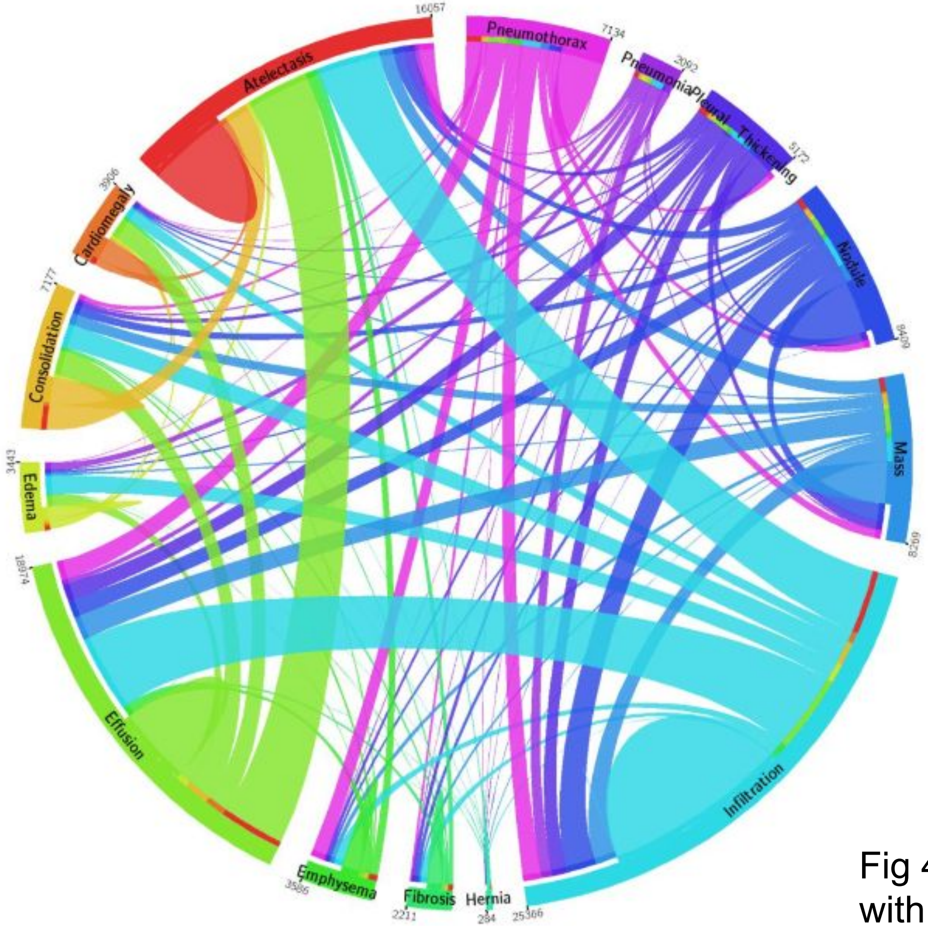


Fig 4. Distribution of 14 disease categories with co-occurrence statistics. Wang et. al.

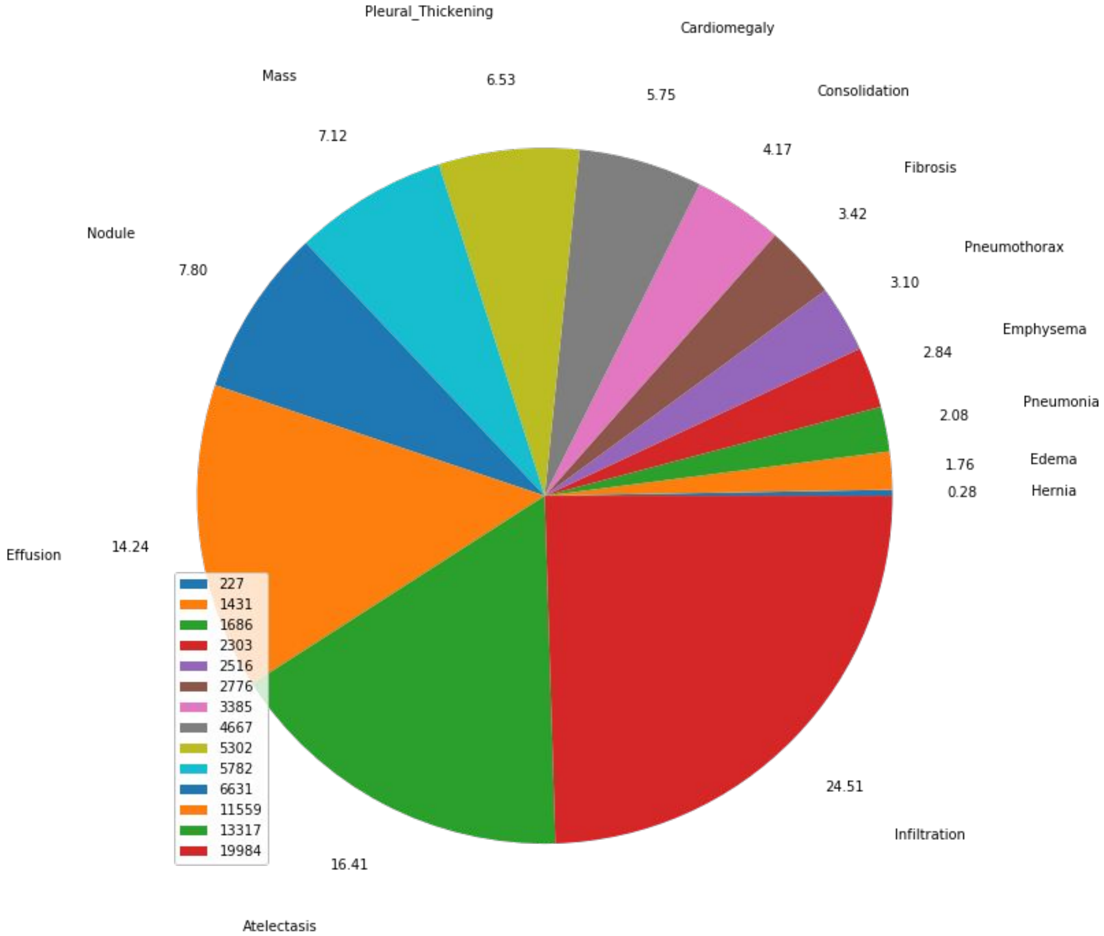


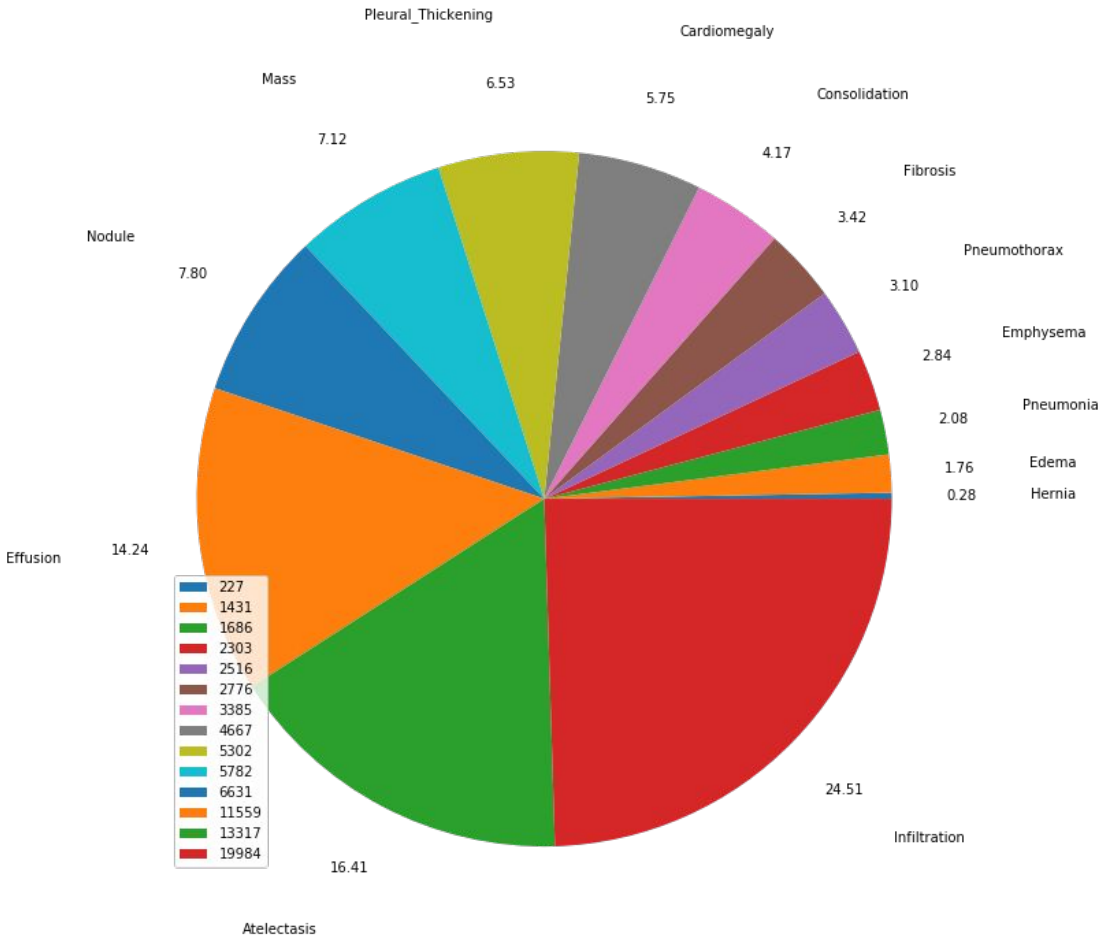
Fig. 3. Number of images per pathology over all the population.

20,796 Images with multiple pathologies (19%)

60,361 Images with No Finding (54%)

Correlations

Most Common Combinations	% of total images with multiple pathologies	Similarity (Accuracy test)
Effusion and Infiltration	8%	0.78
Atelectasis and Infiltration	7%	0.78
Atelectasis and Effusion	7%	0.84
Infiltration and Nodule	4%	0.79
Pneumonia and Consolidation	0.2%	0.95



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3. Data Management

The data

112,120
X-ray Images

117 GB
of data

The images

1024 x 1024
Some Grayscale, some RGB

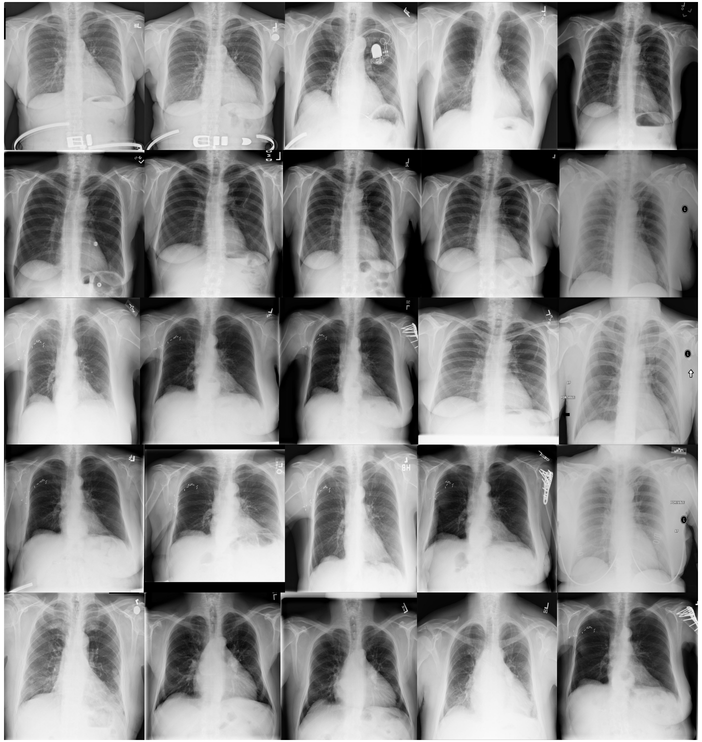
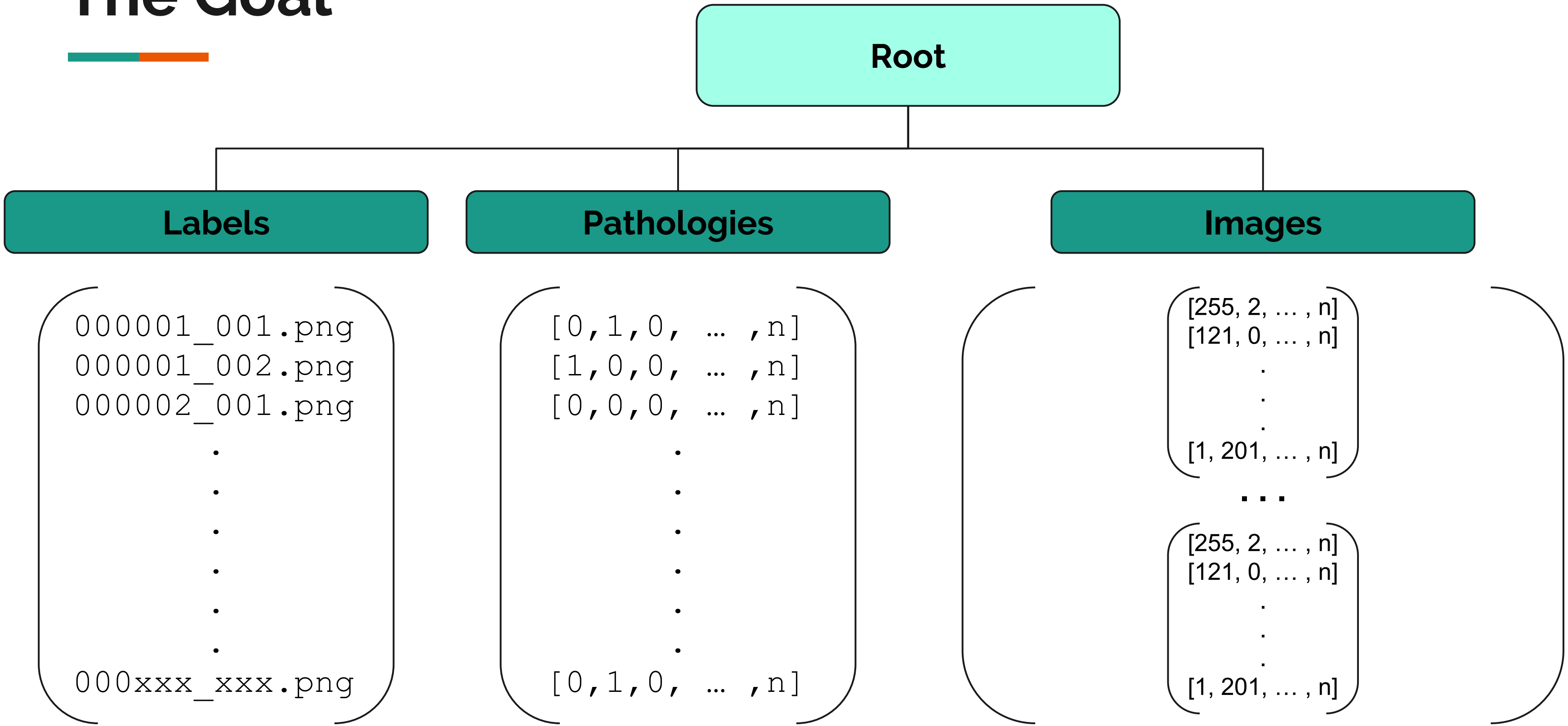


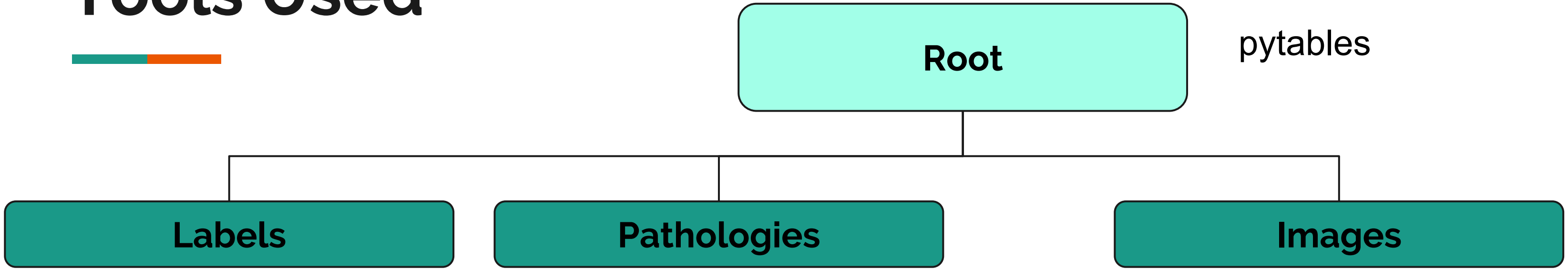
Image Index	Finding Labels	Follow-up #	Patient ID	Patient Age	Patient Genc	View Positio	OriginalImag	Height]	OriginalImag	y]
00000001_000.png	Cardiomegaly	0	1	58	M	PA	2682	2749	0.143	0.143
00000001_001.png	Cardiomegaly|Emphysema	1	1	58	M	PA	2894	2729	0.143	0.143
00000001_002.png	Cardiomegaly|Effusion	2	1	58	M	PA	2500	2048	0.168	0.168
00000002_000.png	No Finding	0	2	81	M	PA	2500	2048	0.171	0.171
00000003_000.png	Hernia	0	3	81	F	PA	2582	2991	0.143	0.143
00000003_001.png	Hernia	1	3	74	F	PA	2500	2048	0.168	0.168
00000003_002.png	Hernia	2	3	75	F	PA	2048	2500	0.168	0.168
00000003_003.png	Hernia|Infiltration	3	3	76	F	PA	2698	2991	0.143	0.143
00000003_004.png	Hernia	4	3	77	F	PA	2500	2048	0.168	0.168
00000003_005.png	Hernia	5	3	78	F	PA	2686	2991	0.143	0.143
00000003_006.png	Hernia	6	3	79	F	PA	2992	2991	0.143	0.143
00000003_007.png	Hernia	7	3	80	F	PA	2582	2905	0.143	0.143
00000004_000.png	Mass|Nodule	0	4	82	M	AP	2500	2048	0.168	0.168
00000005_000.png	No Finding	0	5	69	F	PA	2048	2500	0.168	0.168
00000005_001.png	No Finding	1	5	69	F	AP	2500	2048	0.168	0.168
00000005_002.png	No Finding	2	5	69	F	AP	2500	2048	0.168	0.168
00000005_003.png	No Finding	3	5	69	F	PA	2992	2991	0.143	0.143
00000005_004.png	No Finding	4	5	70	F	PA	2986	2991	0.143	0.143
00000005_005.png	No Finding	5	5	70	F	PA	2514	2991	0.143	0.143
00000005_006.png	Infiltration	6	5	70	F	PA	2992	2991	0.143	0.143
00000005_007.png	Effusion|Infiltration	7	5	70	F	PA	2566	2681	0.143	0.143
00000006_000.png	No Finding	0	6	81	M	PA	2500	2048	0.168	0.168
00000007_000.png	No Finding	0	7	82	M	PA	2500	2048	0.168	0.168
00000008_000.png	Cardiomegaly	0	8	69	F	PA	2048	2500	0.171	0.171
00000008_001.png	No Finding	1	8	70	F	PA	2048	2500	0.171	0.171
00000008_002.png	Nodule	2	8	73	F	PA	2048	2500	0.168	0.168
00000009_000.png	Emphysema	0	9	73	M	PA	2992	2991	0.143	0.143
00000010_000.png	Infiltration	0	10	84	F	PA	2992	2991	0.143	0.143
00000011_000.png	Effusion	0	11	75	M	PA	2638	2449	0.143	0.143
00000011_001.png	No Finding	1	11	75	M	PA	2500	2048	0.168	0.168
00000011_002.png	No Finding	2	11	75	M	PA	2714	2781	0.143	0.143
00000011_003.png	No Finding	3	11	75	M	PA	2500	2048	0.168	0.168
00000011_004.png	No Finding	4	11	75	M	PA	2500	2048	0.168	0.168
00000011_005.png	Infiltration	5	11	75	M	AP	2500	2048	0.168	0.168
00000011_006.png	Atelectasis	6	11	75	M	PA	2992	2991	0.143	0.143

Finding Labels — e.g. Cardiomegaly | Effusion | Hernia

The Goal


Root
Labels
Pathologies
Images
000001_001.png
000001_002.png
000002_001.png
000xxx_xxx.png
[0,1,0, … ,n]
[1,0,0, … ,n]
[0,0,0, … ,n]
[0,1,0, … ,n]
[255, 2, … , n]
[121, 0, … , n]
[1, 201, … , n]
[255, 2, … , n]
[121, 0, … , n]
[1, 201, … , n]

Tools Used



pytables

glob

Excel
pandas

glob
scikit image

Pseudo Code

```
create HDF5 file using pytables

initialize directories for labels, pathologies, and images

def import_labels(filepath) :
     append label

def import_pathologies(filepath) :
     append pathologies array

def import_images(filepath) :
     append 2D image array
```

Results

117 GB

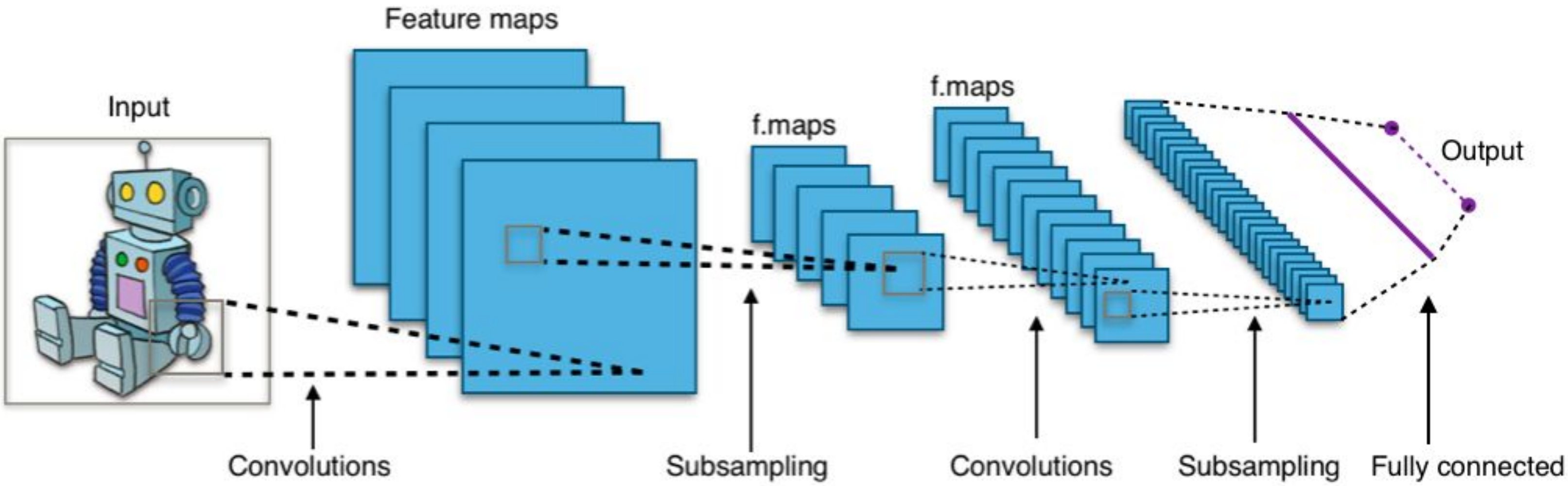
HDF5 File

4. The Neural Network

Convolutional Neural Networks

- State of the art for image recognition.
- Exploit spatial alignment of features through convolutions.
- Faster to train than MLP.
- Usually followed by a maxpooling layer (chooses the maximum of n Pixels) , to reduce complexity.
- After the convolutional part, usually dense layers follow.

Convolutional Neural Networks



Our approach

- Images as input, pathology vector as output
- Relu functions as activation functions for all layers except the last one
- Sigmoid activation function for last layer
- Categorical crosentropy as loss function $H(p,q) = -\sum_x p(x) ln(q(x))$
- As many layers as possible
- Maybe use a pretrained Network

Complications

- Pretrained network not feasible due to timing constraints (5 hours training time for 1000 examples)
- False results due to many false negative results
  - Change the input data not to overrepresent images without pathologies
  - Change the loss function to make bigger steps when encountering pathologies
- Huge images won’t fit into RAM all at once

5. Results

Results for (rather) shallow CNN

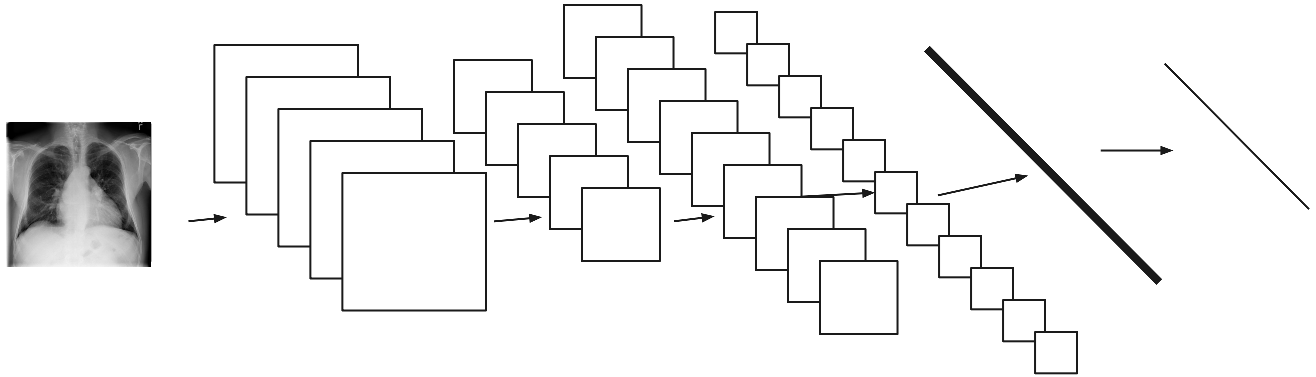
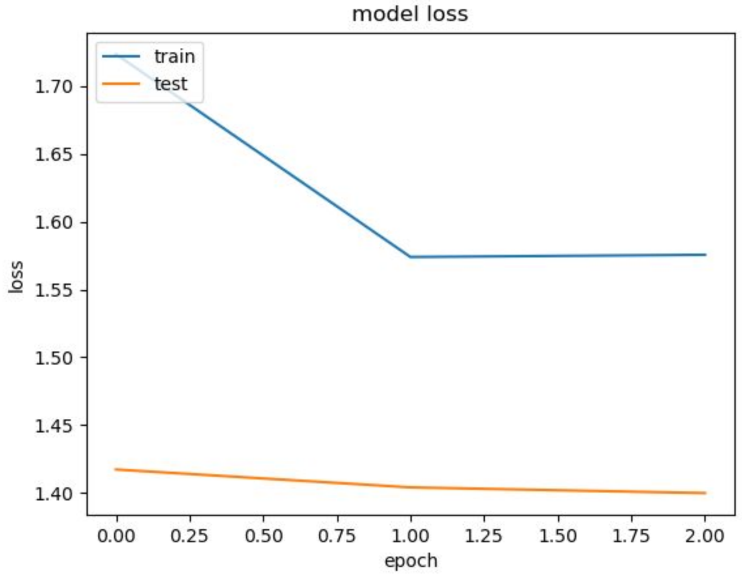


Image Conv (3x3) Max (4x4) Conv (3x3) Max (2x2) Dense (100) Dense (14)

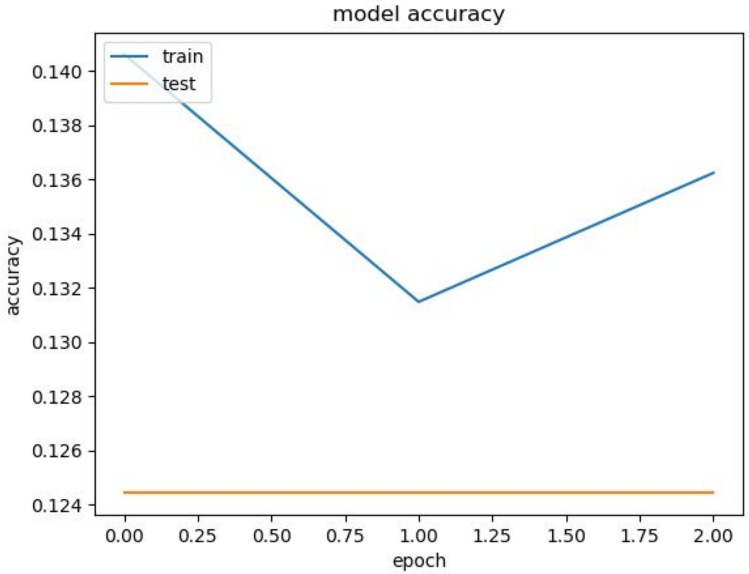
Results

- 3 Epochs
- 8000 training images
- 2000 test images
- Training time of 10 hours
- Test Accuracy: 0.1244
- Test Loss: 1.399 (Categorical Crossentropy)

Results



model loss
train
test
1.70
1.65
1.60
1.55
1.50
1.45
1.40
loss
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
epoch



model accuracy
train
test
0.140
0.138
0.136
0.134
0.132
0.130
0.128
0.126
0.124
accuracy
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
epoch

6. Reflection

Outlook

- Find meaningful statistics to evaluate binary distributions
- Find more efficient packages for converting large batches of images
- More training time is required for images with this size
- The results might be improved with a pretrained network
- Use either another loss function or use different training data to reduce false negative error
- More RAM for bigger batches

Conclusion

- With big databases comes big training time
- Computer aided diagnosis models might help radiologists pretty soon
  - Trained professional will still be required
- A lot of RAM is a must when training on big images