Deep learning in Medical Image Analysis

Lecture 6

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Recap

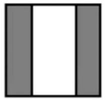
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

$*$

1	0	-1
1	0	-1
1	0	-1

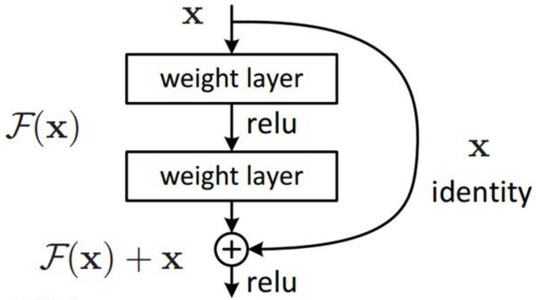
$=$

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0



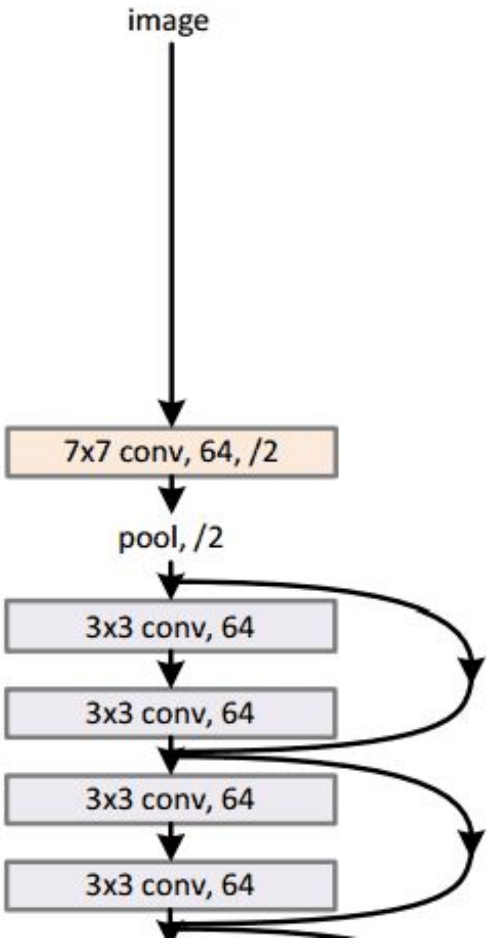
3	0	1	2	7	4
1	5	8	9	3	1
2	7	2	5	1	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9



A residual block

34-layer residual



Agenda

1. Classification
2. Segmentation
3. Object detection (localization)
4. Landmark detection
5. Image Generation
6. Quiz

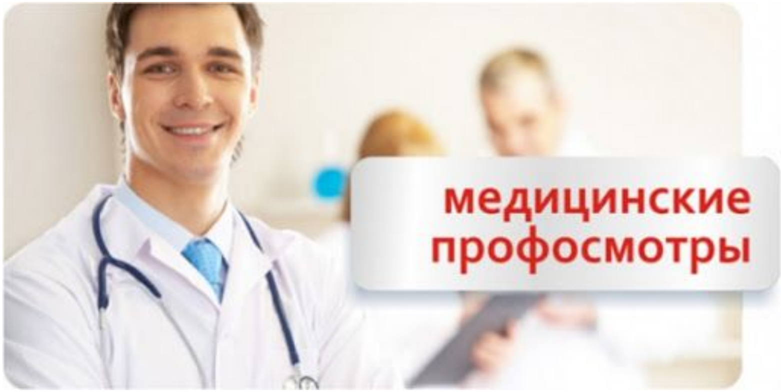
a. Medical need & Examples of applications
b. Input and output formats
c. Relevant datasets
d. DL formalization of the problem

P.S. mostly focusing on 2D chest X-rays in this lecture, keep in mind that all of this concepts are easily transferred to other study modalities

Classification

Medical need

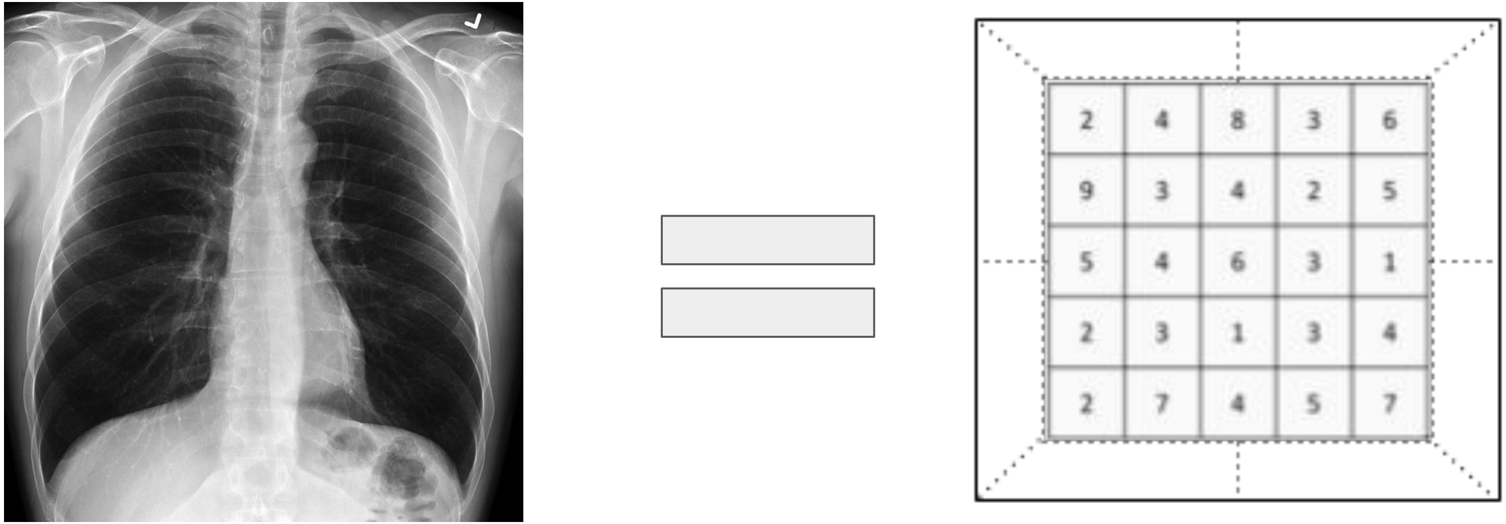
- Discovery of lung pathologies during annual health-check



- X-ray analysis in the districts where the qualified doctors are not available

Input format

Chest X-ray image = a 2D array of of shape (H,W,1)



Output format

Pathology **title**→

single number representing→ the **code** of pathology

Vector representing the **code** (one-hot encoding of the code)

Pahtology	Code	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Atelectasis	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cardiomegaly	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Consolidation	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Edema	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Effusion	4	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Emphysema	5	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Fibrosis	6	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Hernia	7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Infiltration	8	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Mass	9	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
No Finding	10	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Nodule	11	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Pleural_Thickening	12	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Pneumonia	13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Pneumothorax	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Code representing pathology

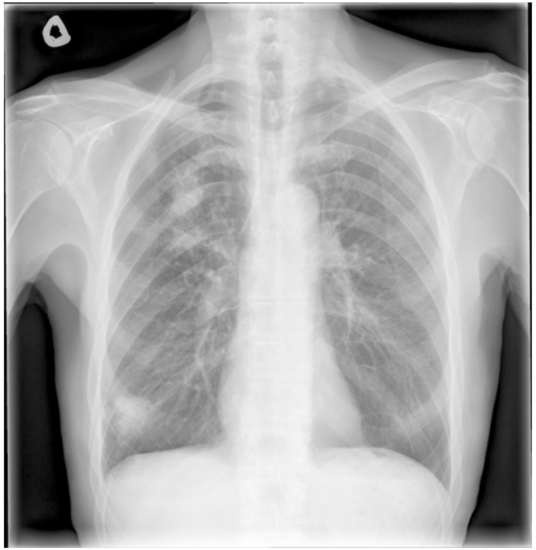
Vector representing pathology (One-hot encoding of the code)

X-ray classification datasets

Link	# of samples	access	Annotation method	annotation type
Chest14	112k	public	NLP	pathology presence
CheXpert	220k	by request,	manually	pathology presence
MIMIC-CXR	370k	by request,	manually	Semi-structured reports
PADchest	160k	public	27% manually / 73% NLP	pathology presence

X-ray classification datasets: PADchest example

PA



L

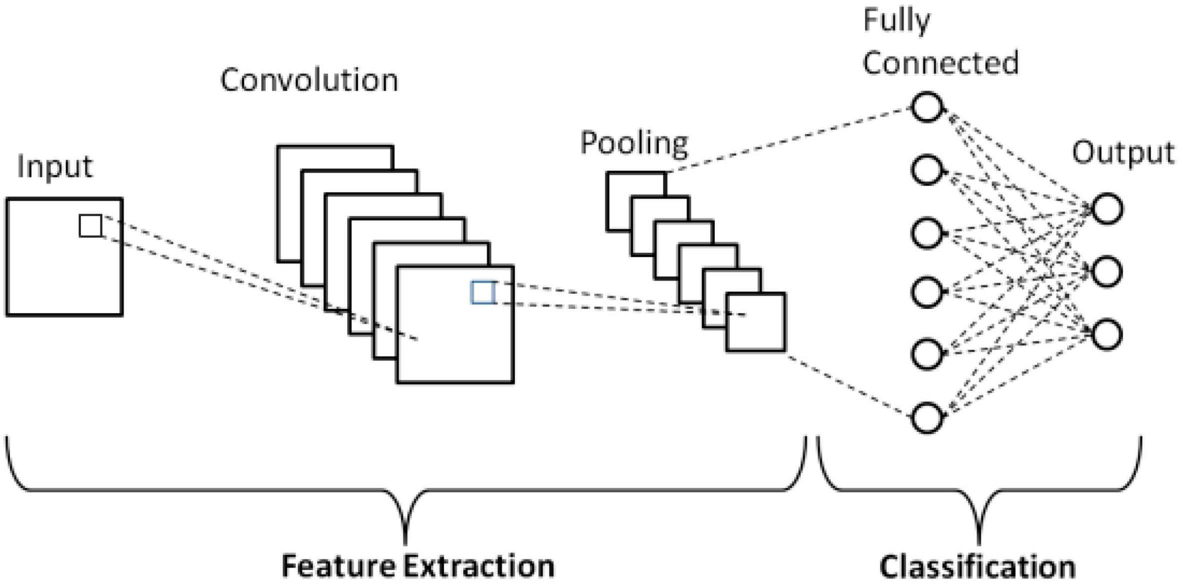
Labels ['pneumothorax', 'pulmonary mass']
Localizations ['loc apical', 'loc right']
LabelsLocalizationsBySentence ['pneumothorax', 'loc apical', 'loc right', 'pulmonary mass', 'loc right']
labelCUIS ['C2073565' 'C0149726']
LocalizationsCUIS ['C0734296' 'C0444532']

DL formalization

Input tensor shape: **(Height,Width,Channels)**

Output tensor shape: **(# of pathologies, 1)**

Architecture



DL formalization

Reason → Final activation → Loss

Multiple pathologies → **Sigmoid activation** → **Binary cross-entropy** loss

$$g(z) = \frac{1}{1+e^{-z}}$$

$$Loss = (Y)(-log(Y_{pred})) + (1-Y)(-log(1-Y_{pred})$$

Remains when Y = 1

Removed when Y = 0

Remains when Y = 0

Removed when Y = 1

Unique pathology → **SoftMax activation** → **Cross-entropy** loss

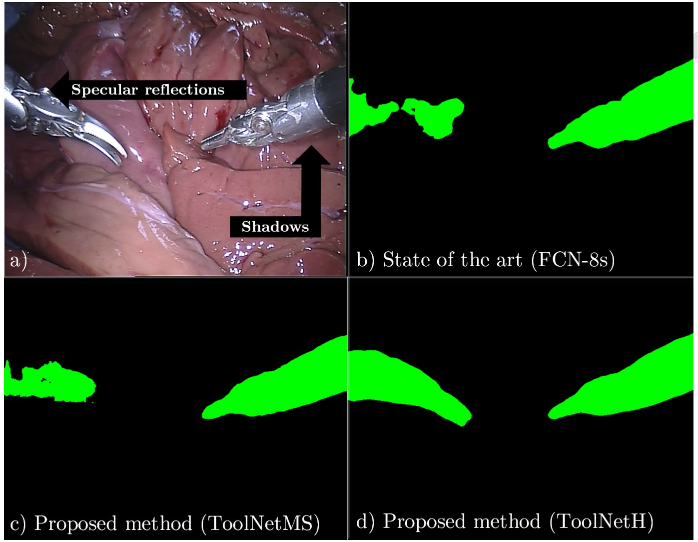
$$\mathrm{softmax}(y)_i = \frac{\exp(y_i)}{\sum_j \exp(y_j)}$$

$$L_{\text{cross-entropy}}(\hat{\mathbf{y}}, \mathbf{y}) = -\sum_i y_i \log(\hat{y}_i)$$

Segmentation

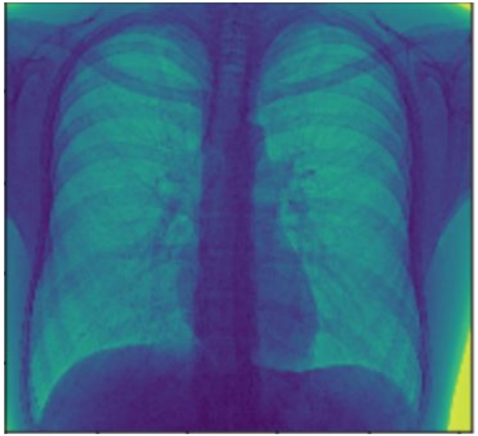
Medical need

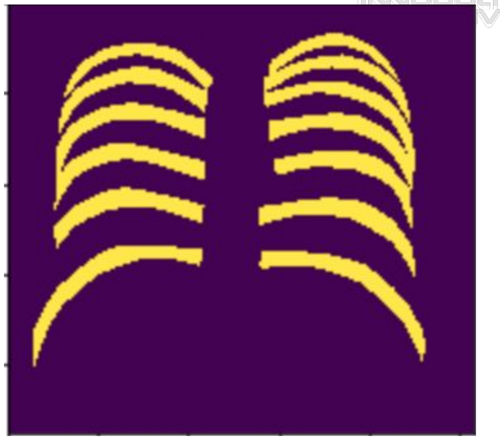
- Segmentation of organs and human body parts is used by doctors during the planning of surgeries.

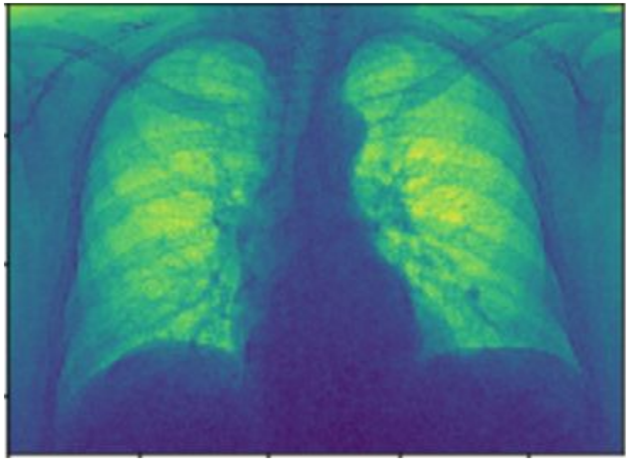


- It also allows us to automatically estimate the volume of organs (e.g. heart, lungs on a 3D study), which is useful to detect some pathologies.

Input and Output formats







X-ray segmentation datasets

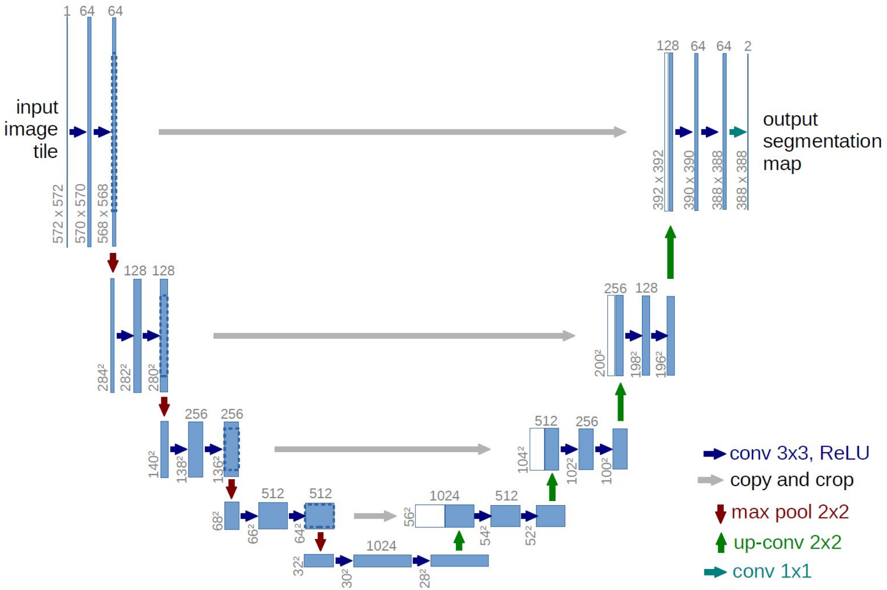
Link	# of samples	access	Annotation method	annotation type
JSRT	~250	by request	manually	lung masks
SIIM ACR Pneumothorax Segmentation	12k	public	manually	pathology masks

DL formalization

Input tensor shape: **(Height, Width, Channels)**

Output tensor shape: **(Height, Width, # of classes)**

Architecture



Activation →

- Sigmoid
- pixel-wise SoftMax

Loss →

- Cross-entropy
- Dice

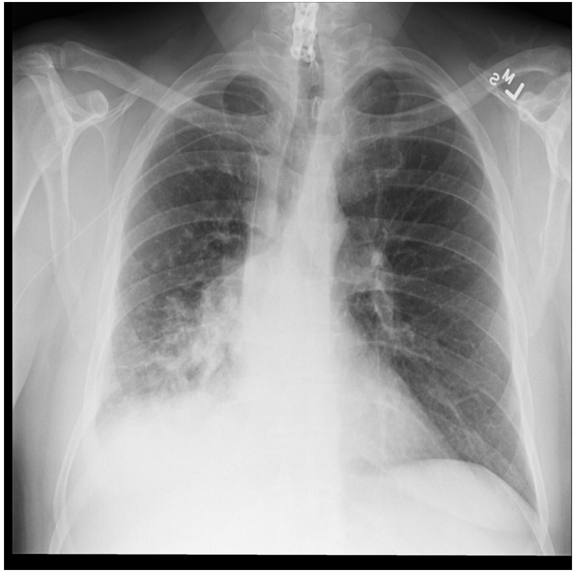
$$DSC = \frac{2|X \cap Y|}{|X| + |Y|}$$

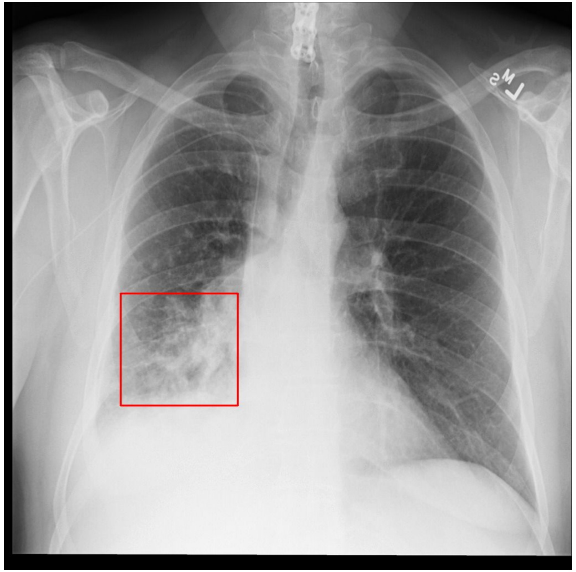
Object detection

Medical need

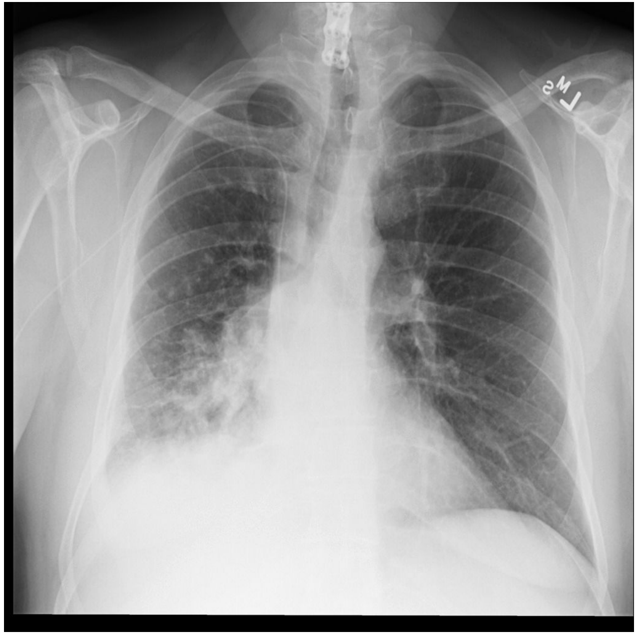
- Localization of the pathology on the X-ray helps to convince doctors in the results of AI

- Detection of Pneumonia

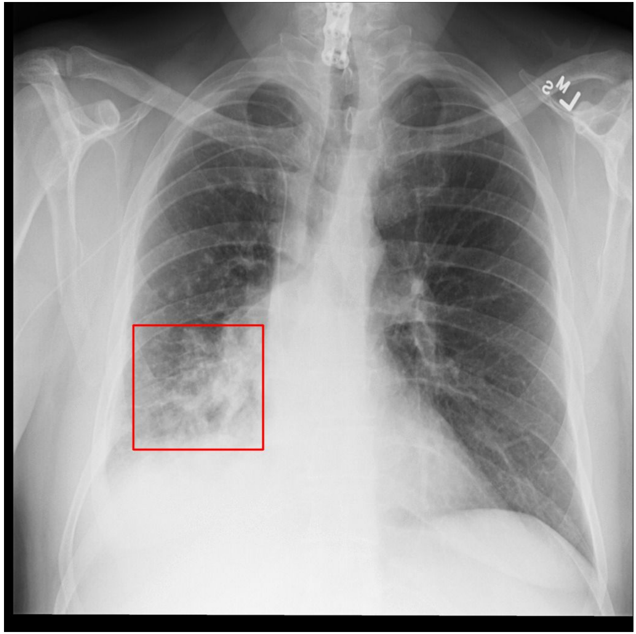




Input and Output formats



y = [Pc , Bx ,By ,Bh ,Bw ,c]



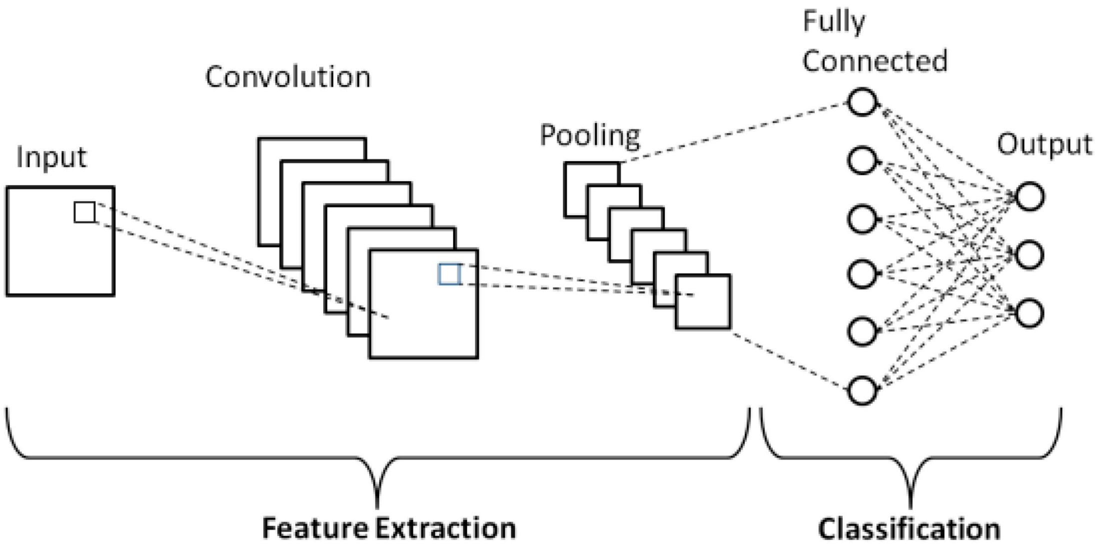
X-ray Object detection datasets

Link	# of samples	access	Annotation method	annotation type
JSRT	154	by request	manually	Circle around nodule
Chest14	79	public	_	Bbo around nodule
RSNA Pneumonia Detection Challenge	26k	public	manually	Bbox around Pneumonia region

DL formalization

Input tensor shape: **(Height, Width, Channels)**
Output tensor shape: **(# of Boxe, 4, 2)**

Architecture



Activation →

- Sigmoid
- ReLU
- Tanh

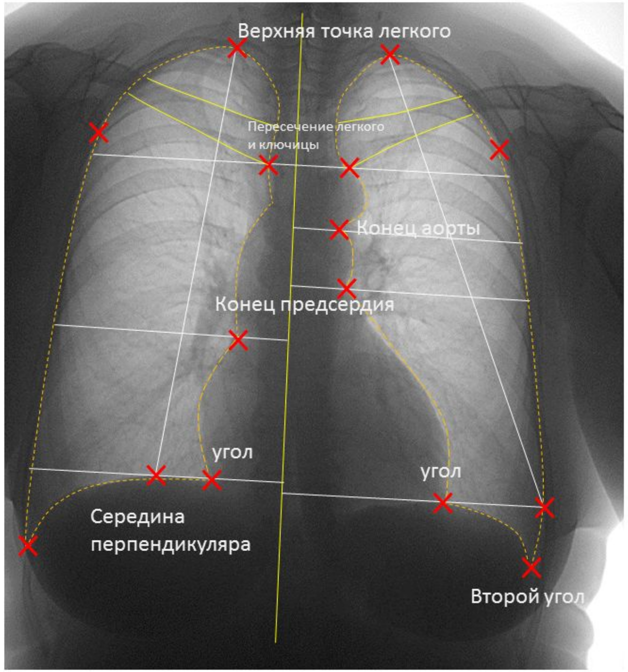
Loss →

- MAE
- MSE
- Wing Loss

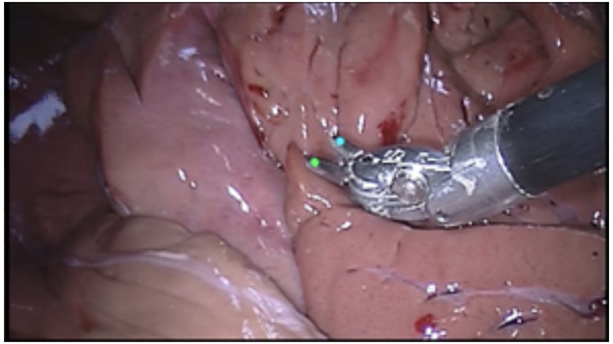
Landmark detection

Medical need

Cardiometry



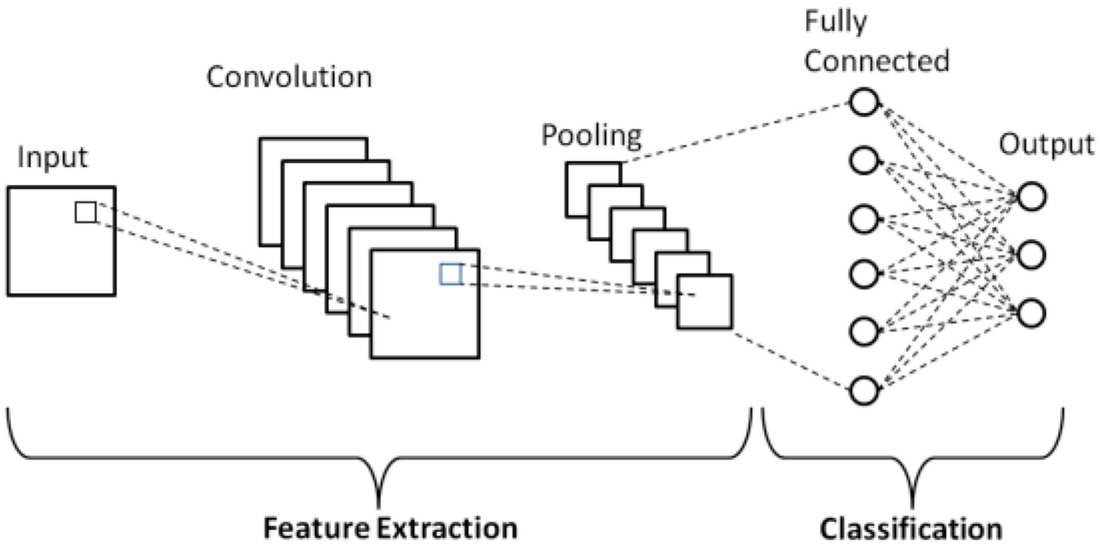
Detection of surgery instrument heads



DL formalization v1

Input tensor shape: **(Height, Width, Channels)**
Output tensor shape: **(# of Points, 2)**

Architecture



Activation →

- Sigmoid
- ReLU
- Tanh

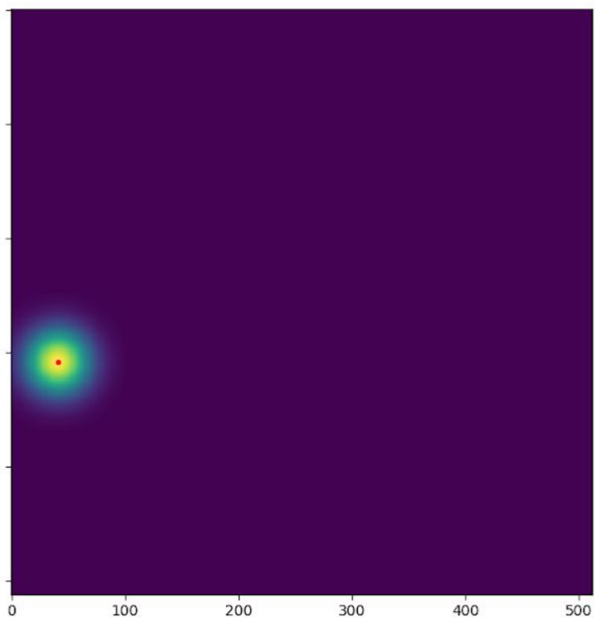
Loss →

- MAE
- MSE
- Wing Loss

DL formalization v2

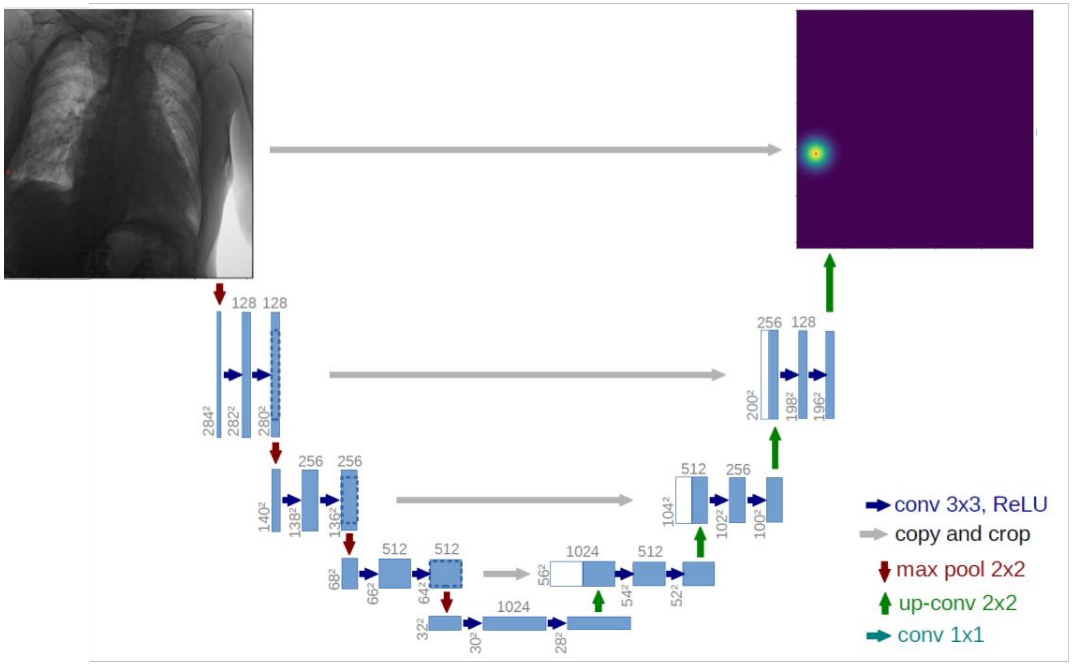
Input tensor shape: **(Height, Width, Channels)**

Output tensor shape: **(Height, Width, # of Points)**



DL formalization v2

Architecture



Activation →

- Sigmoid
- ReLU
- Tanh
- SoftMax 2D

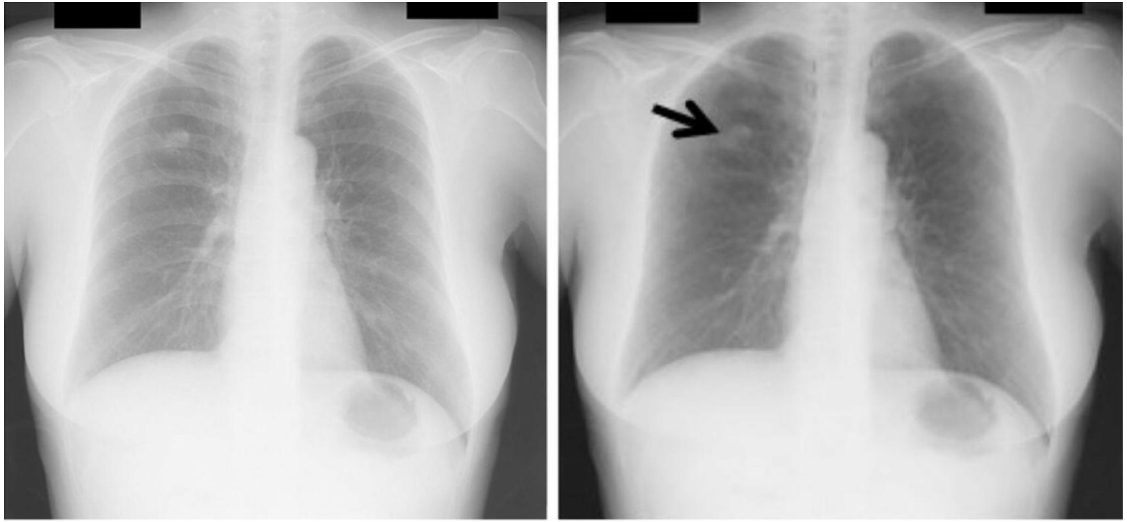
Loss →

- MAE
- MSE
- Wing Loss

Image generation

Medical need

- Removal of redundant image parts
  (e.g. bone suppression)



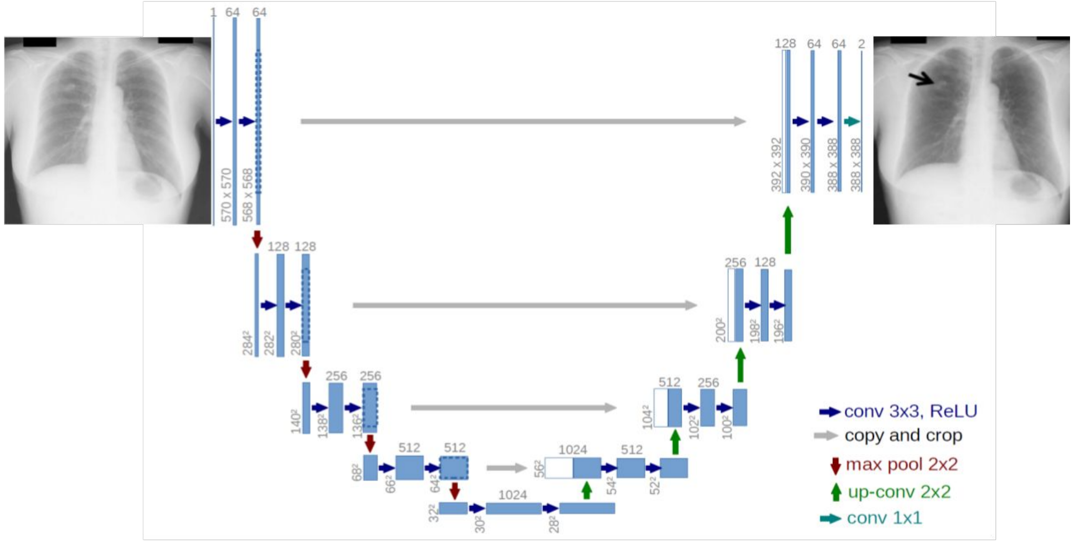
- Generation of pathologic images
  (to address dearth of data in medical imaging)

DL formalization

Input tensor shape: **(Height, Width, Channels)** = image

Output tensor shape: **(Height, Width, Channels)** = image

Architecture



Activation →

- Sigmoid
- Tanh
- ReLU

Loss →

- MSE
- MAE
- SSIM (MS-SSIM)

Quiz

Спасибо за внимание

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