

# Co.R.S.A

Covid Radiographic imaging System based on AI

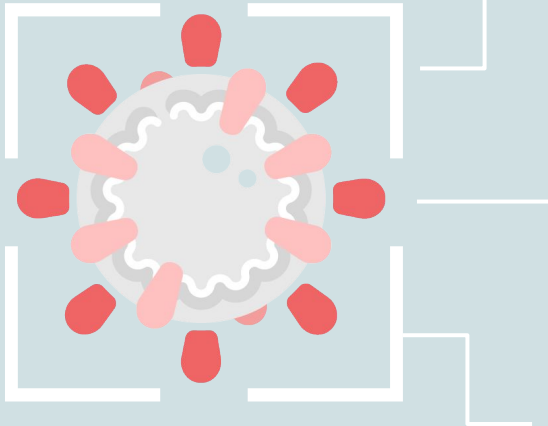
# Le basi dell'Intelligenza Artificiale

Deep Learning applicato al medical imaging

Dissemination event, 10 marzo 2023, Pinerolo



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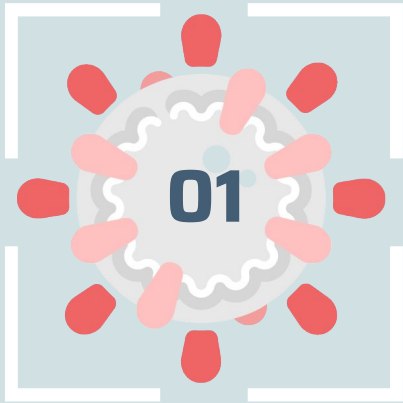
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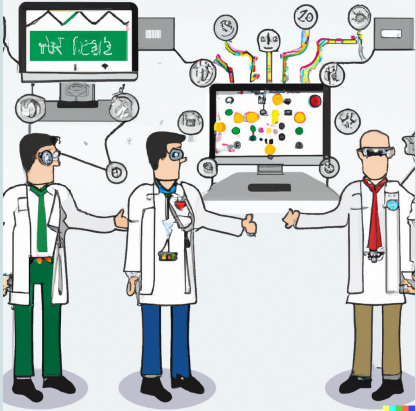
Detection from CXR: dataset, trust and explainability



# AI primer

Introduction to Deep Learning in  
medical imaging

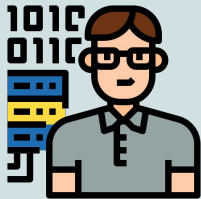
# Actors in the play



Methods&tools



Challenges



# Feature Engineering

## Challenge

Data samples



Problem understanding and method mapping

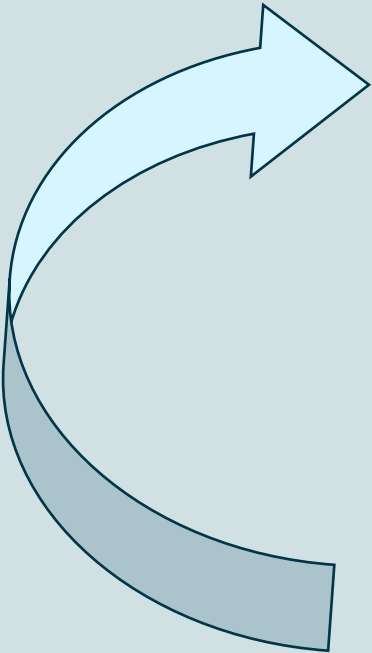


Tool/model selection based on target features



Development and validation



# Learning based approach



**Challenge**



Data

-  Problem understanding and method mapping
-  Dataset
-  Model selection & training
-  Development and validation



# Magic and Threats

- Deep learning is
  - Powerful and **general method**
  - Maps **knowledge** on complex model **through data**
  - Can **tackle ill-posed problem** (missing data, noise, high dimensionality, etc.)



# The Co.R.S.A. Challenge

- Challenge: can we detect Covid-19 from simple CXR imaging?
- Supervised learning approach



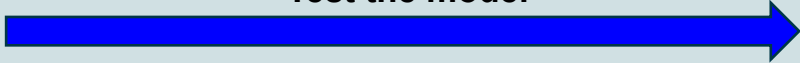
Large labeled image dataset

Deep Learning:  
Convolutional layers + neural classifier

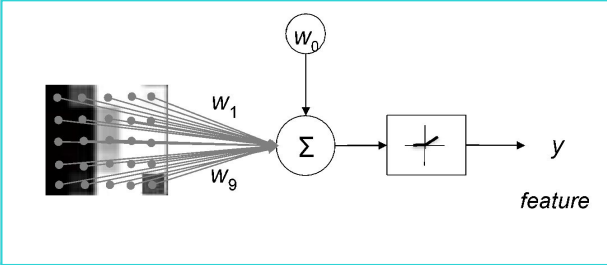


# Deep Learning for dummies (supervised)

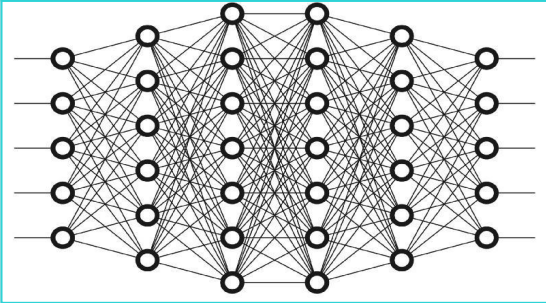
Test the model



Data & labels



Target output & Loss function

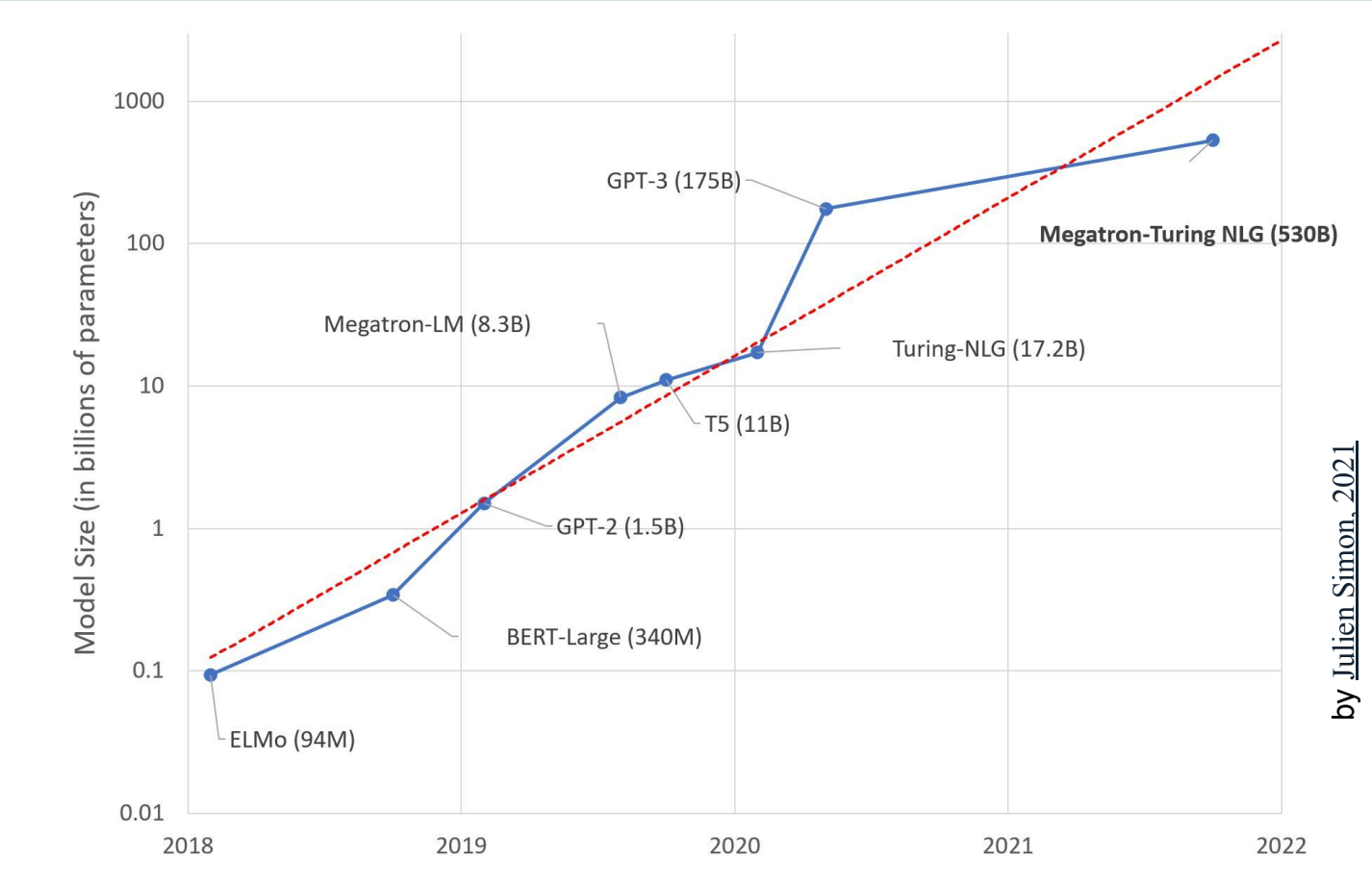


Improve the model



### Parameter count of ML systems through time



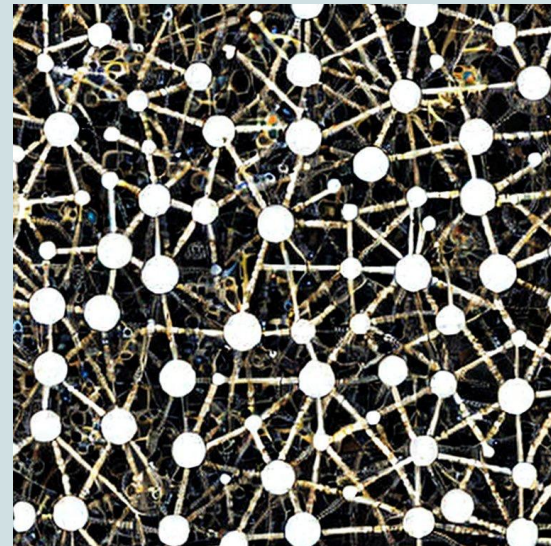


by Julien Simon, 2021



# What it is

- **IS powerful**: allows one to train huge models (billions of parameters)
- **IS general**: can extract knowledge directly from examples
- **IS** getting momentum in **medical imaging** (unsupervised learning, generative models, multimodal)



# and what it is not

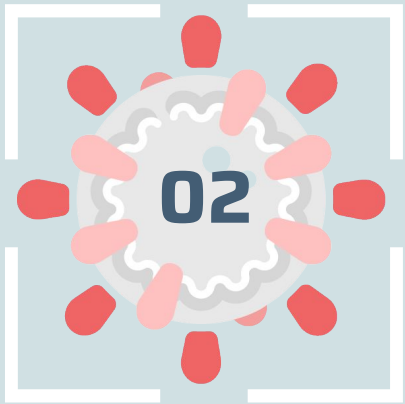


- **is NOT intelligent:** dataset shall be balanced, learn by examples ( with random sampling)
- **is NOT** guaranteed to be explainable (**trust**)
- **is NOT** guaranteed to generalize well (**robust**): biases and collateral learning can limit the learning, new data can cause catastrophic forgetting



# A receipt

- Spend as **much time** as needed to **define/understand the challenge**
- **Data collection**
  - consider all possible correlated/potentially useful information
  - beware biases (age, gender, acquisition method, etc.)
- Importance of **preprocessing/quality of data** (especially on small dataset)
- Discuss and **refine obtained metrics**
- **Inspect** (try to understand, to constrain) **extracted features**
- Exploit learning complexity to unveil unexpected phenomena **challenging prior assumptions**
- **Public dataset** & GDPR and ethical issues



# Lung nodules segmentation

Deep learning for lung nodules segmentation in CT scans



# DeepHealth UC4: A successful collaboration



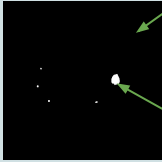
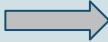
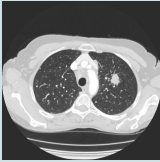
DEEPHEALTH

SALENTO SCIENTIA

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Città della Salute e della Scienza di Torino

di.unito.it

DIPARTIMENTO DI INFORMATICA  
UNIVERSITÀ DEGLI STUDI DI TORINO



background

tumor mass

[https://zenodo.org/record/5797912#.Y\\_uoztLMJhE](https://zenodo.org/record/5797912#.Y_uoztLMJhE)

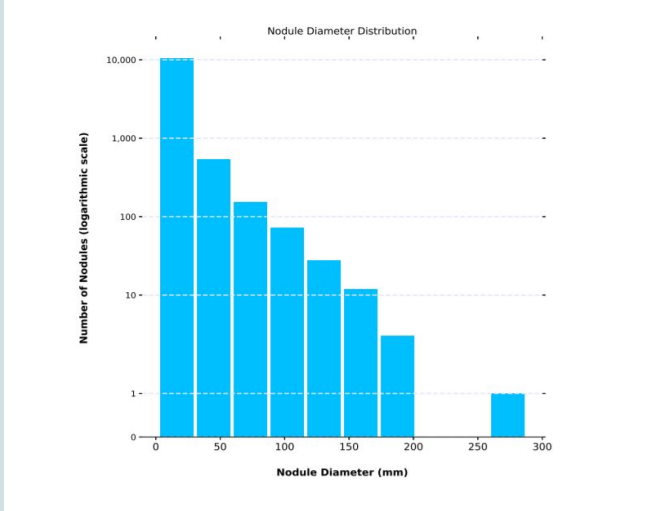




# UniToChest

Attribute	Category	Number of nodules
Nodule diameter	< 03mm	96
	< 10mm	4321
	< 30mm	6031
	> 30mm	847
Splits	Training	9823
	Validation	483
	Test	990
Total		11295

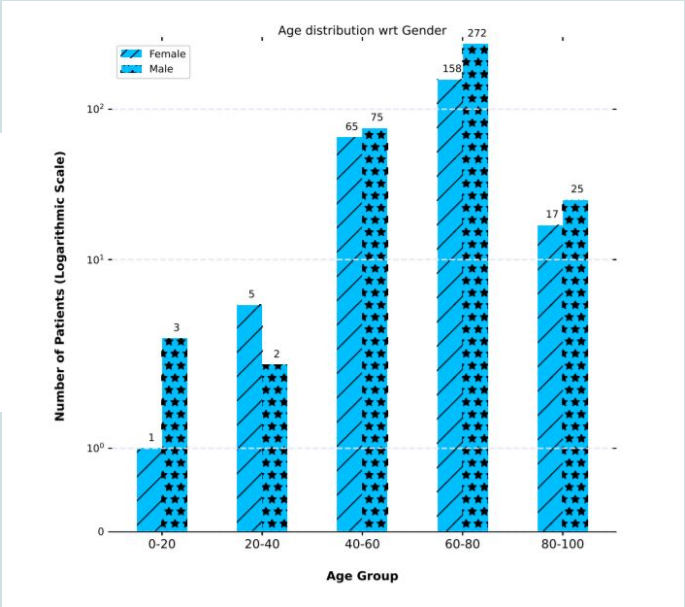
UnitoChest nodules distribution



# UniToChest

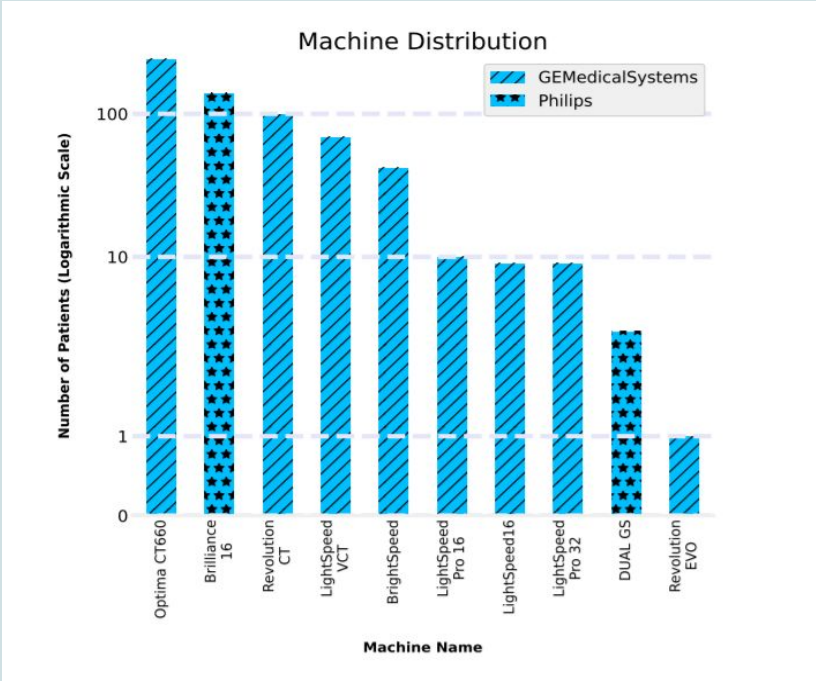
Splits	Number of Patients	Male	Female	Average Age
<i>Training</i>	498	303	195	66
<i>Validation</i>	62	39	23	68
<i>Test</i>	63	35	28	65
Total				623

UnitoChest dataset population

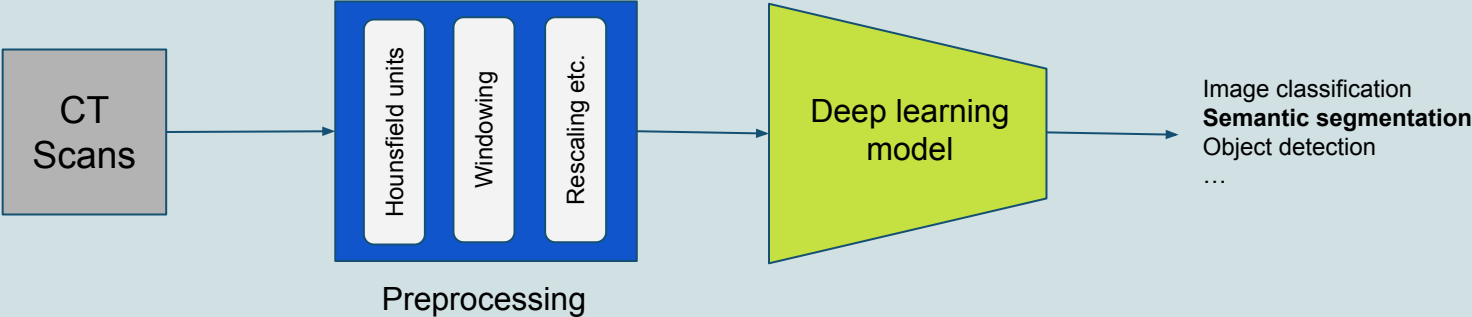


# UniToChest

Robustness to the biases of CT acquisition machines

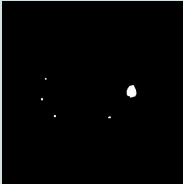
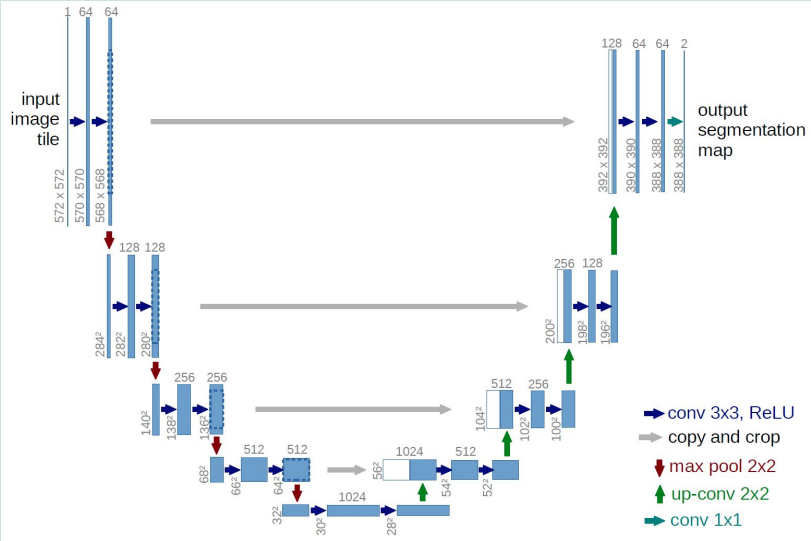
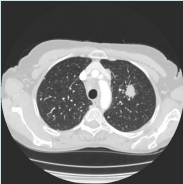


# Pipeline



# AI Model

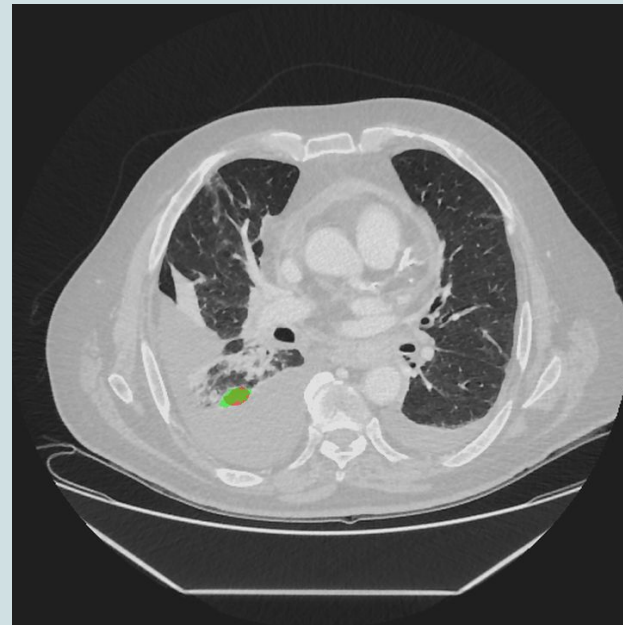
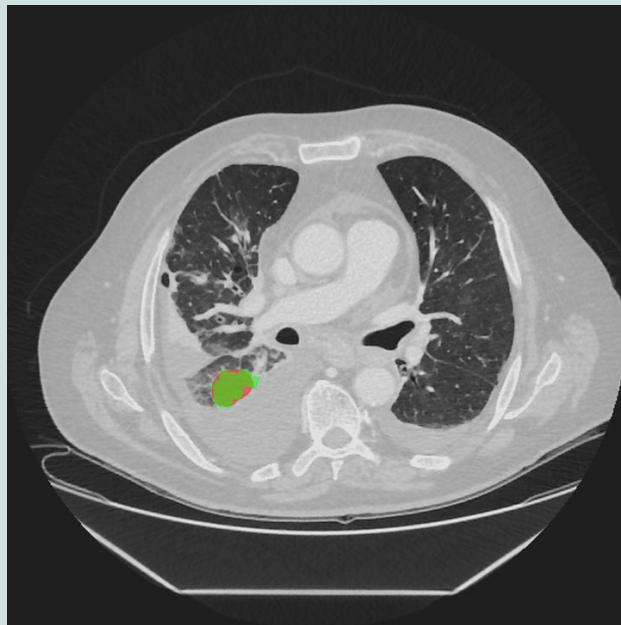
Model presented in 2015 ([pdf](#)) for biomedical image segmentation (UNet-2D).



# Results

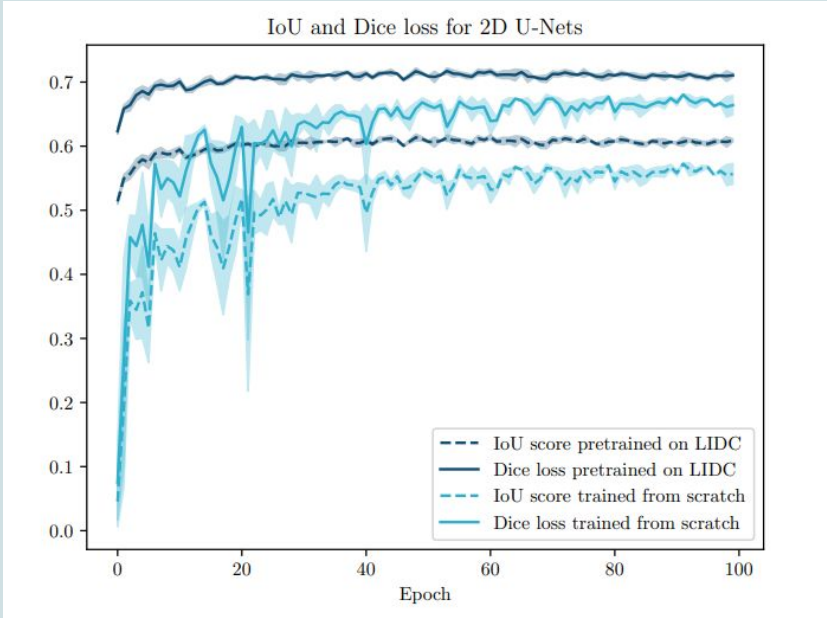
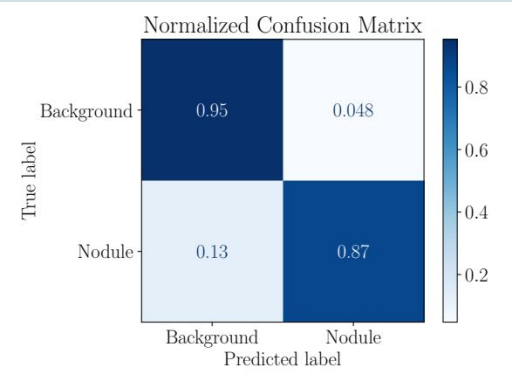
Ground truth

Prediction



# Results

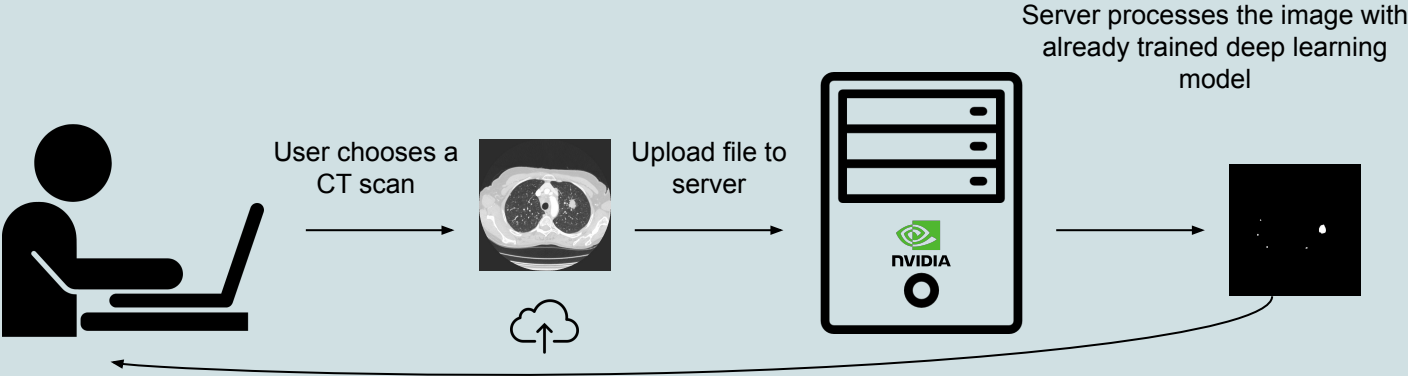
	Trained	Input size	Dice Score	IoU
UNet-2D	from scratch	512x512	0.70	0.59
UNet-2D	pretrained on LIDC	512x512	0.73	0.62



Paper: [https://link.springer.com/chapter/10.1007/978-3-031-06427-2\\_16](https://link.springer.com/chapter/10.1007/978-3-031-06427-2_16)



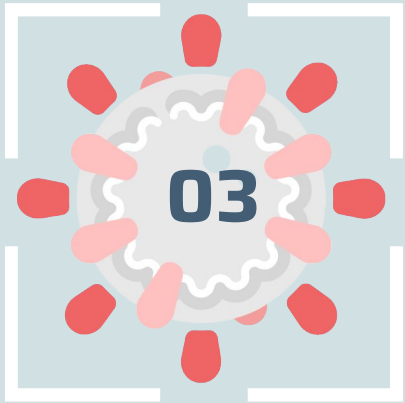
# How AI can help radiologists?



The output mask with lung nodules segmented is returned to the user







# COVID detection

The Co.R.S.A. challenge:  
dataset, trust,  
interpretability

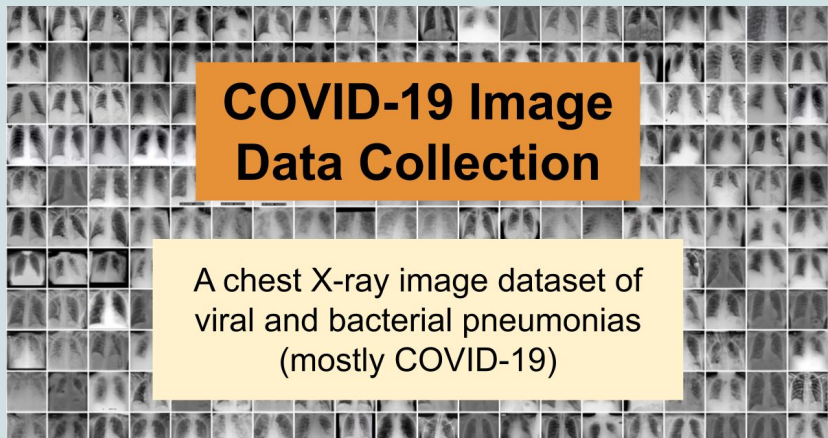


# Imaging, AI and COVID-19

A step back in time ...to ~Sept. 2020

- 28M+ cases worldwide
- RT-PCR as golden standard
- Chest X-Ray (CXR) less sensitive than CT, but easier to deploy
- CXR often used in practice for preliminary screening

# Early efforts to build datasets (< 2020)



**CORDA: Covid Radiographic images Data-set for AI**  
Collaboration with *Città della Salute e della Scienza* and *San Luigi Gonzaga*

- 898 CXRs on patients with fever or respiratory symptoms
- Virus testing to determine COVID infection
- Collected in March and April 2020 (peak of the epidemic in Italy)



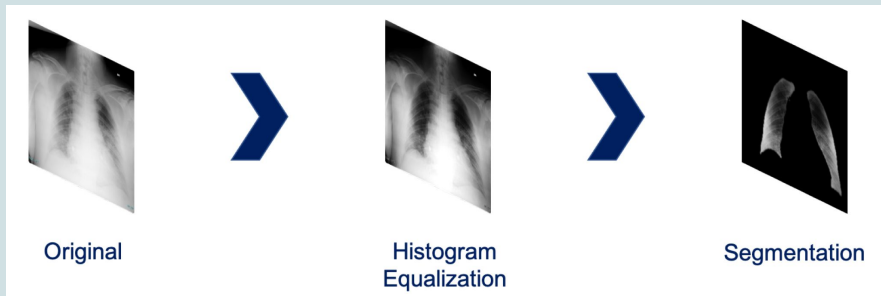
**Covid19-CXR:** Around 100 images at the time (public); gathered from research articles and public sources - *Cohen et al.*

<https://github.com/ieee8023/covid-chestxray-dataset>

**CORDA** (1st iteration): Largest dataset at the time ~900 CXRs; gathered directly from hospitals in Piedmont; however private at the time

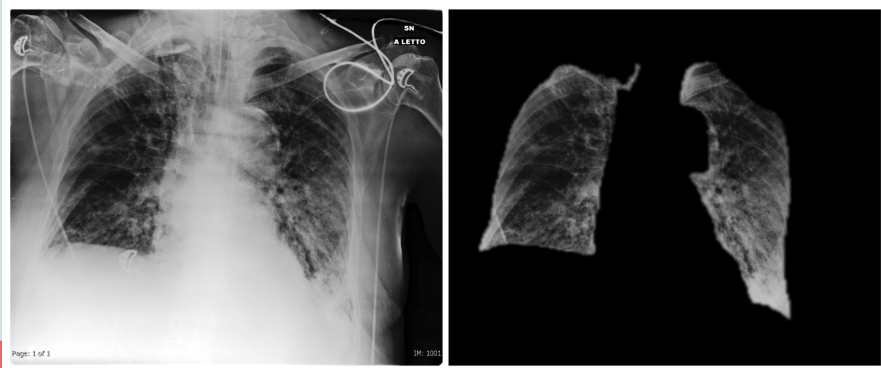
# AI Pipeline

## Preprocessing



Preprocessing ensures that all images are coherent with each other (e.g. histogram normalization). This helps the neural network to converge faster.

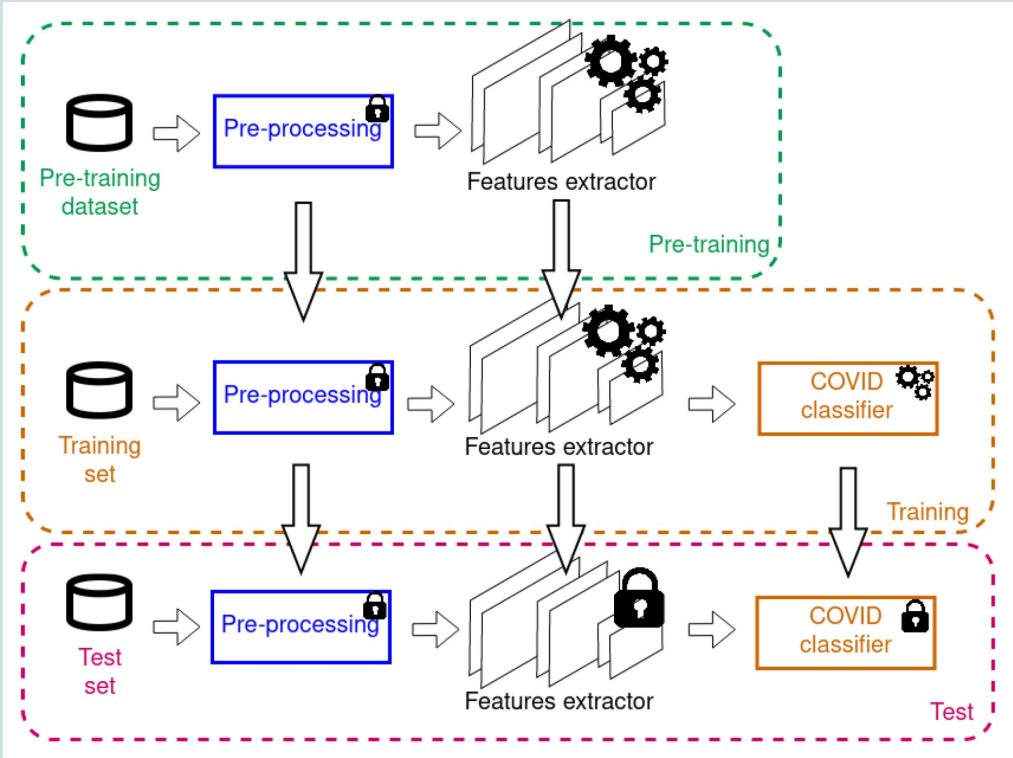
Preprocessing helps in removing noise in the data



Data anonymization is also usually performed as first step

Other operations such as **lungs segmentation** can be used to partially remove polarizing features from the image (e.g. biases such as medical devices and text)

# AI Pipeline



# The problem with small datasets - Biases

New data (>= 2020)



Mostly covid-19 positives

Previously available data (< 2020)

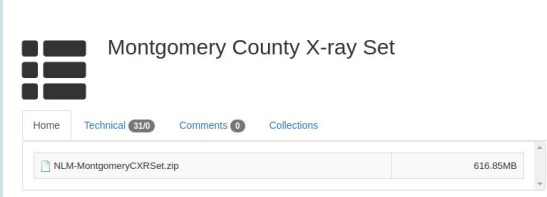
**Brief Report**

**Two public chest X-ray datasets for computer-aided screening of pulmonary diseases**

Stefan Jaeger<sup>1</sup>, Sema Candemir<sup>1</sup>, Sameer Antani<sup>1</sup>, Yi-Xiang J. Wang<sup>2</sup>, Pu-Xuan Lu<sup>3</sup>, George Thoma<sup>1</sup>

<sup>1</sup> Lister Hill National Center for Biomedical Communications, National Library of Medicine, National Institutes of Health, Bethesda, MD 20894, USA; <sup>2</sup> Department of Imaging and Interventional Radiology, Prince of Wales Hospital, The Chinese University of Hong Kong, Shatin Hong Kong, SAR, China; <sup>3</sup> Department of Radiology, The Shenzhen No. 3 People's Hospital, Guangdong Medical College, Shenzhen 518020, China

All negatives



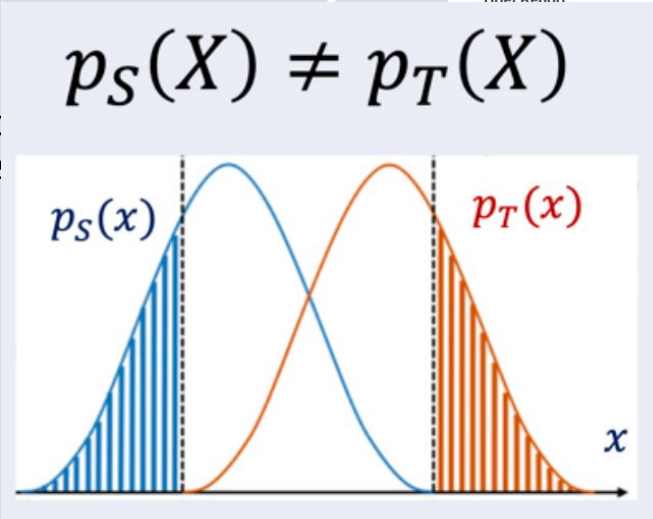
# The problem with small datasets - Biases

New data (>= 2020)

Previously available data (< 2020)



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po



Brief Report

ray datasets for computer-aided screening of pulmonary diseases

ir<sup>1</sup>, Sameer Antani<sup>2</sup>, Yi-Xiang J. Wang<sup>2</sup>, Pu-Xuan Lu<sup>3</sup>, George Thoma<sup>1</sup>

Biomedical Communications, National Library of Medicine, National Institutes of Health, Bethesda, MD  
 Imaging and Interventional Radiology, Prince of Wales Hospital, The Chinese University of Hong Kong, Shatin  
 Department of Radiology, The Shenzhen No. 3 People's Hospital, Guangdong Medical College, Shenzhen

Montgomery County X-ray Set

Home Technical 310 Comments Collections

NLM-MontgomeryCXrSet.zip 616.85MB

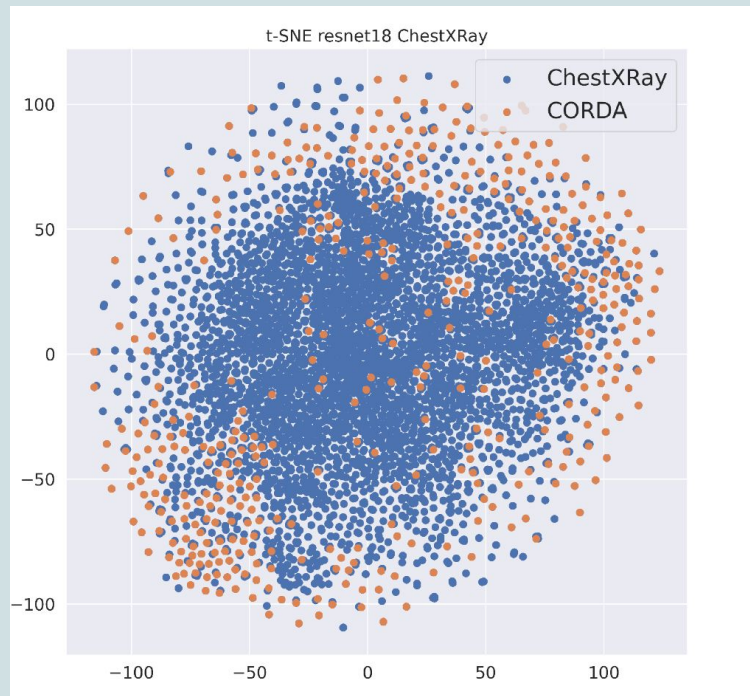


# The problem with small datasets - Biases

The two datasets (e.g. *CORDA* vs *ChestXRay*) are very different, for two reasons:

- Covid19+ vs Covid19- **GOOD**
- Other reasons such as populations (i.e. children vs adults) **BAD**

Deep Learning models are naive: they take the **simplest** solution to the problem

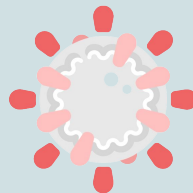




# The problem with small datasets

Despite many works initially claimed detection accuracy of >90%, the real accuracy (BA) is around 67% at max, and the sensitivity is low

Method	Baseline [20]		
<b>Backbone</b>	RN-18	RN-18	RN-18
<b>Classifier</b>	FC	FC	FC
<b>Pretrain</b>	-	RSNA	CXR
<b>Train</b>		CDSS	
<b>Sensitivity</b>	<b>0.56</b>	0.54	0.54
<b>Specificity</b>	0.58	<b>0.80</b>	0.58
<b>BA</b>	0.57	<b>0.67</b>	0.56
<b>AUC</b>	0.59	<b>0.72</b>	0.67



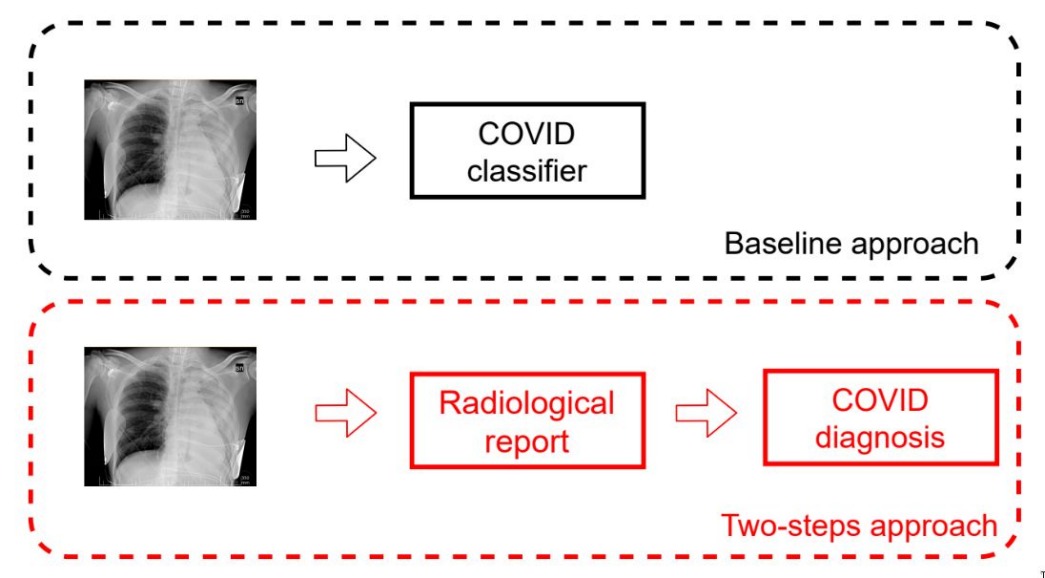
## Takeaway

Direct covid19 diagnosis from CXR is hard with limited data

- Differences in negative vs positive population have a major impact
- Together with the limited number of images, this prevents the model from learning any useful clinical features (e.g. lung pathologies, appearance, etc.)

# Mimicking the radiologist workflow

The direct approach fails to learn relevant features due to lack of sufficient data.



...but if we first explicitly focus on diagnosis objective radiological findings, we might obtain features also relevant for covid-19

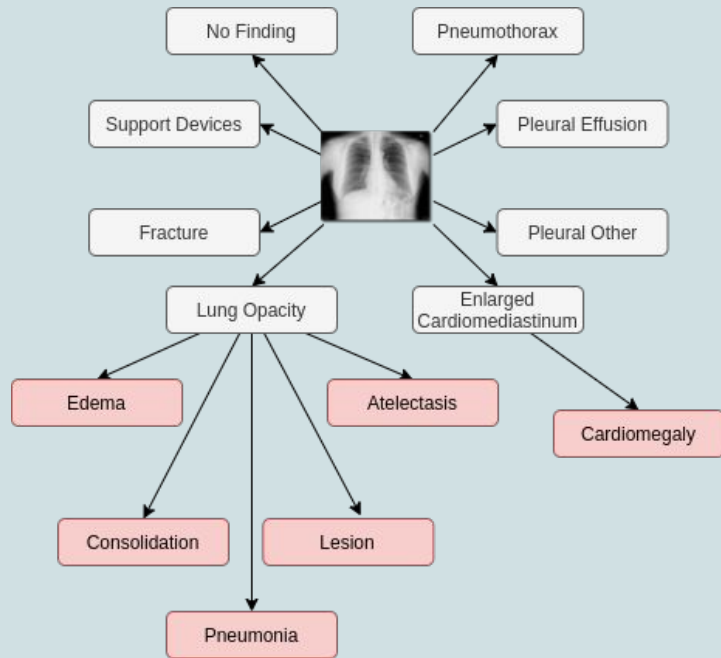
# How to deal with limited data



Some large non-covid dataset exist, e.g. CheXpert, with more than 200k CXR images

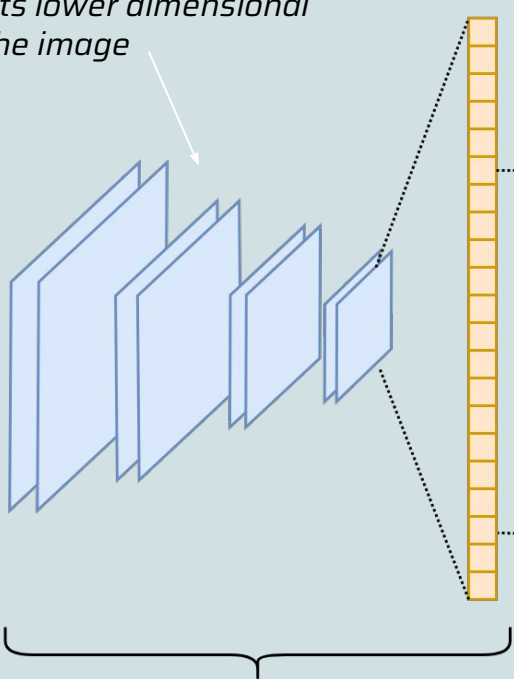
CheXpert is well suited for learning objective radiological findings (e.g. opacity, consolidation, etc.).

The learned knowledge can then be transferred to the smaller covid datasets (*transfer learning*)



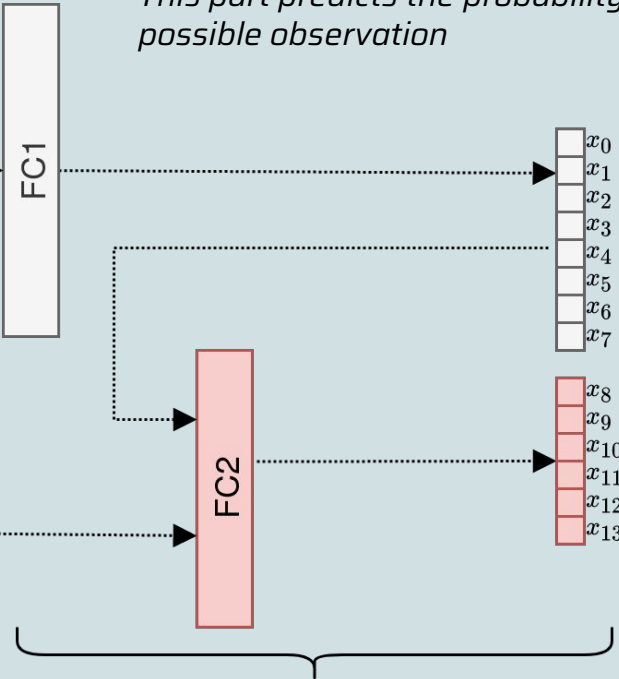
# AI Radiological Report

*This part extracts lower dimensional features from the image*



Encoder

*This part predicts the probability of each possible observation*



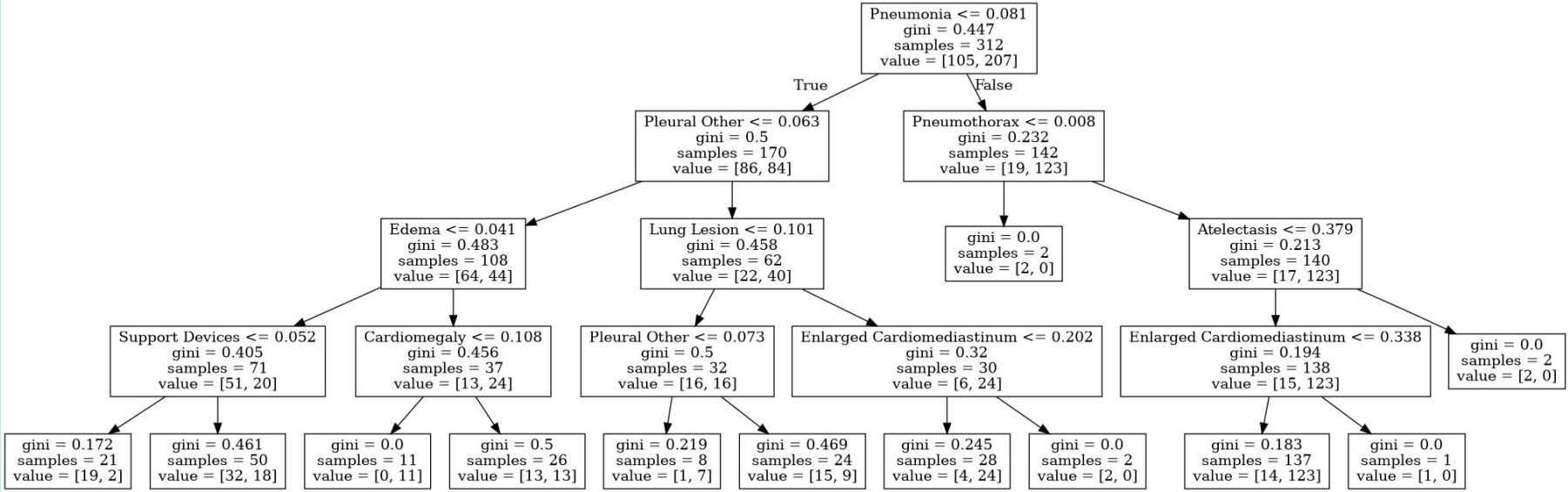
Hierarchical Classifier

- no finding: 1%
- fracture: 2%
- lung opacity: 80%**
- edema: 60%
- consolidation: 70%**
- pneumonia: 70%
- lesion: 60%
- atelectasis: 65%**
- pleural effusion: 55%
- pneumothorax: 35%
- pleural other: 20%
- enlarged cardiom.: 40%
- cardiomegaly: 20%



# Covid-19 diagnosis from report

The AI radiological report can be used to predict the presence of Covid-19. For full explainability, a decision tree (a type AI model) can be employed



# Covid-19 diagnosis from report

With this approach, we are able to improve the results significantly

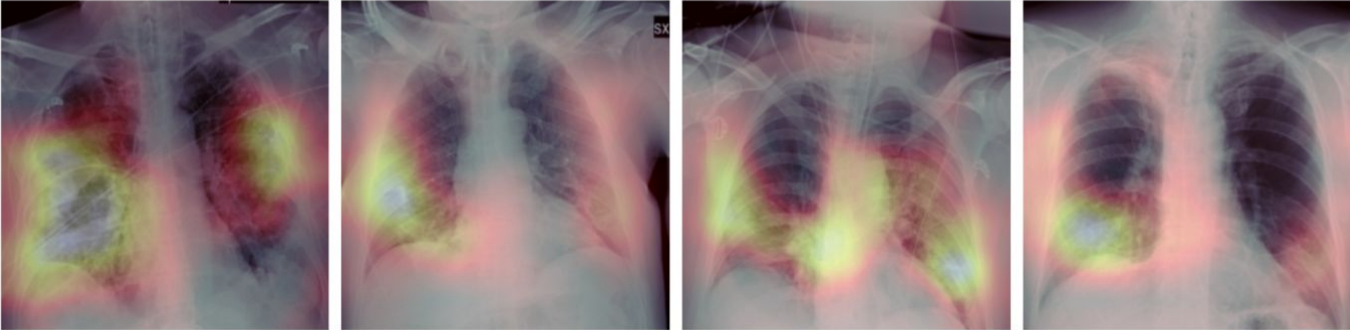
- Previous accuracy 67%, sensitivity 56%
- Improved accuracy **75%** sensitivity **77%**

*With slightly more sophisticated models we achieve:*

- Accuracy 81% sensitivity 79%

# Interpreting AI predictions

- Other than the final covid diagnosis, with this approach we provide the **AI radiological report** which can explain the final decision (at least partially), and provide useful information to the clinician
- We can also visualize which region of the image influenced the most the decision process





# The CORDA data release

The CORDA dataset has since been publicly released, and is now available on Zenodo!

<https://zenodo.org/record/7501816#.ZAeAv9LMJhE>

The kept growing in size and now contains:

- 3000+ images (both CXRs and CTs)
- 4 participating hospitals (mauriziano, molinette, san luigi, monzino)
- **!! IMPORTANT: All images have been anonymized before sharing !!**



More information can be found on the CoRSA website: <https://corsa.di.unito.it/>

# Thanks

**Do you have any questions?**

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[carlo.barbano@unito.it](mailto:carlo.barbano@unito.it)



<https://github.com/EIDOSLab>