xLungs

Lungs vector representations

MI²DataLab Winter Seminar 2022

MI

Agenda

- **Lungs CT** embeddings using **autoencoders**
- **Lungs CT** embeddings using **organs mask**
- **X-Ray** embeddings using **Siamese network**

MI

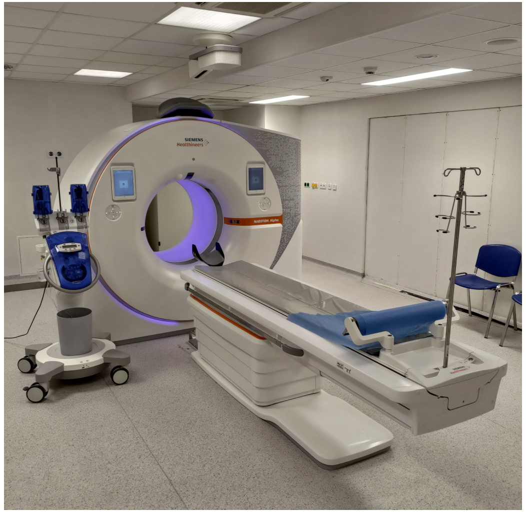
Lungs CT embeddings

using **autoencoders**

MI

Intro to CT scans

A computerized tomography (CT) scan combines a series of X-ray images taken from different angles around your body and uses computer processing to create cross-sectional images (slices) of the bones, blood vessels and soft tissues inside your body.



Challenges with CT scans

In our dataset an average CT scan has size of (500x500x250) and takes around 0.5GB of disk space. And it’s only a single example!

We are unable to train 3D ResNet without resizing CT scans to half of their size.

Some abnormalities can take few voxels which makes it difficult for models to spot them.

Autoencoders

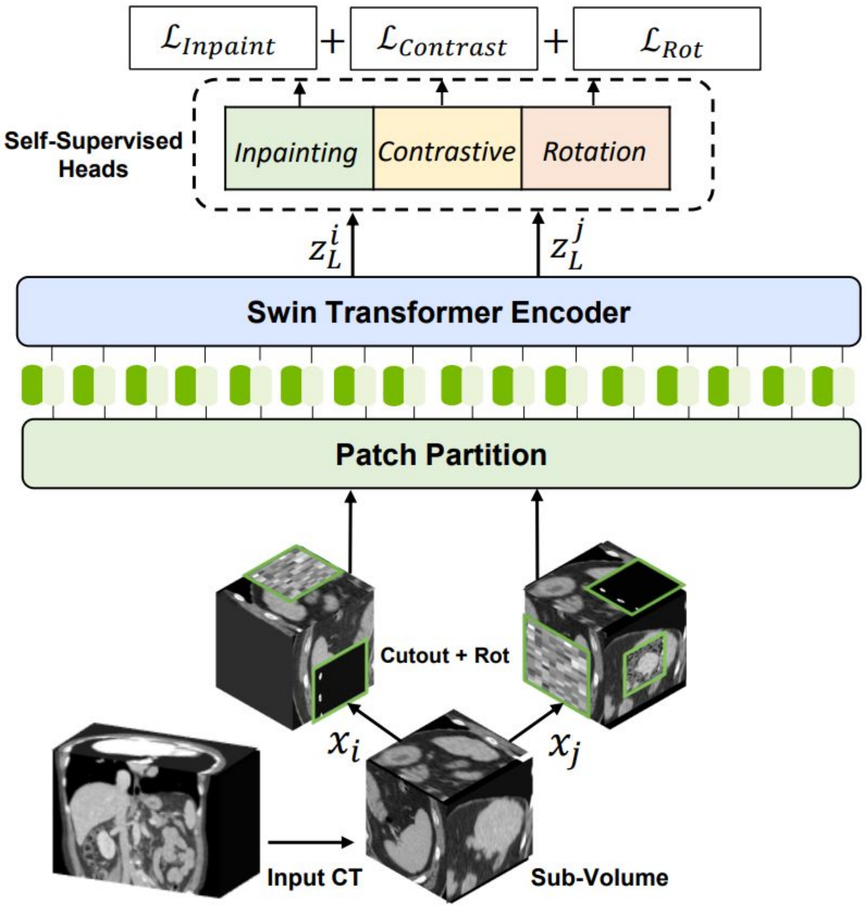
With help of autoencoders we can try to create meaningful embedding of input which is also in a much lower dimension.

Training autoencoders doesn’t require any labeled samples.

Swin-UNETR

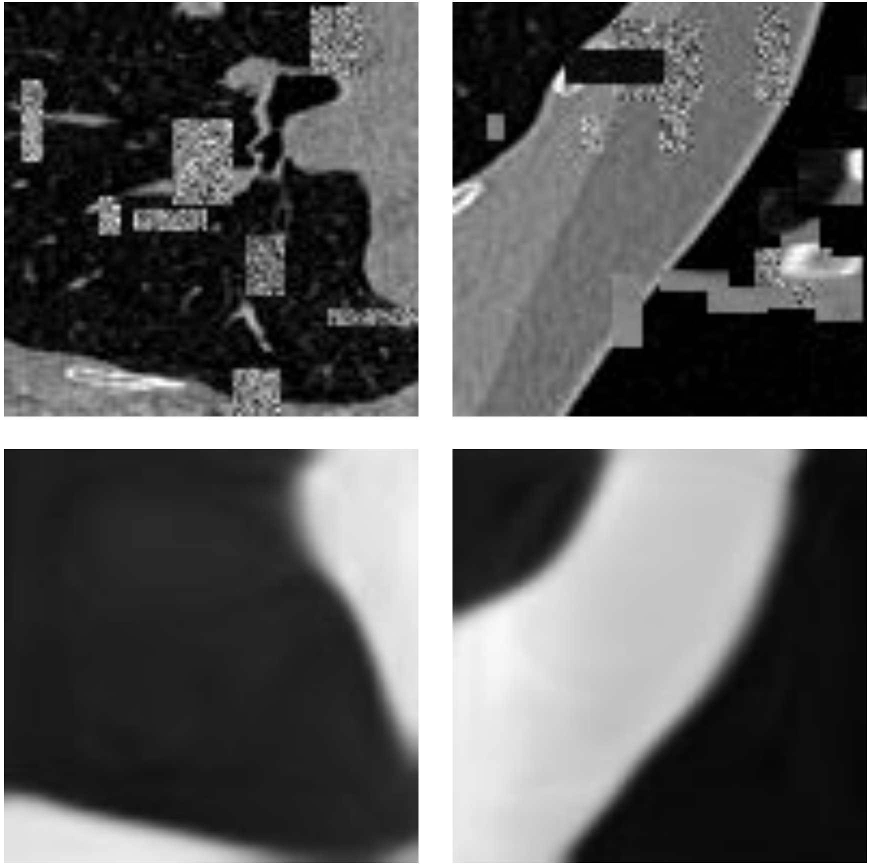
For our problems we trained U-net like transformer architecture. Swin-Unetr is pretrained on multiple losses

- Inpainting
- Constrasive
- Rotation



CT Reconstructions

We can see that reconstructions of CT scans don’t reconstruct details such as alveoli and only focus on shape of a scan.



Embeddings for classification

Guzek

AUC	Accuracy	F1	Kappa	MCC	Prec.	Recall
0.7561	0.7736	0.4928	0.3519	0.3599	0.5865	0.4264

Niedodma lokalna

AUC	Accuracy	F1	Kappa	MCC	Prec.	Recall
0.8092	0.99	0.3388	0.3348	0.3756	0.6091	0.2462

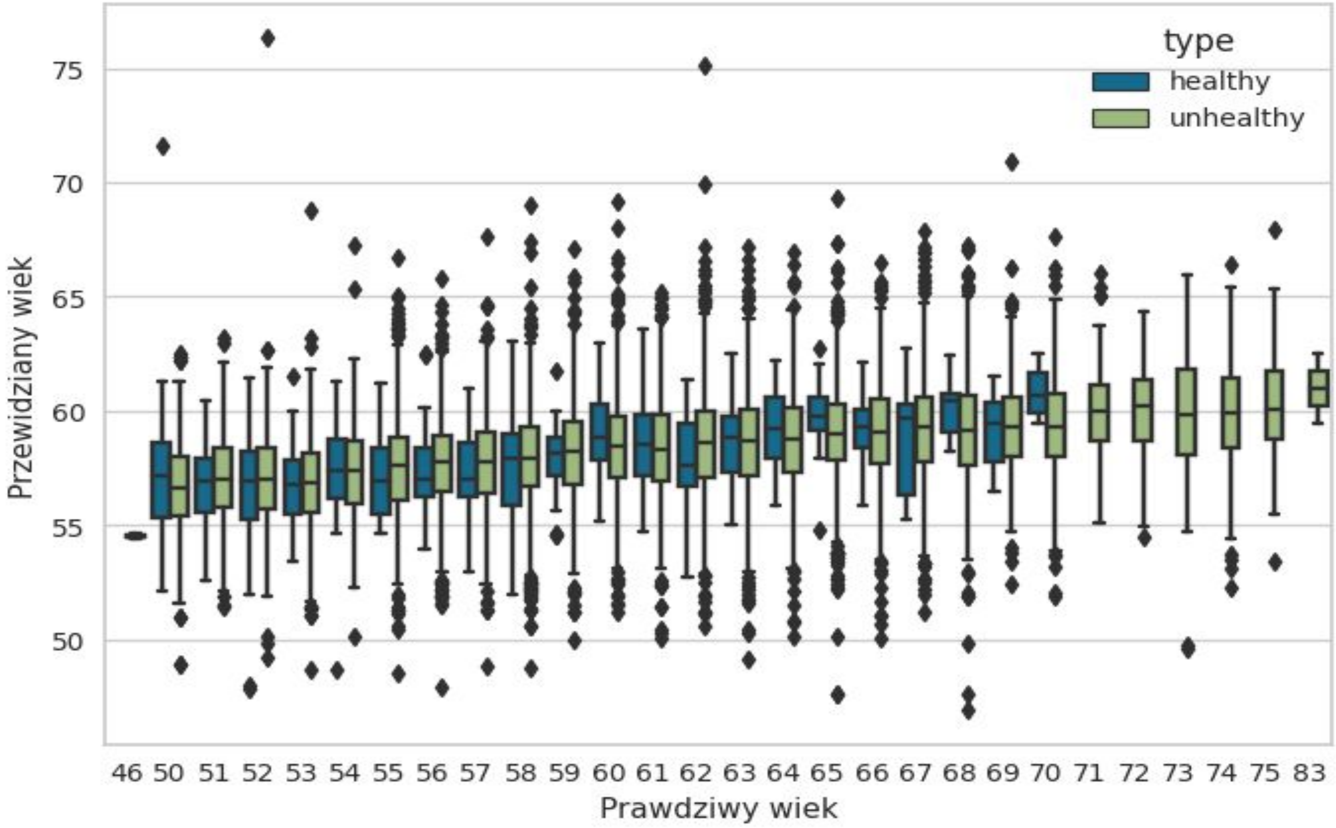
Pogrubienie ścian oskrzeli

AUC	Accuracy	F1	Kappa	MCC	Prec.	Recall
0.7612	0.9121	0.3798	0.3406	0.3768	0.6354	0.2713

Rozstrzenie oskrzeli

AUC	Accuracy	F1	Kappa	MCC	Prec.	Recall
0.8094	0.9591	0.415	0.3972	0.4316	0.6666	0.3049

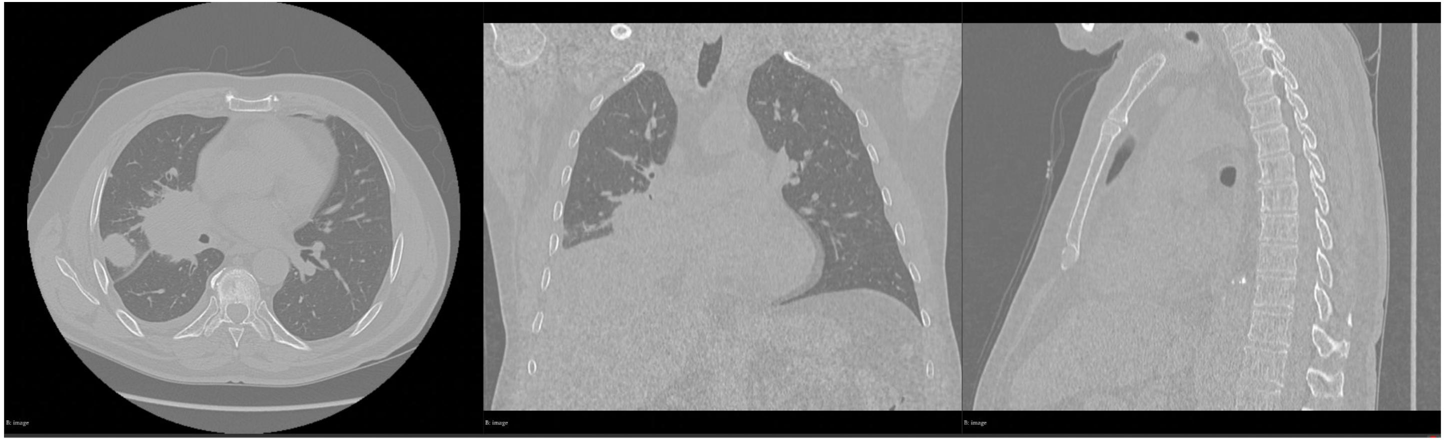
Embeddings for age prediction



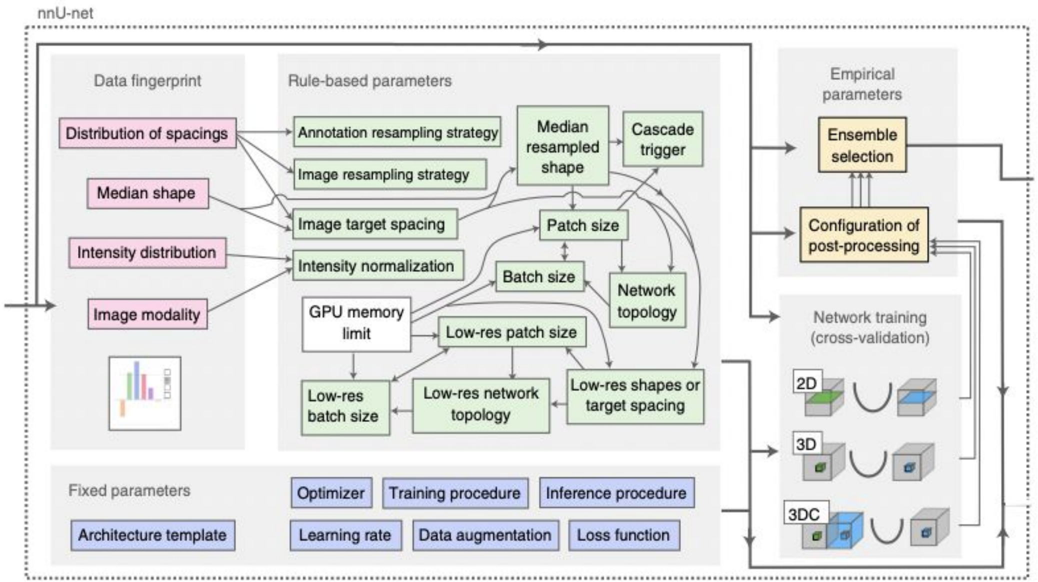
Lungs CT embeddings

using **organs masks**

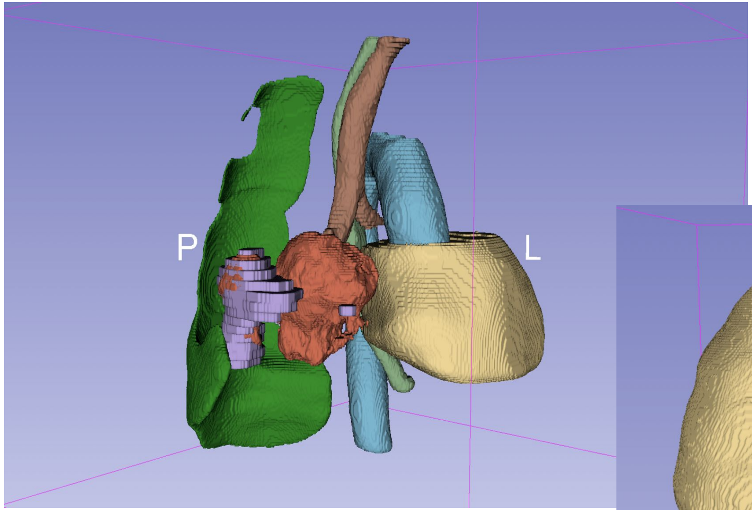
We take a CT scan

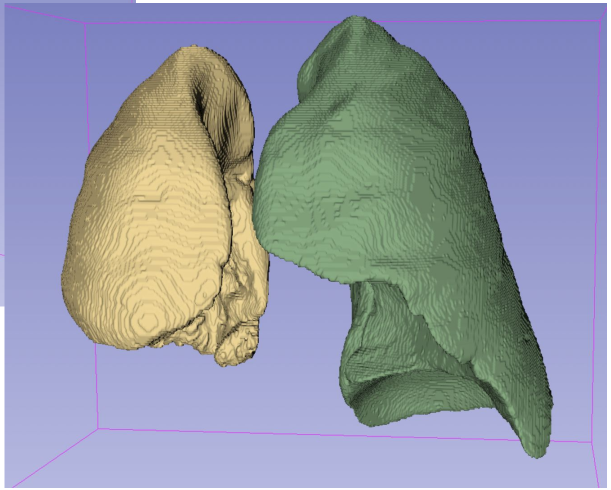


We use it as input to nnU-Net



We obtain segmentation masks for 8 organs





We measure

Volume

Surface area

Dimensions of axis-aligned bounding box

Dimensions of oriented bounding box

We obtain

An interpretable representation of a CT scan consisting of 64 features

And some promising results

	f1	acc	bal_acc	precision	recall
Pleural fluid	0.90	0.96	0.94	0.91	0.90
Air trapping	0.78	0.99	0.92	0.83	0.85
GGO	0.72	0.89	0.85	0.68	0.77
Fibrosis	0.69	0.64	0.67	0.56	0.91
Honeycombing	0.65	0.98	0.99	0.49	1.00
Bone metastasis	0.63	0.98	0.81	0.63	0.63
Bronchiectasis	0.62	0.93	0.83	0.59	0.72
Mass	0.59	0.92	0.85	0.51	0.76
Nodule	0.58	0.57	0.65	0.44	0.88
Emphysema	0.57	0.74	0.74	0.49	0.72
Cardiomegaly	0.57	0.96	0.80	0.61	0.62
Calcification	0.56	0.60	0.68	0.42	0.86
Consolidation	0.55	0.85	0.77	0.47	0.66
Atelectasis	0.51	0.80	0.69	0.60	0.50
Fracture	0.48	0.89	0.74	0.53	0.56
Thickening of bronchial walls	0.45	0.84	0.72	0.40	0.55
Pneumomediastinum	0.44	0.97	0.74	0.45	0.50
Cavity	0.42	0.97	0.74	0.37	0.50
Osteoarthritis	0.41	0.67	0.67	0.30	0.68
Pleural thickening	0.41	0.93	0.72	0.44	0.48
Pericardial effusion	0.39	0.96	0.98	0.25	1.00
Reticular pattern	0.39	0.79	0.76	0.27	0.72
Nodular pattern	0.22	0.83	0.61	0.27	0.38
Pneumothorax	0.11	0.42	0.63	0.06	0.85
Cyst	0.00	0.00	0.00	0.00	0.00

What else can we measure using a CT scan and its segmentation masks?

PyRadiomics

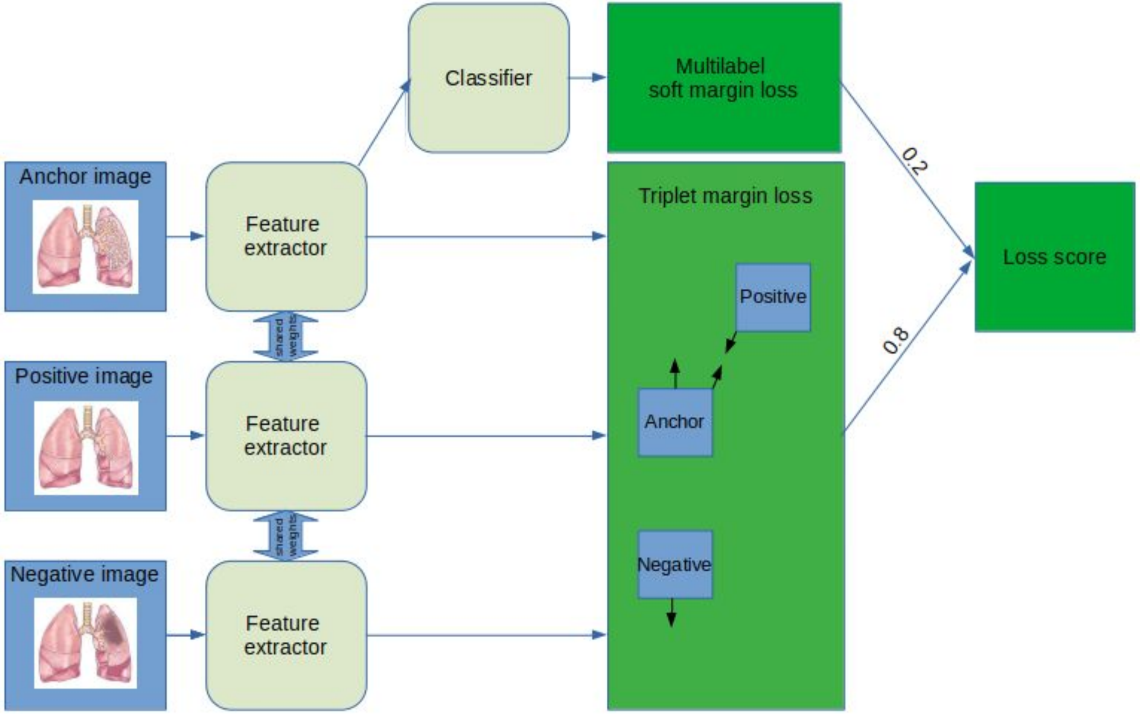
- First order statistics (19 features)
- Shape-based (3D) (16 features)
- Shape-based (2D) (10 features)
- Gray Level Cooccurence Matrix (24 features)
- Gray Level Run Length Matrix (16 features)
- Gray Level Size Zone Matrix (16 features)
- Neighbouring Gray Tone Difference Matrix (5 features)
- Gray Level (5 features) Dependance Matrix (14 features)

~100 features

per object

X-Ray embeddings using **Siamese network**

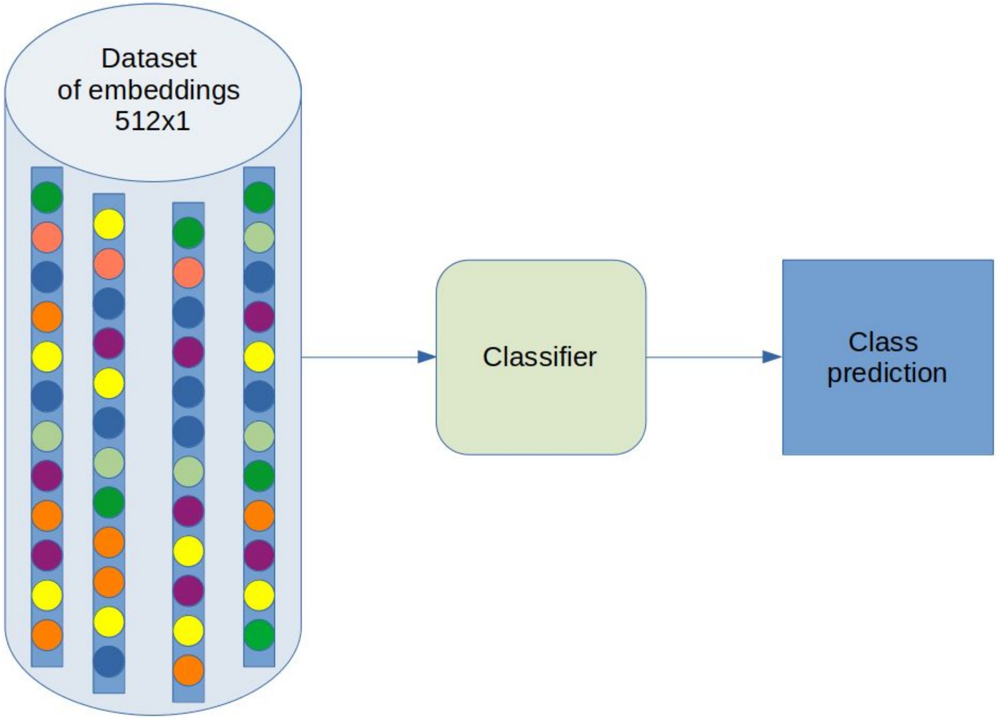
Multi-task siamese network architecture



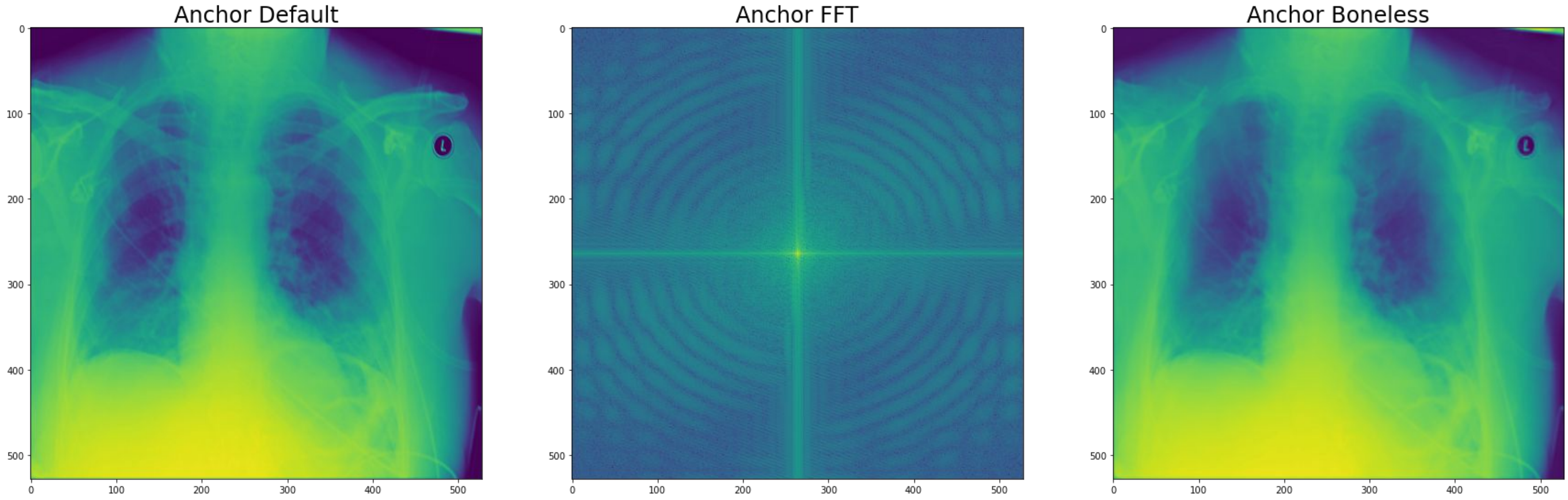
Embeddings

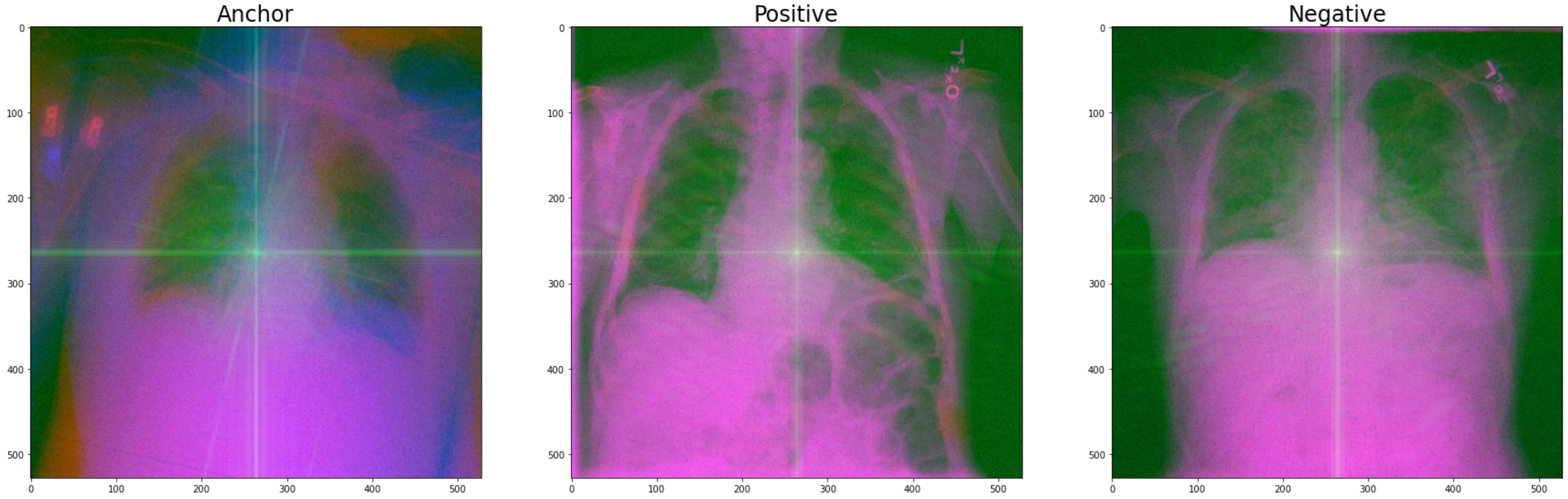
Anchor	class	patient_id	sex	age	projection	0	1	2	3	...	246	247	248	249	250	251	252	253	254	255
NIHCC/raw/images/00001301_012.png	[Edema, Infiltration]	1301	57	F	AP	0.173974	0.074529	-0.047046	-0.092781	...	-0.094285	0.019208	-0.133438	0.059859	0.097254	0.073601	-0.112605	0.066028	-0.036165	-0.016359
NIHCC/raw/images/00001301_013.png	[Infiltration]	1301	57	F	AP	0.162779	0.051648	-0.039454	-0.044978	...	-0.079142	-0.002722	-0.176844	0.074225	0.066215	0.002228	-0.088956	0.026826	-0.012839	-0.050622
NIHCC/raw/images/00017618_031.png	[Mass]	17618	36	M	AP	0.263980	0.088022	-0.071970	-0.106810	...	-0.112654	-0.010609	-0.213591	0.072175	0.112475	0.109974	-0.103658	0.104354	-0.167810	-0.035107
NIHCC/raw/images/00017618_032.png	[Effusion, Mass]	17618	36	M	PA	0.183922	0.007164	-0.102465	-0.093134	...	-0.031587	-0.003246	-0.160646	0.025927	0.212225	0.083053	-0.091072	0.052928	-0.160540	-0.030924
NIHCC/raw/images/00017618_033.png	[Consolidation, Mass]	17618	36	M	PA	0.168860	0.042395	-0.052411	-0.054439	...	-0.044017	-0.051753	-0.180455	-0.025239	0.174075	0.025362	-0.118203	0.026807	-0.082497	-0.021706

What to do with embeddings?



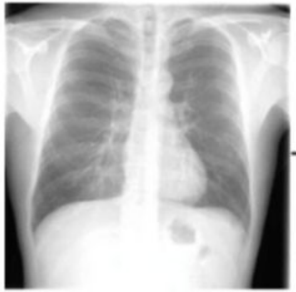
Training images consists of 3 channels

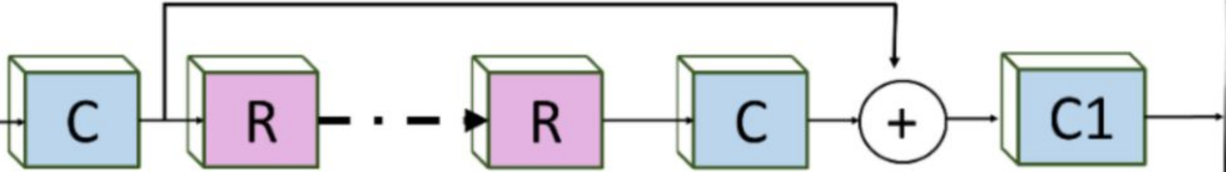



Anchor
Positive
Negative
0
100
200
300
400
500

How to create layer without bones?

ResNet-BS





C - convolutional block (64 filters 3x3)

R - modified ResNet block

Loss function is a combination of:

- MAE (mean absolute error, L1 loss)
- MS-SSIM (multiscale structural similarity index measure)
- PSNR - peak signal-to-noise ratio
- SSIM - similarity index measure

Rajaraman S, Zamzmi G, Folio L, Alderson P, Antani S. Chest X-ray Bone Suppression for Improving Classification of Tuberculosis-Consistent Findings. Diagnostics (Basel). 2021 May 7;11(5):840. doi: 10.3390/diagnostics11050840.

Questions